Palacký University Olomouc
Faculty of Arts
Department of Psychology

VALIDITY OF NON-INVASIVE METHODS FOR MEASURING BEHAVIOURAL AND PHYSIOLOGICAL CHANGES IN DECEPTION DETECTION

Doctoral thesis

Author: **Mgr. Petra Hypšová**

Supervisor: **doc. PhDr. Martin Seitl, Ph.D.**

Olomouc

2025

Acknowledgements

First of all, I would like to express my sincere thanks to my supervisor, doc. PhDr. Martin Seitl, Ph.D. *Martin*, your support, guidance and encouragement throughout my doctoral studies meant – and still means a lot to me. Your thoughtful feedback, constructive criticism and always-positive attitude not only influenced the quality and direction of my research, but also helped me to become a better researcher. I am especially grateful for the motivation you have given me and for the inspiring way in which you have shown me that science can be done with both dedication and integrity.

My sincere thanks also go to you, prof. Konstantinos Kafetsios, Ph.D., for including me in your GACR project. Participating in it was such a valuable experience, it opened up new perspectives for me that I would not have had otherwise. I learned so much, not only about research, but also about academic writing and teamwork.

I would also like to thank you, prof. Aldert Vrij, Ph.D. and Haneen Deeb, Ph.D. for supervising me during my internship at the University of Portsmouth. I am truly grateful for the opportunity to learn from both of you. Your guidance and passion for research left a strong impression on me, you not only enriched my experience but also inspired me to further explore the field of deception detection in my future academic work.

A big thank you goes to you, RNDr. Stanislav Popelka, Ph.D., for your support at the beginning of my eye-tracking research. You developed our first PC algorithm for pre-processing thermal data and helped me to overcome the initial challenges in both thermal imaging and eye-tracking. Your help laid the foundation for everything that followed.

Last but not least, thank you, Ing. Jan Kubíček, Ph.D. for developing the MATLAB-based solution for more flexible and efficient pre-processing of thermal data. I appreciate your insight into the fusion of computer science, bioengineering and physiology, as well as your positive and humorous attitude, even when things do not work as they should.

I would also like to sincerely thank all my research assistants, and participants who took part in my research. Your time, honesty (including deception) and dedication made this research possible.

Outside of the academic community, my deep and unmeasurable gratitude goes to my amazing family and my closest ones. Your support in happy and successful times, but especially during the most difficult phases of my life, helped me overcome all obstacles and taught me that one does not have to be perfect to be loved. And of course, *Ilonka*, thank you for being my sister, my best friend and my “kachna”, with whom I can always laugh, let off steam and just be myself. Not to forget: Thank you, *Churchill* (our family cat) and *Ízinka* (our family dog), for your emotional support in the form of chaos, fur and unsolicited help with writing.

My special thanks belong to you, *Jiřík*. You have brought so much love, joy, calm, laughter, and yes, even a little adrenaline into my life. I really cannot imagine this journey without you and I am grateful to have you by my side. Now, that the “*Get-My-PhD*” chapter is finally coming to an end, we will have more time to dance, ride motorbikes, cycle, travel the world – and maybe even learn to paraglide. I love you to the moon and back.

Finally, I would like to thank all my friends who have patiently endured my endless whinging about how busy I have been writing this thesis. Your support and understanding meant everything to me, especially last year when I was not able to spend as much time with you as I would have liked. I am so grateful that you have stood by me.

I cannot name everyone who has helped me on this journey, but thank you all!

I declare on oath that I have completed my dissertation on the topic "*Validity of non-invasive methods for measuring behavioural and physiological changes in deception detection*" independently under the supervision of my doctoral supervisor and have cited all materials and literature used.

In Olomouc on May, 19, 2025 Signature……

CONTENT

CONTENT 4
INTRODUCTION 7
THEORETICAL PART 9
1 MEANING OF DISHONESTY ON HUMAN INTERACTION 10
1.1. Classic philosophical and moral approaches to deception 10
1.2. On the basic definition of truthfulness, deception, lying and related constructs 12
1.2.1. Defining deception in legal and occupational contexts 13
2 DECEPTION DETECTION 18
2.1. Prevalence of deceptive behaviour 18
2.2. Four general approaches to detecting lies: an overview 20
2.2.1. Physiological responses for deception detection and their measurement 21
2.2.2. Observation of non-verbal behaviour 22
2.2.3. Verbal deception detection 24
2.2.4. Brain activity 29
3 PHYSIOLOGICAL DECEPTION DETECTION 33
3.1. A brief history of physiological deception detection 33
3.2. Polygraph technology and methodology 35
3.2.1. The anxiety-based polygraph methodologies 35
3.2.2. The recognition-based polygraph methodologies 37
3.3. Remote Photoplethysmography 38
3.3.1. Heart rate, its variability and affective states 42
3.3.2. Heart rate, its variability and deception detection 43
3.4. Functional infrared thermal imaging 46
3.4.1. The nature of the thermal print of a face for physiological responses 48
3.4.2. Facial temperature and deception detection 54
3.4.3. The main challenges of using thermal imaging to measure human facial skin temperature 65
4 FACIAL EMOTION (MICRO)EXPRESSIONS AND DECEPTION DETECTION 68
4.1. Facial motor system, action units and emotion expressions 68
4.2.1. Theoretical foundation of facial expressions and deception detection 74
4.2.2. An overview on facial expressions as cues to deception: insights and future directions for improving deception detection 78
5 EYE-TRACKING AND DECEPTION DETECTION 88
5.1. Anatomy and physiology behind oculometry and pupillometry 88

5.1.1. Oculomotor system ... 88
5.1.2. Pupillometry ... 90
5.2. Cognitive and affective influences behind the eye ... 91
5.3. Selected cues to deception from eye-tracking studies: an overview ... 93
6 MODERATION BETWEEN ATTACHMENT AVOIDANCE, DECEIVER'S BEHAVIOUR AND PHYSIOLOGY ... 102
6.1. Existing research on emotion regulation and deception in avoidant individuals ... 105
7 ETHICAL ASPECTS OF DECEPTION DETECTION RESEARCH ... 108
EMPIRICAL PART ... 112
8 THE RESEARCH PROBLEM AND RESEARCH OBJECTIVES ... 113
9 METHODS AND CONDUCTED STUDIES ... 117
9.1. Ethics ... 117
9.2. Case study ... 117
9.3. Pilot study 1 ... 119
9.4. Pilot study 2 ... 120
9.5. Main study ... 123
9.5.1. Aims and hypotheses ... 124
9.5.2. Participants ... 133
9.5.3. Materials and equipment ... 134
9.5.4. Procedure ... 137
9.5.5. Data pre-processing ... 139
9.5.6. Statistical analyses ... 143
9.5.7. Physiological results ... 148
9.5.8. Behavioural results ... 157
9.5.9. Hypotheses summary ... 171
10 GENERAL DISCUSSION ... 176
10.1. Discussion of physiological results ... 176
10.1.1. Facial temperature ... 176
10.1.2. Heart rate ... 179
10.1.3. Attachment avoidance as a moderator of physiological responses to deception ... 180
10.2. Discussion of behavioural results ... 181
10.2.1. Emotional valence and emotional arousal ... 181
10.2.2. Eye fixations ... 186
10.3. Contributions of this study ... 189
10.4. Limitations and future research ... 192
Spontaneous condition design ... 192

Emotional valence and arousal metrics 193
Heart rate metrics and its acquisition 194
Eye-fixations metrics 196
Data extraction 197
Statistical analyses 198
10.5. Practical implications 198
11 CONCLUSION 201
12 ANNOTATION 205
13 CZECH SUMMARY / ČESKÝ SOUHRN 213
14 LITERATURE 220
SUPPLEMENTARY MATERIALS 288
ABSTRACT OF THE DOCTORAL THESIS 289
CZECH ABSTRACT OF THE DOCTORAL THESIS 290
ORIGINAL APPROVAL OF THE FF UP ETHICS PANEL FOR RESEARCH 291

INTRODUCTION

Deception is an inherent part of human interaction. Whether lies are told to spare the feelings of others, to protect personal interests, or to manipulate a situation, they are a common feature of social life. Although society tends to condemn dishonesty, deceptive behaviour is common in a variety of settings. In some situations, such as court proceedings, security screenings or personnel selection, accurately recognising deception is not only important, but often necessary. Given the widespread occurrence of deception and the potential consequences of undetected lies, the study of deception detection has become an important and inherently multidisciplinary endeavour.

However, scientific efforts to detect deception often struggle with the same complexity that defines deception itself. People are not machines; they are influenced by psychological, emotional and situational factors that make it difficult to isolate single cues to deception. Despite decades of research, there is no universal or definitive method for distinguishing lies from the truth. Conventional instruments such as polygraphs have long been used, but rely on contact-based physiological measurements and have key limitations, namely intrusiveness, subjectivity in interpretation and susceptibility to countermeasures.

Recent advances have focussed attention on non-invasive, technology-based approaches, such as remote photoplethysmography (rPPG), functional infrared thermal imaging (fITI), facial expression analysis and eye-tracking. These methods aim to detect subtle behavioural and physiological responses without the constraint of direct physical contact, which can improve both accuracy and ecological validity.

This doctoral thesis examines the potential of non-contact technologies through a series of empirical studies. Its primary aim is to evaluate the validity of selected non-invasive measures for detecting behavioural and physiological responses associated with deception. Specifically, facial thermal patterns, heart rate, eye fixations,

and emotional valence and arousal are examined as separate indicators in the context of truthful and deceptive statements. Rather than looking for a single physiological or behavioural “signature” of lying, deception is viewed as a context-dependent phenomenon. Accordingly, the study also investigates the influence of cognitive load by comparing behavioural and physiological reactions to rehearsed and spontaneous questioning. To increase the reliability of thermal data analysis, a special pre-processing framework is developed to improve the quality and consistency of facial temperature measurements. Finally, the moderating role of individual differences, especially attachment-related avoidance, in the expression of physiological and behavioural responses during deception and truth-telling is investigated, with moderation effects assessed separately for each modality.

By providing a theoretical foundation and empirical analysis, this work contributes to the broader quest for non-invasive deception detection. It demonstrates the potential of selected methods and recognises that there are still several methodological and conceptual challenges. Whilst the work does not aim to provide definitive solutions, it does provide important steps towards investigating new tools and refining analytical techniques, particularly in the area of thermal imaging. As such, it supports future research and the eventual integration of these technologies into real-world applications.

THEORETICAL PART

1 MEANING OF DISHONESTY ON HUMAN INTERACTION

From birth, we are socialised to believe that lying and other forms of dishonest behaviour are bad (Saxe, 1991). Probably everyone has heard at least once in their lives that "*honesty is the best policy*", "*a lie has short legs*", "*lies will catch up with you*", "*half a truth is a whole lie*" and so on. We are taught that lies are immoral and that communication is based on the assumption of truth (Bok, 1999). In interpersonal interactions in general, telling the truth is considered the norm, while deception is the anomaly (Kalbfleisch & Docan-Morgan, 2019). However, when considering the meaning of dishonesty in interpersonal interaction, it is important to note that it encompasses more than just the distinction between truth and lies, as deception can be mixed into a partially truthful message to gain the trust of the listener (Sip et al., 2012). To understand how dishonesty can affect human functioning, we need to look at the moral and philosophical aspects of deception, as they have laid the foundation for later theories of deception and related constructs.

1.1. Classic philosophical and moral approaches to deception

Many people believe that truthfulness is a moral principle that must be learnt, cultivated or instilled. This belief is based on social expectations and a natural desire to avoid deception, as dishonesty can undermine the basic trust that holds social relationships together. In philosophy, two major traditions have grappled with this idea: (a) the Platonic tradition, and (b) the Aristotelian tradition (MacIntyre, 1994; Mahon, 2018).

The Platonic tradition sought to justify deception under certain conditions (Mahon, 2018). In his most important work, the *Republic,* Plato explicitly defended lying (Santas, 2006) claiming it to be a nuanced and complex phenomenon (Baima & Paytas, 2020). He distinguished between *intentional falsehoods* and *lies* based on the intention behind the deception. Plato (Plato's *Republic*, In Baima & Paytas, 2020) described lying as an intentional act of misleading someone without their consent and emphasised

the importance of the intention behind the deception. Deliberate falsehood, on the other hand, refers to all cases in which the truth is not told without the intention to deceive (Plato's *Republic*, In Baima & Paytas, 2020). However, the term ψεῦδος in Greek is open to interpretation, as it can refer both to a "lie" and to a "mere falsehood". All cases of ψεῦδος involve a falsehood, but not all cases involve the deliberate passing on of false information. It depends on the context whether "lie" or 'falsehood' is the more appropriate translation for ψεῦδος (Plato's *Republic*, In Baima & Paytas, 2020). He also provided others with concept of *the noble lie* in which philosophers deliberately mislead the population in order to promote and preserve a fair and just society (Plato's *Republic*, In Baima & Paytas, 2020). In general, Plato's theory offers a nuanced perspective on ethical considerations related to deception by taking into account the circumstances under which falsehoods or lies arise. This approach highlights the subtleties of moral decision-making in different situations, and was later continued by John Milton, Samuel Johnson and John Stuart Mill (Mahon, 2018).

The Aristotelian tradition condemned all lies (Mahon, 2018). Aristotle essentially viewed lies in a negative light due to three main reasons: (a) lies are typically detrimental both to individuals and society (*polis*) because they harm the trust in general, (b) lies are often a sign of character weaknesses related to a lack of autonomy or self-confidence, and (c) lies can potentially harm the liar themselves (Zembaty, 1993). While Aristotle rejected lying, he acknowledged that certain forms of deception could be ethically acceptable in certain circumstances, depending on the intention behind them (Mahon, 2018). Nonetheless, lies can be seen as morally acceptable in certain situations, especially when they cause no harm, show no undue disrespect, and stem from virtues like independence and excellence rather than flaws in character (Zembaty, 1993). Interestingly, his followers, especially Immanuel Kant, Augustine of Hippo or Thomas Aquinas, shared more radical views on deception, as they declared that lying is *always* wrong and never justified (Mahon, 2018). For Kant, telling the truth is a universal moral duty, and one must always tell the truth because it is a binding moral obligation (Ikuenobe, 2002). Kant further argued that the immorality of lying lies in deliberate deception, which violates the moral responsibility we owe to one another in society (Ikuenobe, 2002). Similarly, St Augustine

held an absolutist perspective rooted in religion, claiming that all acts of deception are inherently wrong because they contradict the truth of God (Hermanowicz, 2018).

Both the Aristotelian and Platonic traditions agree that deception is not a simple or absolute moral principle – not all forms of dishonesty are universally regarded as equally immoral (Ikuenobe, 2002). Based on the philosophical theories discussed, a statement is only considered deception if certain criteria are met: (a) the person knowingly communicates a falsehood, (b) the intent is to mislead, and (c) the person successfully deceives (Ikuenobe, 2002). Metaethical discussions suggest that deception should be considered in its various forms or "shades" (Ikuenobe, 2002; Englehardt & Pritchard, 2019), which has led to the development of nuanced taxonomies of deception that distinguish between morally acceptable and less justifiable (Bryant, 2008).

1.2. On the basic definition of truthfulness, deception, lying and related constructs

One could say that deception is the opposite of truthfulness and vice versa. However, this distinction is not so simple and clear. Telling the *truth* means communicating faithfully by sharing information that is accurate for both the communicator and the sender (Kalbfleisch & Docan-Morgan, 2019), without any “deceptive purpose, intent or awareness” (Levine, 2014). However, honest communication is not necessarily always completely accurate or with full disclosure. It varies from person to person as the information shared may change over time. What is important is that the communicator shares what they genuinely believe to be true and accurate at the time (Kalbfleisch & Docan-Morgan, 2019).

On the other hand, *deceptive communication* involves the violation of the fidelity in the interpersonal interaction (Kalbfleisch & Docan-Morgan, 2019). In the literature, the terms deception and lying are often used interchangeably, although there are differences between the two (Ekman, 2009). *Deception* is usually defined as “a successful or unsuccessful deliberate attempt, without forewarning, to create in another a belief which the communicator considers to be untrue” (Vrij, 2000, p. 6), or simply as “a deliberate attempt to mislead others” (DePaulo et al., 2003, p. 74). Deception is any action that misleads someone, while *lying* is “a subtype of deception that involves

an outright falsehood, which is consciously known to be false by the teller, and is not signalled as false to the message recipient" (Levine, 2014, p. 3). Deception is therefore a superordinate concept that encompasses a range of deceitful, cunning, and/or misleading actions – including lying (Knapp et al., 2016). A widely used approach to understand deception, developed by DePaulo et al. (1996, p. 983), categorizes lies based on five dimensions: content, reason, type, referent, and the lie's effects. Self-oriented lies are generally seen as more harmful, violating trust, while other-oriented lies, or "white lies," are often viewed as more acceptable and common (Di Battista, 1994; Knapp & Comaden, 1979). Englehardt and Pritchard (2019) have described five basic forms of dishonesty: *(1) outright lying*, i.e. the use of language to convey a message that the deceiver knows to be untrue or significantly misleading, with the aim of misleading others, *(2) deliberate deception*, which, strictly speaking, does not involve lying – it usually involves extolling the virtues of something without mentioning its shortcomings, *(3) withholding or concealing information, (4) the secret and unauthorised use of confidential information* plays a crucial role in many successful business projects and requires careful protection of data that could be seen by unauthorised persons, and *(5) the failure to find out the truth when one is responsible* is especially evident in research, where avoiding further investigation can be deceptive, even without outright lying.

Given the complexity and overlap with related concepts such as lying, misleading and withholding information, the term *deception* is used in this thesis as a comprehensive and inclusive construct that allows for the exploration of its different forms and possible detection.

1.2.1. Defining deception in legal and occupational contexts

Deception is shaped by the context in which it takes place (Markowitz et al., 2023) and is influenced by the interpreter's perception of factors such as purpose and outcome (Kalbfleisch & Docan-Morgan, 2019). It permeates various aspects of human interaction (DePaulo et al., 1996; Serota et al., 2010; Sip et al., 2012), but it is particularly common in high-stakes situations such as courtrooms (Green, 2015; Scarpazza & Sartori, 2020; Strömwall & Granhag, 2003) and job interviews (Levashina & Campion, 2007; Roulin, 2016; Roulin et al., 2014, 2015; Roulin & Powell, 2018; Weiss & Feldman, 2006). By focusing

on deception in these contexts, we can better understand its mechanisms and consequences, which can later help to understand its detection (Vrij, 2009).

Deception in legal processes

Professionals in these fields are routinely faced with the challenge of assessing the trustworthiness of witnesses and suspects at various stages of criminal investigations and court proceedings. The ability to distinguish between honest and misleading communication is a key to maintain the credibility of the justice system (Bradford & Goodman-Delahunty, 2008). In criminal law, the central role plays confession, defined as "a detailed written or oral statement in which a person admits to having committed some transgression, often acknowledging guilt for a crime" (Kassin & Gudjonsson, 2004, p. 35). Confessions are surrounded by controversy, particularly about whether the statement was authentic, reliable, voluntary, etc. (Brooks, 2005). They are inherently associated with the possibility of deception, usually as perjury, misdirection and false denial (Green, 2004). *Perjury* is a false statement under oath about facts that are relevant to a particular trial, with various consequences, e.g., an innocent person can be wrongly convicted and even imprisoned, while a guilty person can be released (Green, 2015). *Misleading* refers to a particular form of deception where it is not necessary for the communicator to tell a direct untruth. Rather, it involves creating a deceptive perception or tricking a person into accepting something through indirect methods or the omission of details, which is considered less ethically problematic than outright lying (Green, 2004). *False denial* refers to denying an accusation of alleged wrongdoing without admitting the truth (Green, 2004).

A special category of deception in the forensic context are *false confessions* by innocent people to crimes they did not commit (Gudjonsson, 2003; Kassin, 2005; Kassin & Gudjonsson, 2004). Such confessions can be coerced under a range of psychological influences, which ultimately leads to innocent people admitting their guilt (Bradford & Goodman-Delahunty, 2008). Kassin and Wrightsman (1985, In Kassin, 2005, 2014) introduced a taxonomy of three types of false confessions: voluntary, coerced-compliant and coerced-internalised. *Voluntary confessions* are self-incriminating statements made without external pressure, often to protect another person or to attract attention in high-

profile crimes (Kassin, 2005, 2014). The other two are elicited through an interrogation process (Kassin, 2014) that can sometimes lead to cognitive and behavioural confirmation bias (Meissner & Kassin, 2004) without the suspect intentionally trying to deceive the court (Kassin, 2005). *The coerced-compliant false confessions* occur when a person admits guilt to avoid coercive interrogation, to escape direct or implied intimidation, or to secure a promised or suggested advantage (Kassin, 2005). *The coerced-internalised false confessions* refer to cases in which an innocent person is convinced that he or she is actually guilty of a crime after being tired, disorientated and subjected to suggestive procedures that may lead to the formation of a fabricated memory (Bradford & Goodman-Delahunty, 2008; Kassin, 2005, 2014). After the initial stress and pressure of the interrogation is over, people who confess under compliant coercion are more likely to recant their confession. Conversely, the coerced-internalised confession subjects are very unlikely to retract their statements because they truly believe they are guilty when in fact they are innocent (Gudjonsson, 2003).

In summary, when investigating deception and confessions in a forensic context, researchers and practitioners should consider: (a) the influence of police interrogation techniques, (b) the behaviour and personality of the confessor, (c) possible investigator bias that may affect the detection of deception, and (d) supporting evidence or external circumstances surrounding the confession (Bradford & Goodman-Delahunty, 2008).

Deception in personnel selection

In personnel selection, the exchange of information between companies and applicants is characterised by both cooperation and competition, as their goals and expectations often differ (Bangerter et al., 2012). According to Frank (2015), parties whose goals are not aligned are less motivated to share accurate information unless it benefits them. Organisations seek to accurately assess applicants' skills and commitment to predict their potential to achieve company goals, while applicants may strategically withhold or distort information to increase their chances of being hired (Bangerter et al., 2012; Roulin & Krings, 2020). In addition, applicants often recognise the selection criteria before or during the interview and adapt their answers to what they think the recruiters want to hear (Bangerter et al., 2012), which may lead to honest, altered or completely

fabricated answers (Donovan et al., 2014; Roulin et al., 2015; Roulin & Bourdage, 2017; Roulin & Krings, 2016, 2020; Roulin & Powell, 2018; Seitl et al., 2024). Consequently, impression management and faking are among the most widespread phenomena affecting the validity of personnel selection procedures.

Impression management (IM) encompasses a wide range of self-presentation strategies used by individuals to influence the perception others have of them (Leary & Kowalski, 1990). In personnel selection it has been defined as a deliberate attempt by the applicant to create a certain image in the minds of the interviewer (Roulin et al., 2015). It is a continuum of different tactics, ranging from complete honesty to outright lies (Bourdage et al., 2018; Levashina & Campion, 2007). Many studies have focused on identifying different types of IM, such as emphasising one's own qualifications, experience, skills, abilities (e.g., Kristof-Brown et al., 2002), flattering the interviewer (e.g., Ellis et al., 2002; Higgins & Judge, 2004) or exaggerating or even inventing one's own experiences (e.g., Levashina & Campion, 2007). Despite widespread interest in IM in personnel selection, a key focus has emerged on distinguishing between honest and deceptive IM (Bourdage et al., 2017; Ellis et al., 2002; Levashina & Campion, 2006, 2007; Melchers et al., 2020; Roulin et al., 2015; Weiss & Feldman, 2006). The *honest IM* include tactics like honest self-promotion, honest ingratiation and honest defensive IM (Roulin & Bourdage, 2017). It is the way of emphasising the desirable qualities that the candidate actually possesses (Levashina & Campion, 2007), which is often viewed as appropriate (Jansen et al., 2012). In contrast, deceptive IM is more problematic as it involves describing and emphasising skills that the candidate does not possess (Melchers et al., 2020). The prevailing view is that an honest IM could enable the interviewer to improve their decision-making process by providing accurate, work-related information, whereas deceptive IM could mislead the interviewer, lead to an incorrect judgement and therefore must be monitored (Bourdage et al., 2018).

A close construct to IM is *faking*, "a conscious distortions of answers to the interview questions in order to obtain a better score on the interview and/or otherwise create favourable perceptions" (Levashina & Campion, 2007, p. 1639). Although these terms are often used interchangeably in personality research, they represent different but related concepts in the context of interviews (Melchers et al., 2020). The key

difference between faking and IM lies in the continuous and multidimensional nature of the latter, while faking refers specifically to its deceptive forms. However, some scholars argue that faking can also encompass more honest forms of IM (Melchers et al., 2020). Levashina and Campion (2007) distinguish between four key types of applicant faking behaviours: slight image creation, extensive image creation, image protection, and ingratiation. *Slight image creation* involves practises such as embellishing and tailoring information, while *extensive image creation* includes constructing or borrowing false information. *Image protection* is about hiding or distancing oneself from negative information, and *ingratiation* is about aligning one's views or enhancing the interviewer or organization. Each type includes more and less honest forms of IM. Levashina and Campion's model was partly derived from the general IM literature and therefore some of the fake tactics described there may be incorporated into honest IM; for example, slight image creation is conceptually similar to self-promoting IM tactics that could be honest (Melchers et al., 2020). Despite the differences in terminology, from the perspective of interview outcomes, dishonest IM or faking is more problematic than honest IM as it affects the validity of the interview (Levashina & Campion, 2007), can lead to counterproductive work behaviours (Peterson et al., 2011), lower job performance (Law et al., 2016; O'Neill et al., 2017) and overall negative work outcomes (Donovan et al., 2014; O'Neill et al., 2013). Applicants tend to engage in faking when they perceive the interview as difficult and challenging (Seitl et al., 2024). In contrast, fair interviews are more likely to result in honest IM, demonstrating the importance of asking appropriate and relevant questions (Bourdage et al., 2018).

In summary, the definition of deception in the legal and occupational contexts reveals the complexity of deceptive behaviour and the importance of situational influences. In the legal field, deception can manifest itself in the form of false confessions, perjury or misleading statements, often shaped by interrogation practises. In the occupational domain, particularly in personnel selection, deception is often observed in the form of IM and faking, whereby the degree of intentionality varies. These findings emphasise the need for context-sensitive approaches to understanding and detecting deception. They illustrate that their manifestation and impact are closely interwoven with the situational demands and individual motivations in each situation.

2 DECEPTION DETECTION

In our daily interactions, we cannot avoid being dishonest at times. In general, the vast majority of untruths are not categorised as serious, with a significant proportion falling into the category of so-called social lies, which are necessary for our social interactions and serve both self-interest and the interest of others (Vrij & Ganis, 2014). Imagine a situation where you see your friend with a new haircut which you really do not like, but your friend is absolutely delighted with the hairdresser's work. It would be unacceptably rude to say the truth: "*I think your new haircut is terrible and I preferred the old one.*" Saying something like this would probably not only make your friend angry, but could also damage your friend's self-confidence and self-esteem. People benefit from giving and receiving compliments in social interactions (Aron et al., 1989) and a small social lie can help people avoid an unpleasant situation or discussion (Vrij & Ganis, 2014). Sometimes, however, the situation is different and the lies told are serious and could significantly affect the outcome of the situation in which the liar finds themselves (DePaulo et al., 1996). The police officers want to know whether the suspect's confession is credible or not; the recruiter in a company wants to know if the applicant is honest about his or her abilities; the customs officer wants to know if the traveller has nothing to hide and so on and so forth (Vrij & Ganis, 2014). Because of the high frequency of deception, researchers have investigated how liars react and how they can be recognised in order to prevent wrong decisions, as this would not only be beneficial for the individual but for society in general (Granhag et al., 2015; Vrij, Granhag, et al., 2010).

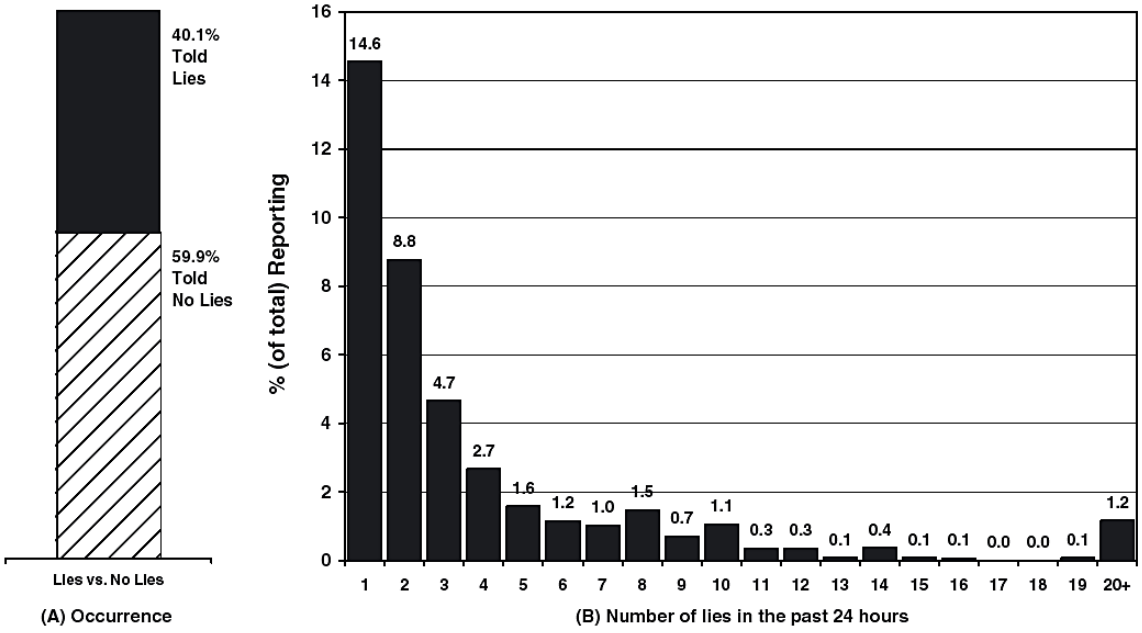
2.1. Prevalence of deceptive behaviour

In one-week diary study, DePaulo et al. (1996) found that almost all participants admitted to lying at least once, an average of 1.9 lies per day or one lie in every four social interactions, most of which were small lies. Since then, studies have repeatedly shown that people tell one or two lies a day (e.g., DePaulo & Kashy, 1998). Hancock et al. (2004) found that participants told an average of 1.6 lies per day, with one in four interactions involving deception. In addition, they found that the medium of communication influenced

the frequency of lies. While most interactions were face-to-face, deception was more common in telephone conversations (37%) than in face-to-face interactions (27%). The lowest rate of deception was found in email (14%), with the rate of deception in instant messaging being almost as high as in face-to-face communication (Hancock et al., 2004). The question of the prevalence of misleading communication in relation to the media was the focus of a further study by George and Robb (2008), replicating both DePaulo et al. (1996) and Hancock et al. (2004). Similar to previous research, they found that 20-25% of social interactions involved deception, emphasising the prevalence of lies in everyday life. However, in contrast to previous studies, they found no significant differences between face-to-face conversations and other media in terms of the frequency of lying, which they attribute to the ubiquity of mobile phones, which made telephone conversations much more accessible until 2008 (George & Robb, 2008).

In 2010, Serota and his team investigated the frequency and distribution of lying in the adult population. They conducted three national studies in US samples (a total of 1,000 adults reported the number of lies told in 24-hours) and found that the average rate is 1.65 lies per day, but the data is not normally distributed, as depicted in Fig. 1 (Serota et al., 2010).

Figure 1: The prevalence of lying in U.S. adults

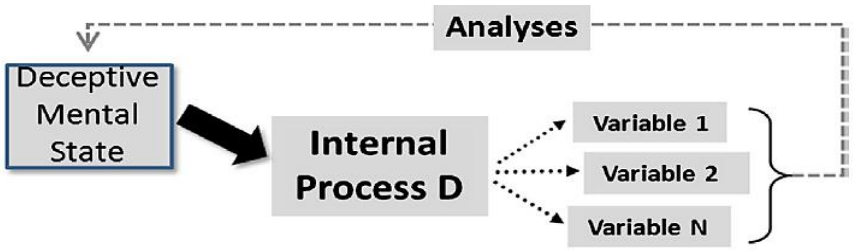


It shows that the majority of lies are told by a small proportion of the population, while almost 6 in 10 Americans claim not to have lied at all, emphasising that truthfulness varies from person to person and that the propensity to deceive can play an important role as a moderator (Serota et al., 2010).

2.2. Four general approaches to detecting lies: an overview

Needless to say, recognising deception is a difficult task (Bond & DePaulo, 2006), with many challenges faced by scientists throughout history. Probably any researcher or practitioner dealing with deception would be thrilled if there was a simple way, an internal mental process that correlated perfectly with a deceptive mental state and was perfectly detectable (Vrij & Ganis, 2014). However, the way to recognise deception is not so straightforward. One could say that it is more like a mountain road full of bends, turns and other obstacles that the driver must overcome to reach the destination. This complexity is perhaps one of the many things that make deception detection so attractive and challenging. Before we open the chapter on the different approaches to deception detection, we would like to introduce the theoretical framework presented by Vrij and Ganis (2014, p. 306) with three core components that provides the reason why the accuracy of deception detection methods is far from perfect. The first component is the correlation of one or more internal processes with the deceptive mental state. The second component presents a set of variables that we can use to measure these processes, and the third component provides us with a set of different analyses that we can perform on these variables to prove the deception.

Figure 2: Theoretical framework of deception (Vrij & Ganis, 2014, p. 306)



In ideal research, there would be one internal process ("*Process D*", e.g., heightened cognitive load, increased physiological arousal) that could be detected by a set of variables by means of a specific statistical analysis. However, we are far from an ideal world,

so in reality we are confronted with several non-deceptive mental states that also influence "*Process D*". This leads to the typical Type I and Type II errors when non-deceptive states are misclassified as deceptive and vice versa (Vrij & Ganis, 2014). If only recognising lies were as easy as in the story of Pinocchio, where his nose grew longer each time he lied, while his nose size remained stable when he told the truth. In deception, there is no such measure between truth tellers and liars. Rather, there are four general approaches to detecting lies: (a) physiological, (b) behavioural, (c) verbal, and (d) neural (Vrij & Ganis, 2014; Vrij & Granhag, 2006).

2.2.1. Physiological responses for deception detection and their measurement

The core of physiological deception detection lies in the assumption that bodily functions are linked to various mental processes and can therefore serve as a signal for deceptive mental states (Ambach & Gamer, 2018). From this perspective, deception is usually associated with increased stress (Tsiamyrtzis et al., 2007), increased arousal, negative experiences (Colwell et al., 2007) and greater cognitive effort (Vrij, Fisher, et al., 2008). Therefore, deception can be reflected in various physiological changes. For example, Kreißig & Krautz (2019) measured skin conductance response of 26 participants during deception. They found that the mean relative skin conductance peaks were larger for false claims than for true statements. Higher skin conductance responses during deception compared to truthful responding were also found in studies by Gödert et al. (2001), and Suchotzki and Gamer (2018). Gödert et al. (2001) also measured the electroencephalogram and found a lower mean acceleration in heart rate on deceptive trials than on honest trials in a time window of 9-14s after the start of the question.

Previous studies have described the importance of periorbital blood flow and significant warming in the periorbital region due to anxiety during lying (Pavlidis & Levine, 2002), or the liar's fear of being caught (Panasiti et al., 2016). Regarding the cheeks temperature, researchers reported a significant increase as an index of deception (Gálvez-García et al., 2021; Pollina et al., 2015) which could be related to convincing impression (Gálvez-García et al., 2021). The most valid facial thermal cue for deception appears to be the nose, which shows both a significant increase (Moliné

et al., 2018; Panasiti et al., 2016) and decrease (Gálvez-García et al., 2021; Moliné et al., 2017) during deceptive behaviour. The forehead, contrarily, is the least sensitive to thermal changes (Gálvez-García et al., 2021), although some studies found a significant thermal increase during deception (Zhu et al., 2007).

The measurement of pupil dilation plays a further role in the physiological detection of deception (Cook et al., 2012; Dionisio et al., 2001; Nurçin et al., 2017; Seymour et al., 2013; Webb, Hacker, et al., 2009; Webb, Honts, et al., 2009), where the average pupil size was found to be smaller during truth-telling than during deception (Cook et al., 2012; Dionisio et al., 2001; Webb, Hacker, et al., 2009; Webb, Honts, et al., 2009).

While physiological responses are often used to detect mental states that might indicate deception, it is important to consider the limitations of interpreting this data to detect deception. The anxiety-based approach, which assumes that liars are more anxious and therefore show more prominent physiological manifestations than truth tellers, is prone to several errors (Vrij & Ganis, 2014). For example, the basic mechanism behind cardiovascular activity is that increased blood pressure and heart rate are the result of the release of the postganglionic neurotransmitter noradrenaline by sympathetic nervous system activity, whereas a decrease in blood pressure and heart rate is due to parasympathetic nervous system activity releasing postganglionic acetylcholine (Synnott et al., 2015). However, cardiovascular activity is modulated by many factors other than this basic mechanism, such as “perceived threat, increased physical or mental activity, anticipation of threat or activity, and indeed any form of specific or generalised arousal”, which vary to a greater or lesser extent from person to person (Synnott et al., 2015, p. 63). Respiratory rate, which is influenced by both autonomic and central nervous activity, can be voluntarily controlled to some degree, which presents a challenge in polygraph testing as it can influence not only respiration but also heart rate and electrodermal response (Synnott et al., 2015). This may lead to innocent people being falsely accused of deception due to increased anxiety during the test (Vrij & Ganis, 2014).

2.2.2. Observation of non-verbal behaviour

During social interactions, people perceive numerous non-verbal cues (Hall et al., 2009), to assess the other person's emotions, intentions, thoughts, and also deception (Vrij

et al., 2019). Non-verbal deception detection has a long history dating back to 900 BC, when it was claimed that liars exhibit fidgeting behaviour and that they tremble (Trovillo, 1939). Since then, numerous books and articles have been published, many of which are even aimed at a wide audience (e.g., Houston, 2012; Meyer, 2010). As a result, laypeople or even professionals still believe that non-verbal behaviour can be the window to the liar's soul (Nortje & Tredoux, 2019). However, research on non-verbal cues to deception is controversial in academia, as its results generally have a low hit rate (Vrij et al., 2019).

The meta-analysis by DePaulo et al. (2003) of 116 studies examined 158 behaviours, of which 102 were classified as non-verbal cues to deception. Significant results based on effect size (Cohen's d) indicated that non-verbal cues such as nervousness (*.27*), chin lifting (*.25*) and fidgeting (*.16*) were positively associated with deception, while behaviours such as the use of illustrators like hand movements (*–.14*) and pleasant facial expressions (*–.12*) were negatively associated with deception. The study concluded that the relationship between non-verbal cues and deceptive behaviour is weak and unreliable.

In 2006, the Global Deception Research Team found that 65% of respondents from 63 countries believed that liars avoid eye contact, change their posture and fidget. However, the current research found no evidence to support the assumption that liars avoid eye contact – on the contrary, liars often try to maintain eye contact to hide their dishonesty (Griffin & Oppenheimer, 2006; Hypšová et al., 2024; Mann et al., 2013), or to observe the other person's reaction and assess whether they are believed (Schweitzer et al., 2002). Deceivers may deliberately minimise gestures such as head and body movements and prolong eye contact to counteract the social perception of dishonesty (Nortje & Tredoux, 2019). Sporer and Schwandt (2007) conducted a meta-analysis of non-verbal indicators of deception and found that of the 11 behaviours studied, only three – nodding, foot and leg movements and hand movements – could be reliably associated with deception, with all showing a decrease when people were lying. Contrary to popular belief, behaviours such as eye contact and gaze avoidance were not significantly correlated with deception. The meta-analysis also highlighted that factor such as the content of the lie, the motivation behind it and preparation influences non-verbal behaviours, contributing to the variability of results.

Non-verbal approaches to deception detection also rely on facial micro-expressions, which is even more controversial. One side considers them unreliable, while the other argues that emotional expressions provide important clues to dishonesty (Zloteanu et al., 2021). Most studies used non-verbal features, especially action units (AUs) combinations, such as eyebrow or mouth movements (Avola et al., 2019; Mathur & Matarić, 2020; Matsumoto & Hwang, 2018; Nam et al., 2023; Shen et al., 2021). For example, significant differences were found in the occurrence of AU4 (Brow lowerer), AU5 (Upper lid raiser), AU10 (Upper lip raiser), AU12 (Lip corner puller), and AU14 (Dimpler) between truthful and deceptive behaviours (Avola et al., 2019). In addition, activation of AU20 (Lip stretcher) was significantly shorter in lying conditions, averaging 15.21 frames (507 ms), compared to 20.77 frames (692 ms) in truth-telling conditions (Shen et al., 2021). In the Nam et al. (2023) study, AU14 (Dimpler), AU23 (Lip Tightener), and AU45 (Blink) were identified as key indicators of deception. A reduction in blinking (AU45) and fewer movements around the mouth (AU23 and AU14) were strong cues of deception. Matsumoto and Hwang (2018) reported that micro-expressions of negative emotions (such as anger, contempt, disgust, fear, sadness) at ≤0.40 s and ≤0.50 s duration were more frequently observed under deceptive conditions. Liars also exhibited significantly higher standard deviations in facial valence and facial arousal than truthful speakers (Mathur & Matarić, 2020). In summary, although automatic lie detection systems using facial features have potential, they face significant challenges in terms of accuracy, generalisability and theoretical foundations, and further interdisciplinary research is needed to improve their effectiveness (Delmas et al., 2024). We address these challenges in more detail in Chapter 4.

2.2.3. Verbal deception detection

The systematic investigation of verbal cues to detect deceit has gained momentum since the 1950s (Deeb et al., 2023, 2024; DePaulo et al., 2003; Masip et al., 2005; Vrij et al., 2000, 2022; Vrij & Granhag, 2006). DePaulo et al. (2003) found that verbal cues have the strongest effect size (Cohen's d) for deception detection. The most important verbal indicators included clarity and directness (*–.55**), inconsistent communication (*.34**), detailed responses (*–.30**), uncertainty (*.30**), logical structure (*–.25**), plausibility (*–.23**),

negative statements (*.21**), personal involvement (*–.21**), and contextual embedding (*–.21**) (DePaulo et al., 2003).

Given the potential of verbal analysis to detect deception (DePaulo et al., 2003; Vrij et al., 2022), researchers have explored various techniques to obtain or strengthen verbal cues that exploit the different verbal strategies of truth-tellers and lie-tellers (Vrij & Granhag, 2012). Typically, verbal cues are examined with: (1) Statement Validity Assessment (SVA) including Criteria-based Content Analysis (CBCA); (2) Reality Monitoring; (3) Scientific Content Analysis (SCAN); 4) Cognitive Credibility Assessment including (a) imposing cognitive load, (b) asking unexpected questions, and (c) encouraging interviewees to say more; (5) Strategic Use of Evidence (SUE); (6) Verifiability Approach (VA); and (7) Assessment Criteria Indicative of Deception (ACID) (Vrij, 2018). As it is not the intention of this thesis to use verbal analysis for deception detection, we will briefly outline these tools and then direct the reader to references where they can find more detailed information on each approach described.

Statement Validity Assessment

The SVA was originally developed to determine the credibility of child witnesses' testimonies in trials for sexual offences (Vrij, 2015a). It consists of four stages (Köhnken, 2004; Vrij, 2008; 2015b; 2018): (a) *a case file analysis* – obtaining the most important information about the child victim; (b) *a semi-structured interview* in which the child themselves reports on the allegations; (c) *CBCA to systematically assess the quality of the transcribed interview* – systematic evaluation of the transcribed interview on the basis of 19 criteria (e.g., contextual details, descriptions of interactions, speech reproduction), which are more likely to be present in truthful statements, as lies are generally considered more cognitively demanding. Also, truth tellers make spontaneous corrections and admit to memory gaps as they are less concerned about appearing credible (Vrij, 2015b, 2018). Studies have shown that CBCA assessments can distinguish liars from truth tellers with 71% accuracy (Vrij, 2015b); and (d) *validity checklist* – an assessment of the CBCA result with two factors: quality of the interview and consistency with other statements. Although the SVA was originally developed for the assessment of child witnesses, it is also widely used in the assessment of adult testimony (Köhnken, 2004).

For more information about SVA, see for example Amado et al. (2015), Köhnken (2004), Oberlader et al. (2016), Vrij (2005, 2009, 2015b), Vrij et al. (2022).

Reality Monitoring

The essence of reality monitoring is that real memories (i.e., based on real experiences) are distinct from those based on fiction (Johnson & Raye, 1981). Johnson and Raye (1981) argued that real memories are likely to contain sensory information (e.g., details of sight, sound, smell, touch, or taste) and contextual information (e.g., spatial details – where, who, when, etc.). In contrast, false memories contain more cognitive operations (e.g., thoughts, reasoning, etc.) and tend to be more vague and less concrete (Johnson & Raye, 1981). The content of lies should be less detailed than the telling of the truth (Amado et al., 2015; Bogaard et al., 2019; DePaulo et al., 2003; Sporer & Sharman, 2006). Research has shown that truth tellers not only provide more contextual and sensory details (Harvey et al., 2017; Oberlader et al., 2016), but also more PLATO details (i.e., person, location, action, temporal, object) (Deeb et al., 2021, 2022; Leal, Vrij, Deeb, et al., 2018). However, some factors may mitigate the differences between liars and truth tellers in terms of the total details (Deeb et al., 2023), such as culture or country of data collection (Leal, Vrij, Vernham, et al., 2018), coding scheme (Nahari, 2023), coding method (Deeb et al., 2024; Kleinberg et al., 2018), used metric (Schutte et al., 2021) or interview protocol (Bogaard et al., 2020). For more details about reality monitoring, see for example Masip et al. (2005), Oberlader et al. (2016), Vrij (2009, 2015b).

Scientific Content Analysis

In the SCAN method, a suspect or witness is asked to write a detailed account of an event, which is then assessed by an expert on the basis of certain criteria (Vrij, 2015b, 2018). Sapir (2005), the developer of SCAN, argues that some SCAN criteria such as social introductions (e.g., the introduction of a person in the narrative), occur more frequently in truthful reports. If the respondent does not include such an introduction, it is considered a sign of deception (Bogaard et al., 2016). According to SCAN, 20% of the written information should be facts that led up to the event, 50% information about the main event and the remaining 30% about what happened afterwards – the more that deviates from this structure, the higher the likelihood that the person is being dishonest (Bogaard et al.,

2016). This method is popular worldwide (Vrij, 2015a), but lacks theoretical basis for why its criteria distinguish liars from truth-tellers (Bogaard et al., 2016), with no evidence that the criteria described are indicators of deception (Bogaard et al., 2016; Bogaard, Meijer, & Vrij, 2014; Nahari et al., 2012; Vanderhallen et al., 2016). For more detailed information about SCAN, see for example Bogaard et al. (2016), Nahari et al. (2012), Vrij (2015b), Vrij et al. (2022).

Cognitive Credibility Assessment

This technique include three elements: (a) imposing cognitive load, (b) asking unexpected questions, and (c) encouraging interviewees to say more (Vrij, 2018; Vrij, Fisher, et al., 2017). Imposition of cognitive load assumes lying is more mentally demanding than telling the truth (Christ et al., 2009; Vrij et al., 2011; Vrij, Granhag, et al., 2010; Vrij, Mann, et al., 2006). Interviewers increase difficulty, such as asking for reverse storytelling or maintaining eye contact, to strain cognitive resources. This should lead to more cues of deception as liars struggle with the increased cognitive load (Vrij, 2015a). Asking unexpected questions challenges liars, who usually prepare for interviews (Hartwig et al., 2007; Vrij & Granhag, 2012), and have more difficulty answering unexpected questions than truth tellers (Lancaster et al., 2013). Warmelink et al. (2012), found that liars gave more details in response to prepared questions, but fewer in response to unexpected questions. Interestingly, these results were not replicated in the later work of Warmelink et al. (2019) and the reasons for this remain unclear and require further investigation. Encouraging interviewees to say more affects truth-tellers more, as they naturally provide more details, while liars keep their stories simple (Vrij et al., 2022). A current approach to facilitating recall of particularly visual experiences is sketching, which supports visual memory performance (Deeb et al., 2022, 2024). The use of the CCA led to a moderate effect (d = .42) in distinguishing between liars and truth tellers (Vrij, Fisher, et al., 2017). A further meta-analysis showed 60% accuracy in detecting deception using the CCA (Mac Giolla & Luke, 2021). For more detailed information about CCA, see for example Vrij (2015a), Vrij et al. (2018, 2022), Vrij, Mann et al. (2008, 2010).

Strategic Use of Evidence

The SUE is based on the cognitive differences between truth tellers and liars and different tactics to persuade (Granhag & Hartwig, 2008; Hartwig et al., 2014). SUE aims to exploit these differences by asking evidence-related questions without revealing the evidence (e.g., not mentioning footage before the interview). Truth tellers are assumed to be forthcoming (Granhag & Hartwig, 2014; Granhag & Hartwig, 2008), and more consistent with their statements than liars, who are more prone to inconsistencies within statements (Hartwig et al., 2014). The tendency to contradict the evidence increases more when the evidence is withheld from the suspect (Hartwig et al., 2014). For more detailed information on SUE, see for example Granhag and Hartwig (2014), Hartwig et al. (2014), Vrij (2015a), Vrij et al. (2022).

Verifiability Approach

VA suggests that liars face a dilemma – providing more details increases credibility (Nahari et al., 2012), but too many details risk scrutiny (Bell & Loftus, 1989; Nahari, 2018; Nahari et al., 2014a; Vrij, 2009; Vrij et al., 2022). The solution is to provide as much details as possible, but avoid the verifiable details (i.e., activities leaving physical or digital traces) (Nahari et al., 2014a). Studies show liars provide fewer verifiable details than truth-tellers (e.g., Harvey et al., 2017; Nahari et al., 2014a, 2014b) A meta-analysis confirmed VA's potential but called for more field studies and replications (Palena et al., 2021). For more detailed information on VA, see for example Nahari (2018), Nahari et al. (2014b), Palena et al. (2021).

Assessment Criteria Indicative of Deception

The ACID system evaluates the length of responses, recognises possible errors and uses reality monitoring criteria to detect differences in terms of memory, IM or information control (Colwell et al., 2007). It is based on the cognitive interview, memory/cognition and communication (Fisher & Geiselman, 1992). The ACID process begins with free recall, followed by memory aids such as recalling events from a different perspective (see Fisher & Geiselman, 1992). Truth-tellers benefit from these techniques and provide more details, while liars offer fewer additional details (Colwell et al., 2007,

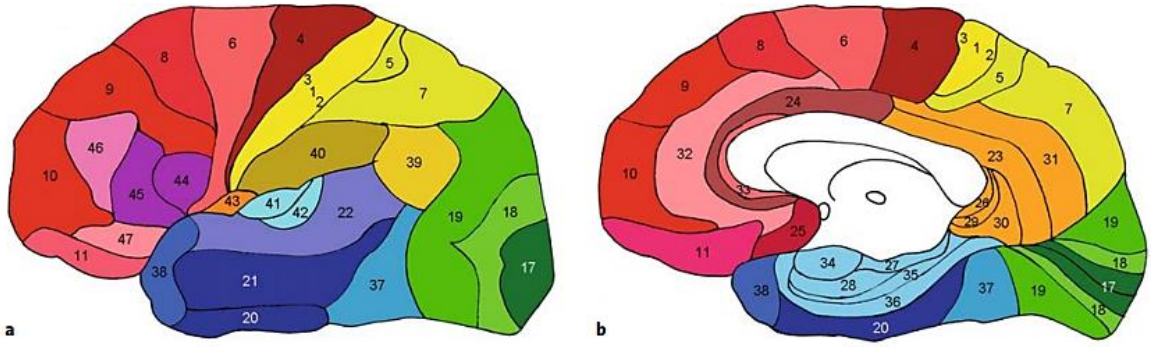
2013). For more detailed information on the ACID, see for example Colwell et al. (2007, 2013).

Nowadays, verbal lie detection has gained attention and many scholars world-wide use different paradigms and transfer these findings to real-life conditions. Nahari et al. (2019), Vrij et al. (2023) or Vrij et al. (2022) suggested several possibilities for future research on verbal deception detection, including cross-cultural studies, different scenarios, the use of interpreters, etc. For more details, see Nahari et al. (2019), Vrij et al. (2023).

2.2.4. Brain activity

The neuroimaging approach suggests that deception is associated with specific brain activity, which can be measured in particular by functional magnetic resonance imaging (fMRI) (Ganis, 2014). To clarify the results discussed later, we provide an illustration of Brodmann areas (BA) in the brain in Fig. 3 (Strotzer, 2009, p. 182).

Figure 3: Color-coded illustration of Brodmann's cortical maps (Strotzer, 2009, p. 182)



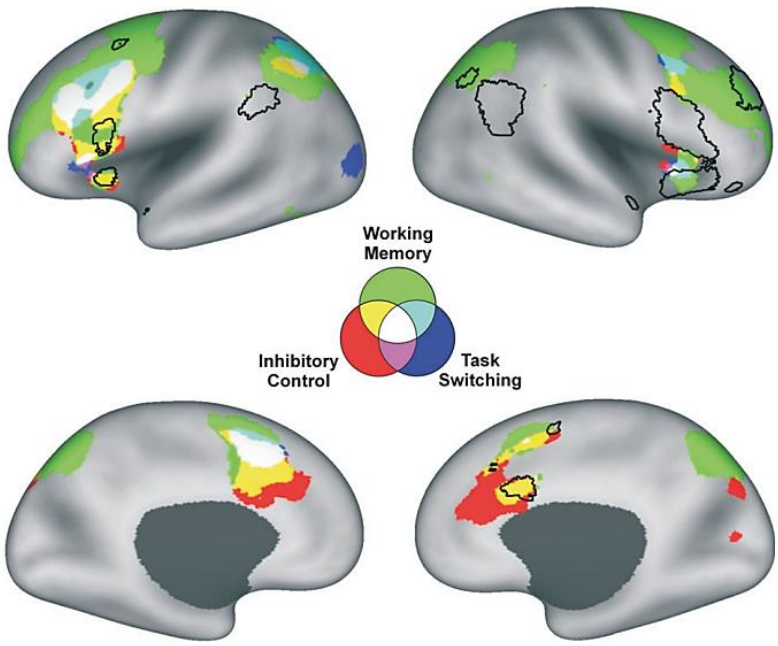
Note. (a) Lateral, and (b) medial surface.

In 2001, Spence et al. (2001) conducted the first study on behavioural and functional anatomical correlates of deception. They showed that both behavioural and functional anatomical responses increase significantly during lying. They found reliable activation in the prefrontal cortex, particularly in the bilateral ventrolateral prefrontal cortex, the medial prefrontal and premotor cortex, and the left inferior parietal and lateral premotor cortex. Increased activation during deception was observed in regions such as the right and left ventrolateral prefrontal cortex (BA 47), the medial prefrontal (BA 32/8), the medial premotor (BA 6), the left lateral premotor (BA 6) and the left inferior parietal

cortex (BA 40), with these areas showing higher activation during both visual and auditory tasks (Spence et al., 2001).

Since then, brain activity during deception has been widely studied (e.g., Davatzikos et al., 2005; Delgado-Herrera et al., 2021; Kozel et al., 2009; Langleben, 2008; Langleben et al., 2005; Langleben & Moriarty, 2013; Lee et al., 2002; Meijer & Verschuere, 2017; Zheltyakova et al., 2020). In 2009, Christ et al. (2009) conducted a meta-analysis to identify brain regions involved in deception and executive functions (e.g., working memory, inhibitory control). Their results supported previous findings that prefrontal regions are important for deception, in particular the bilateral inferior parietal lobule (IPL) and the right inferior frontal gyrus (IFG). Overlaps between executive functions and deception were found in activity in the bilateral anterior insula (regions 1 and 9), the left inferior frontal gyrus (region 6), the left middle frontal gyrus (region 10), the right intermediate frontal sulcus (region 3), the right anterior cingulate cortex (ACC, region 12) and the right intraparietal sulcus (region 13) (Christ et al., 2009), as depicted in Fig. 4.

Figure 4: Results of the working memory (green), inhibitory control (red), task switching (blue), and deception (black borders) (Christ et al., 2009, p. 1562)



The activation of the ACC, linked to executive control during deception (Christ et al., 2009), is also evident in studies of social-interactive deception (Lisofsky et al., 2014). This shows that liars can feel internal conflict during social interaction tasks, consistent with

the ACC's role in conflict detection and monitoring (Carter & van Veen, 2007). When liars try to conceal their behaviour, the ACC is activated (Lisofsky et al., 2014), highlighting its role in executive control and moral reasoning, especially in dilemmas (Greene et al., 2004).

Compared to non-interactive deception, social-interactive deception shows a stronger activation of the right temporo-parietal junction (TPJ), the angular gyrus and the bilateral temporal pole (TP) (Lisofsky et al., 2014), as these areas are involved in social cognition and moral decision-making (Fumagalli & Priori, 2012; Mar, 2011). Zheltyakova et al. (2020) further investigated this using the game paradigm, where participants played a game with the opponent by intentionally sending honest or deceptive signals. During deception, they found increased brain activation in the TPJ (bilateral), left medial frontal gyrus, left superior frontal gyrus, right insula, left praecuneus, left middle temporal gyrus (MTG), right superior temporal sulcus (STS), the right superior temporal gyrus (STG), the left occipital cortex, the left putamen, the left caudate nucleus and the bilateral cerebellum. In addition, they examined the neural correlates of the intention to deceive/tell the truth, sophisticated deception/truth, while both sophisticated and simple deception were associated with increased BOLD signals in several brain regions including the TPJ in both cerebral hemispheres, which is also consistent with the findings of Volz et al. (2015). The intention to lie was associated with increased BOLD signalling in the left TPJ. They demonstrated the importance of socio-cognitive processes as an initial part of deception and should be included in the future neuropsychological laboratory paradigm (Zheltyakova et al., 2020).

Yu et al. (2019) analysed 49 studies on deception versus truth telling and 28 on false versus true memories and found that both tasks consistently activated the left superior frontal gyrus (SFG). Deception also showed increased activation in the right superior temporal gyrus (STG), insula and inferior parietal lobule (IPL). In the most recent meta-analysis, Delgado-Herrera et al. (2021) found that the intention to lie activates the left lateral occipital cortex, while deception under instruction involves the left angular gyrus and right inferior frontal gyrus. The right inferior frontal gyrus appears to play a role in the social dimension of deception and the right insular cortex and bilateral anterior cingulate cortex serve as indicators of highly ecologically valid tasks. However, only 20.33% of 59 studies analysed were found to have high ecological validity (e.g., Sip et al., 2010;

Volz et al., 2015; Yin et al., 2017). Based on their findings and previous research on the ecological validity of deception tasks (e.g., Abe, 2009; Wright et al., 2013), Delgado-Herrera et al. (2021) proposed that future fMRI studies on deception should include three key criteria: (a) spontaneous intention to lie, (b) social interaction, and (c) motivation (e.g., rewards for lying).

To summarise, although fMRI shows promises, the results are not statistically robust enough to justify the use of fMRI in high-stakes legal contexts to detect deception, because it is not always used with fraudulent intent, but due to false memory recognition (Yu et al., 2019). Furthermore, many laboratory paradigms lack ecological validity as they often omit crucial components such as spontaneous intentions, genuine social interaction or meaningful motivation (Delgado-Herrera et al., 2021). Until future studies utilise more ecologically valid designs and improve the ability to distinguish deception from related cognitive phenomena, the use of brain imaging techniques in deception detection should be approached with caution and likely remain relevant for research rather than immediate forensic or applied implementation.

3 PHYSIOLOGICAL DECEPTION DETECTION

Throughout human history, it has always been assumed that lying is associated with certain physiological reactions in the body of the person who deceives (Vrij & Ganis, 2014). In particular, the assumption that deception is accompanied by feelings of fear of being caught was the essential core of early physiological deception detection attempts (Trovillo, 1939).

3.1. A brief history of physiological deception detection

Physiological deception detection dates back to 1000 BC. In the sacred Hindu Yajurveda, discolouration of the face, trembling or itching of the big toes and the roots of the hair were markers of guilt (Chand, 1980, In McGlone & Knapp, 2019). In ancient China, suspected liars chewed dry rice – if the rice was dry, indicating stress and reduced saliva, the suspected person was convicted of deception (Ford, 2006). These methods tacitly point to the prevailing notion that deception is linked to emotional response – especially fear (Grubin & Madsen, 2005).

In 1895, Cesare Lombroso, the father of modern criminology, used volumetric displacements of the hand during forensic interrogations with a modified hydrosphymograph to measure emotional changes and detect deception by measuring changes in blood pressure and heart rate (Ambach & Gamer, 2018; Gordon, 2016). His method was later improved by Professor M. L. Patrizi, who developed a volumetric glove to track changes in air pressure based on heart pulsation. In 1897, psychologist Harold Sticker proposed using the galvanic skin response (GSR) to detect lies, which led to the development of GSR instruments in the 1950s. In 1909, law professor Hugo Munstenberg developed the concept of using various instruments to measure different physiological parameters such as GSR, respiration, cardiovascular activity, etc. and recommended their monitoring during testimony (Gordon, 2016). In 1914, Vittorio Benussi used respiratory changes to distinguish liars by detecting faster inhalation and slower exhalation during deception (Ambach & Gamer, 2018). In 1917, William Marston, a student of Hugo Munstenberg, published his first findings on the use of systolic blood pressure as

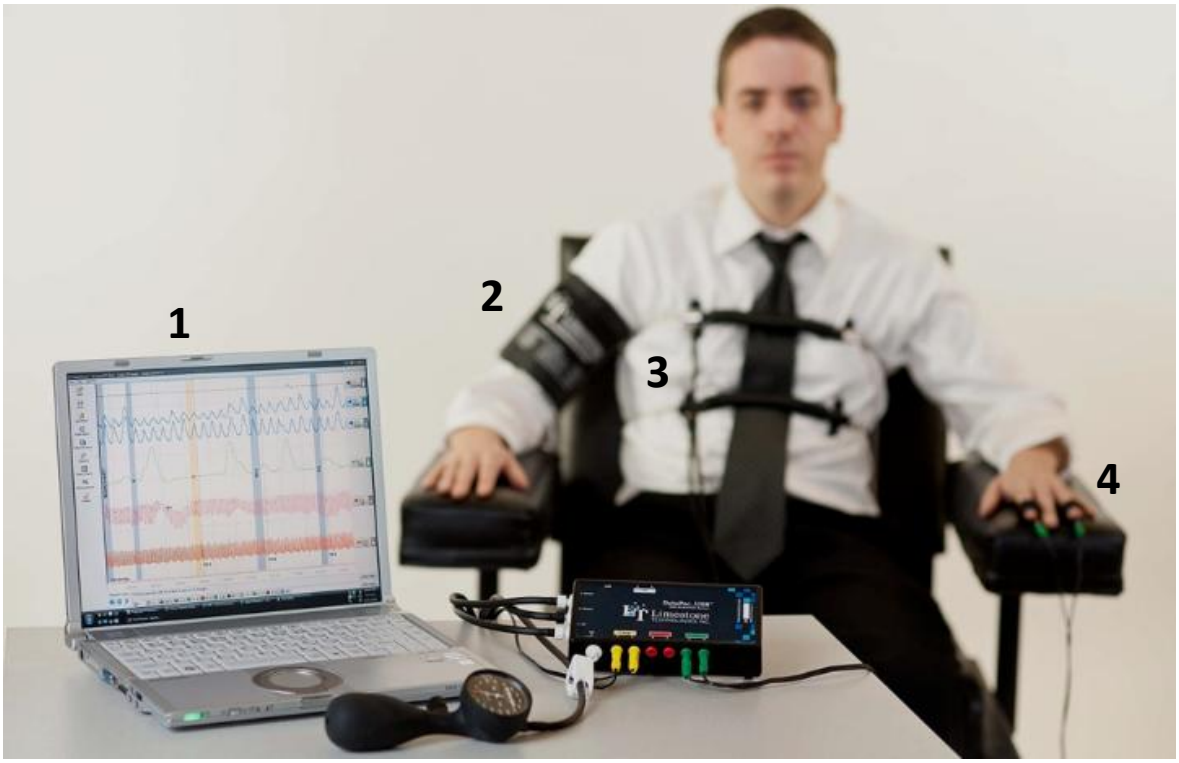
an indicator of deception (Ford, 2006; Gordon, 2016). The simultaneous measurement of blood pressure, pulse, respiration and galvanic responses was further defined and combined into a single device – the famous "*polygraph*" (from the Greek words *poly* = many and *grapho* = to scratch/write) (Ambach & Gamer, 2018; Gordon, 2016; Vrij & Ganis, 2014). The first polygraph, developed by police officer John Larson in 1921, measured heart rate, blood pressure and respiration (Ambach & Gamer, 2018; Synnott et al., 2015). Larson's protégé, Leonarde Keeler, made the polygraph portable and added the GSR (Synnott et al., 2015; Ford, 2006). Currently, there are two groups of polygraph tests: (a) the anxiety-based (i.e., Relevant-Irrelevant Test, RIT; Comparison Question Technique, CQT), which assumes that liars show greater arousal than truth tellers due to increased anxiety, and (b) the recognition-based (i.e., Concealed Information Test, CQT), that assumes that liars show an orienting reflex when they recognise a crucial detail of a crime (Vrij, 2015a). To date, the polygraph has the longest tradition among all other deception detection devices (Meijer & Verschuere, 2014).

However, with the advancement of technology and digital innovation, new opportunities have emerged to improve the monitoring of human physiological states, to address key challenges in deception detection (Speth et al., 2021; Ambach & Gamer, 2018), and to overcome the contact characteristics of polygraphs that may affect the respondent's anxiety level or compromise the authenticity of interview sessions (Derakhsan et al., 2020). A promising tool in modern physiological and non-invasive deception research is (a) functional infrared thermal imaging (fITI) for remote measurement of human temperature (Ioannou, Gallese, et al., 2014), (b) remote photoplethysmography (rPPG), a video-based technique that measures pulse rate by detecting variations in skin pixel intensity to track changes in blood volume (Benedetto et al., 2019), and (c) pupillometry for pupil size measurement (Proudfoot et al., 2016). Despite the technological innovations, the search for a fully reliable and universally accepted method remains. Future research is needed to refine these techniques and address ethical concerns, especially for their integration into practise.

3.2. Polygraph technology and methodology

Polygraphs are often misleadingly referred to as *lie detectors*, but they do not detect lies. Instead, they measure physiological arousal, which is thought to accompany deception (Granhag & Vrij, 2005). Polygraphs combine four tools to track these responses: (1) a computer with the polygraph software, (2) sphygmomanometer arm cuff around the upper arm for registering blood pressure, (3) two pneumatic rubber bellows positioned around the thorax and the abdomen for respiration recording, and (4) two electrodes on the fingers to measure electrodermal activity as depicted in Fig. 5 (Meijer & Verschuere, 2014).

Figure 5: Polygraph technology



Obtained from: https://iamscpd.org/polygraph-psych-medical (*Santa Clara Police Department*, n.d.), edited by the thesis' author.

3.2.1. The anxiety-based polygraph methodologies

The anxiety-based approach detect deception by measuring physiological arousal linked to emotional states such as anxiety and stress (Synnott et al., 2015; Vrij, 2015a; Vrij & Ganis, 2014). The first widely used polygraph test was the *RIT (Relevant-Irrelevant Test),* compared physiological response to two types of questions – crime-relevant

(e.g., *"Did you steal the silver necklace?"*) and crime-irrelevant (e.g., *"Is today Tuesday?"*) (Vrij & Ganis, 2014). Greater physiological responses to criminally relevant questions are categorised as indicative of deception than to criminally irrelevant questions. However, physiological differences may result from factors other than deception, making the RIT unsuitable for accurate lie detection (Raskin & Honts, 2002).

In response to criticism of the RIT, the *CQT (Comparison Question Test, formerly known as the Control Question Test*, Raskin & Kircher, 2014) was developed and became the dominant forensic test in the United States (National Research Council, 2003; Vrij & Ganis, 2014). It consists of a pre-test phase, where the examinee shares their version of events, followed by a polygraph phase with three types of questions: relevant, comparison, irrelevant (Ginton, 2017; Synnott et al., 2015). Relevant questions (RQs) are specific questions about the crime (e.g., "*Did you do it?*"). Comparison or control questions (CQs) are designed to be emotionally charged but not directly related to the topic under investigation. They are generally vague and phrased in such a way that the answer "*no*" is likely to be misleading (e.g., *"Have you ever stolen anything?"*) (Ginton, 2017; Granhag & Vrij, 2005; Iacono, 2017; Vrij & Ganis, 2014). The irrelevant questions focus on neutral questions (e.g., *"Is today Monday?"*). Liars are expected to show greater physiological responses elicited by relevant questions, whereas innocent subjects show greater physiological responses when answering comparison questions (Ginton, 2017; Iacono, 2017; Vrij & Ganis, 2014). Innocent subjects typically show weaker physiological responses to the relevant questions because they are less anxious. In contrast, comparison questions (CQs) elicit more stress or discomfort in innocent examinees because they can be perceived as deceptive. Therefore, innocent individuals respond more strongly to CQs, while guilty individuals respond more strongly to RQs (Iacono, 2017; Vrij & Ganis, 2014; Granhag & Vrij, 2005).

However, innocent individuals can sometimes show a stronger physiological response to RQs than to CQs (National Research Council, 2003) for two main reasons: (a) RQs may evoke more emotion in innocent individuals – for example, in a situation where an innocent man accused of murdering his beloved wife is asked about her – this may reawaken his strong feelings towards her and thus influence his physiological responses, and (b) innocent examinees may actually feel more anxiety because they fear being falsely

accused by the polygrapher (Synnott et al., 2015). Proponents of CQT argue that experienced polygraphers should be able to make CQs more stressful for innocent individuals by phrasing them carefully (Raskin & Honts, 2002). However, this highlights the non-standardised nature of the CQT, making it highly dependent on the skills of the examiner (Ben-Shakhar, 2008; Fiedler et al., 2002; Iacono, 2008). Nonetheless, the accuracy of the CQT ranges from 74% to 89% for guilty individuals, with false negatives of 1-13%, and from 59% to 83% for innocent individuals, with false positives of 10-23% (Grubin, 2010). Despite its strengths, the limitations of the CQT suggest that its accuracy is unlikely to improve without a stronger theoretical basis (Vrij & Ganis, 2014). As stated by the National Research Council (2003), the CQT is "well above chance, though well below perfection."

3.2.2. The recognition-based polygraph methodologies

The recognition-based approach is concerned with the fact that liars show an orienting reflex when they recognise a crucial detail of a crime (Vrij & Ganis, 2014). According to Sokolov (1990, p. 142), the orienting reflex is "a specific behavioural act directed towards extraction of information from the environment." It triggers decrease in heart rate and breathing patterns and increase electrodermal activity – the higher the increase, the more significant the perceived stimuli (Bradley, 2009).

In the late 1950s, David Lykken, a strong critic of the CQT, developed an alternative polygraph test called *The Guilty Knowledge Test (GKT*, Lykken, 1959), now commonly referred to as the *Concealed Information Test (CIT)* (Verschuere, Ben-Shakhar, et al., 2011). The standard CIT examination consists of three phases: pre-test (similar to CQT), test and post-test (data analysis and decision making) (Synnott et al., 2015; Verschuere & Ben-Shakhar, 2011). During the test, the examiner asks for details of the crime that only the guilty person would know. The test person answers from a series of predetermined alternative answers – some of which are correct, others plausible but incorrect (e.g., *"Was the victim killed with (a) a gun, (b) a knife, (c) a rope, (d) a bat or (e) an ice pick?"*). It is assumed that the guilty suspect elicits a heightened physiological response when the correct answer is given, while the rest would be salient (Granhag et al., 2015). For example, several studies showed that the heart rate slows down with stimuli associated with crime

(Ambach et al., 2008; Geven et al., 2022; Verschuere et al., 2009; Verschuere, Meijer, et al., 2011; Verschuere & Crombez, 2008).

Despite its clear theory, many concerns have been raised about its effectiveness. The number of questions depends on available crime-related details, and formulating them so that only the guilty person knows the correct answer can be challenging (Vrij & Ganis, 2014). Media exposure or memory changes may influence the results, as both innocent or guilty subject may remember or forgot certain details differently (Gamer, 2010; Vrij & Ganis, 2014). Furthermore, innocent people with prior trauma may also show responses to certain stimuli unrelated to the current crime (Synnott et al., 2015). CIT accuracy rates ranged from 76% to 86% for individuals categorised as guilty, while rates for innocent individuals ranged from 83% to 99% (Vrij, 2009). While CIT is a recognition test rather than a direct deception test (Synnott et al., 2015), it can sometimes reveal new, relevant information (Matsuda et al., 2019).

To summarise, research to date suggests that recognition-based approaches to physiological polygraph testing are more reliable than anxiety-based methods, both have the limitations mentioned above (Vrij & Ganis, 2014). Although polygraph techniques differ, they all rely on contact-based measurement, which may limit the duration and nature of the interview and increase subject anxiety, which in turn may affect the accuracy and reliability of the results (Cardone & Merla, 2017; Derakhshan et al., 2020). The development and establishment of non-contact measurement could overcome these problems by providing more flexibility, reducing anxiety-related interference (Cardone & Merla, 2017; Derakhshan et al., 2020; Gołaszewski et al., 2015), and increasing the number of potential situations (e.g., personnel selection procedures, airport security checks, workplace health and safety interviews, etc.) in which deception detection would be a valuable source of information. To date, two main non-invasive techniques are used to measure physiological responses during deception: rPPG and fITI.

3.3. Remote Photoplethysmography

In the context of physiological deception, the cardiovascular system is of central importance as it provides insights through metrics such as heart rate, vasoconstriction and blood pressure (Ambach & Gamer, 2018). It consists of the heart, which pumps the

blood, and the circulatory system – a network of arteries, capillaries and veins, which supplies the body's organs with blood, nutrients, oxygen and hormones while also removing waste products (Al-Naji et al., 2017). The circulatory system functions via two primary circulatory systems: the pulmonary and the systemic circulation. The pulmonary circulation transports blood from the heart to the lungs, where it absorbs oxygen (O_2) and releases carbon dioxide (CO_2), and then returns the oxygen-rich blood to the heart (Saladin et al., 2018). The systemic circulation distributes this oxygen-rich blood throughout the body and brings the deoxygenated blood back to the heart to restart the circulation (Syed et al., 2023). The heart is regulated by both the sympathetic and parasympathetic nervous systems by modulating heart rate (chronotropic control) and electrical conduction (dromotropic control). While both branches of the autonomic nervous system influence cardiac activity, the parasympathetic nervous system exerts greater control over heart rate than the sympathetic nervous system (Berntson et al., 2017). Although changes in sympathetic activity take a few seconds to influence the heart rate, the parasympathetics can change the heart rate in less than a second (Somsen et al., 2004).

Heart rate and its variability (HRV) have recently gained attention as biomarkers of ANS activity due to the ability to measure them passively via wearable devices or remotely through rPPG (Owens, 2020). Heart rate is the number of beats per minute (Shaffer & Ginsberg, 2017), while HRV refers to the variation in time between heartbeats (Gullett et al., 2023). Typically, three HRV indicators are being used to quantify ANS activity:

1. *Time-domain HRV measures* reflect the variability between heartbeats, such as HR Max – HR Min (bpm), which describes the average difference between the highest and lowest heart rate in a respiratory cycle, or RMSSD (the root mean square of successive respiratory rate interval differences), which is used to quantify vagal activity (Shaffer & Ginsberg, 2017).
2. *Frequency-domain HRV measures* decompose HRV signal into its individual frequencies to examine the proportion of the signal presents within various frequency bands (Gullett et al., 2023; Shaffer & Ginsberg, 2017). The frequency-domain HRV indices are divided into ultra-low-frequency (ULF, ≤ 0.003 Hz), very-low-frequency (VLF, 0.0033 – 0.04 Hz), low-frequency (LF, 0.04 – 0.15 Hz), high-frequency (HF, 0.15 – 0.4 Hz) bands (Shaffer

& Ginsberg, 2017). In terms of efferent vagal activity, the HF-HRV is a reliable indicator of parasympathetic activity (Shaffer et al., 2014), while LF-HRV is not such a pure sympathetic activity indicator as it reflect both the parasympathetic and sympathetic activity (Hayano & Yuda, 2019; Thomas et al., 2019; Valenza et al., 2018).

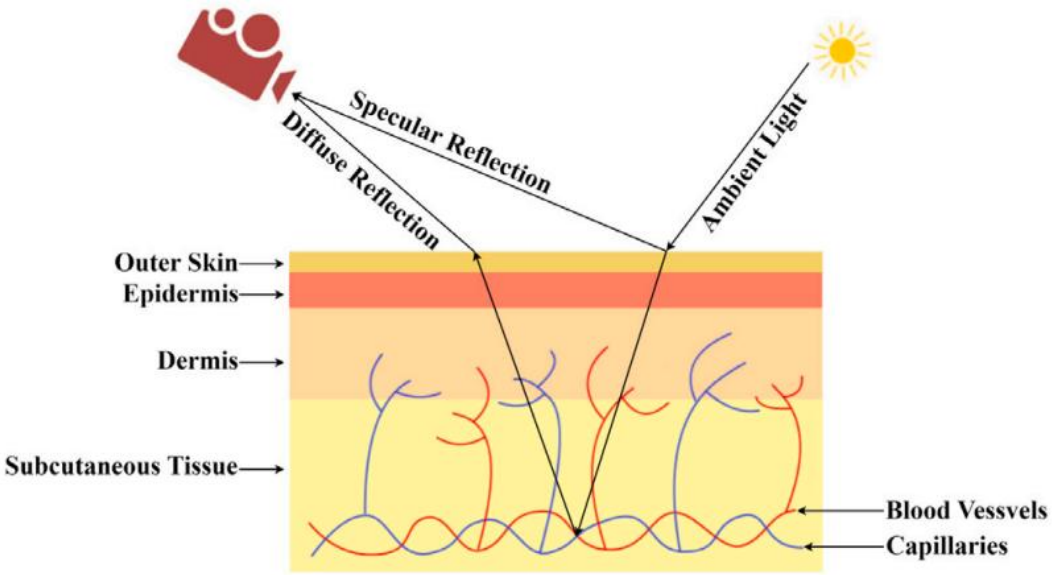
3. *Non-linear measurements for quantification of the unpredictability of a time series* (Shaffer & Ginsberg, 2017). Non-linear HRV indices such as correlation dimension, SampEn (sample entropy measuring the regularity and complexity of a time series) and ApEn (approximate entropy measuring the regularity and complexity of a time series) are proposed as indicators of parasympathetic activity (Gullett et al., 2023; Shaffer & Ginsberg, 2017). Other nonlinear HRV measures, such as those derived from Poincaré plots (plotting each R-R interval against the previous one), including SD1 (standard deviation perpendicular to the identity line) and SD2 (standard deviation along the identity line), are also associated with parasympathetic activity (Rahman et al., 2018).

Typically, the activity of the cardiovascular system is measured using photoplethysmography (PPG) devices such as pulse oximeters, smartwatches, etc., which rely on the basic principle of using a light source and a photodetector to measure changes in blood flow volume in the subcutaneous vessels (Xiao et al., 2024). The PPG can be explained by the modified Beer-Lambert law, which states that the haemoglobin concentration in the blood and skin is proportional to the amount of light absorbed by the blood (Kyriacou & Chatterjee, 2022). In short, during the cardiac cycle, slight changes in haemoglobin concentration lead to fluctuations in the amount of light absorbed by the blood vessels, resulting in fluctuations in the intensity value of the skin (Xiao et al., 2024). While PPG is cost-effective (Gudi et al., 2020; Kyriacou & Chatterjee, 2022; Scalise, 2012; Schrumpf et al., 2021), its contact-based nature can be uncomfortable for long-term use or unsuitable for people with skin diseases (Aarts et al., 2013). To address these issues, rPPG was developed as a non-contact alternative.

rPPG is a technique that uses video recordings to remotely capture physiological parameters such as heart rate, respiratory rate and oxygenation by detecting light changes

on the skin surface (Benedetto et al., 2019; de Haan & Jeanne, 2013; van der Kooij & Naber, 2019). The schematic of the basic mechanism behind rPPG is shown in Fig. 6 (Xiao et al., 2024, p. 2).

Figure 6: Schematic diagram of rPPG signal generation (Xiao et al., 2024, p. 2)



For further explanation of the rPPG principle based on the Dichromatic Reflection Model (DRM), see for example de Haan and Jeanne (2013) or Tominaga (1994).

Licensed rPPG software solutions include the FaceReader system from Noldus, or Philips Biosensing, available to third-party manufacturers. rPPG can also be performed using conventional or supervised deep learning methods. An example of conventional methods is chrominance model, CHROM (de Haan & Jeanne, 2013), Independent Component Analysis, ICA (Poh et al., 2010), Joint Blind Source Separation, JBSS (Qi et al., 2017), Spatial Subspace Rotation, 2SR (Wang et al., 2016) or POS (Wang et al., 2017). Examples of supervised deep learning methods include Eulerian Video Magnification with 2D CNN, EVM-CNN (Qiu et al., 2019), SynRhytm with Special Temporal Map (Niu et al., 2018), Cross-Verified Disentangling, CVD (Niu et al., 2020), Neural Architecture Search for Heart Rate Estimation, NAS-HR (Lu & Han, 2021), Spatial-Temporal Attention Module Based on 3D CNN, SAM-rPPGNet (Hu et al., 2022) or Meta-rPPG (Lee et al., 2020). To evaluate an rPPG method, different data sets are useful to compare methods – the datasets with the largest amount of videos include: VIPL-HR with 2,378 videos in visible light and 752 videos in near infrared (Niu et al., 2019), Synthetic for Camera Measurement

of Physiological Signals, SCAMPS with 2,800 videos (McDuff et al., 2022), Vision for Vitals, V4V with 1,358 videos (Revanur et al., 2021) or DEAP with 874 videos (Koelstra et al., 2012). For more information on the rPPG methods and the existing datasets, refer to a complex review on this topic by Xiao et al. (2024).

It is worth noting that the accuracy of rPPG measurements is affected by lighting conditions, with strong shadows or uneven lighting leading to inaccuracies. Different skin tones can affect the optical properties of the tissue being measured, which can lead to variations in the performance of the device for different users. Head and body movements can lead to signal artefacts, so minimising movement is crucial (Benedetto et al., 2019). The technical characteristics of the camera used for rPPG, such as resolution and frame rate, play a crucial role in measurement accuracy. Recommended settings include a resolution of 1280 x 720 and a frame rate of at least 15 fps, preferably 30 fps. When using an existing dataset or when developing own dataset, checking the correct description of the hardware used and the laboratory environment in which the video recording took place should be the first step in using rPPG in data acquisition (Benedetto et al., 2019; Xiao et al., 2024).

3.3.1. Heart rate, its variability and affective states

Research into recognizing affective states has grown, with physiological signals becoming key in emotion recognition (Gasparini et al., 2020). For example, heart rate (bpm) varies significantly between the different affective states, with amused states showing lower heart rates (78.03 bpm) than angry (82.03 bpm), fearful (82.73 bpm), and neutral (83.88 bpm) states (Wu et al., 2019). Similarly, Kop et al. (2011) found heart rate increases during anger (from 71.9 ± 3.5 bpm to 77.6 ± 3.3 bpm) and happiness (from 71.7 ± 3.2 to 77.3 ± 3.3 bpm), indicating a positive autonomic response.

However, rather than heart rate alone, HRV indicators are typically used to assess affective states (Appelhans & Luecken, 2006; Choi et al., 2017; Gasparini et al., 2020; Kop et al., 2011; Sin et al., 2016; Suzuki et al., 2021; Wu et al., 2019; Yamuza et al., 2019). Several studies found a reduction in HF-HRV during negative affect (Bleil et al., 2008; Dimitriev et al., 2023; Sin et al., 2016; Young et al., 2017). On the other hand, Wu et al. (2019) found that HRV activity increased not only during positive affect (e.g., amusement),

but also during negative affect, especially anger. More specifically, the RMSSD was significantly higher in the state of amusement (154.74 ms) than in the state of fear (80.81 ms), neutrality (91.42 ms) and anger (111.46 ms), indicating that amusement strongly activates the parasympathetic nervous system. In addition, the RMSSD was significantly higher in the angry condition than in the fearful condition (Wu et al., 2019). Negative affect triggered by videos also led to increased HF-HRV, but the authors did not measure self-reported emotions, so it is unclear whether the intended affective states were felt (Shi et al., 2017). The importance of controlling individual responses was demonstrated by Kop et al. (2011), who investigated how positive and negative mood influence HRV in the form of LF-HRV and HF-HRV. HF-HRV showed no significant differences – however, when controlling for individual response to the task, participants who experienced the expected feeling of happiness during the positive mood induction task showed an increase in HF-HRV (Kop et al., 2011). This emphasises the need to assess individual responses rather than assuming the intended effect of the task. Furthermore, video clips do not always elicit the expected emotions (Gilman et al., 2017), meaning that HRV only accurately reflects emotion when the elicitation task is strong (Choi et al., 2017).

Empirical studies also show that HRV reflects the brain's adaptability to various tasks (Paige et al., 2022). Increased HRV levels have been associated with improved performance on cognitive tasks requiring executive functions (Hansen et al., 2003; Johnsen et al., 2003), improved emotion regulation in stressful situations (Fabes & Eisenberg, 1997; Lane et al., 2009), better impulse control (Allen et al., 2000), improved memory inhibition (Gillie et al., 2014), and decreased personal distress (Guendelman et al., 2024). These results suggest that HRV may serve as a physiological marker of individual differences in inhibitory control, highlighting its potential role in understanding cognitive processes (Gillie et al., 2014).

3.3.2. Heart rate, its variability and deception detection

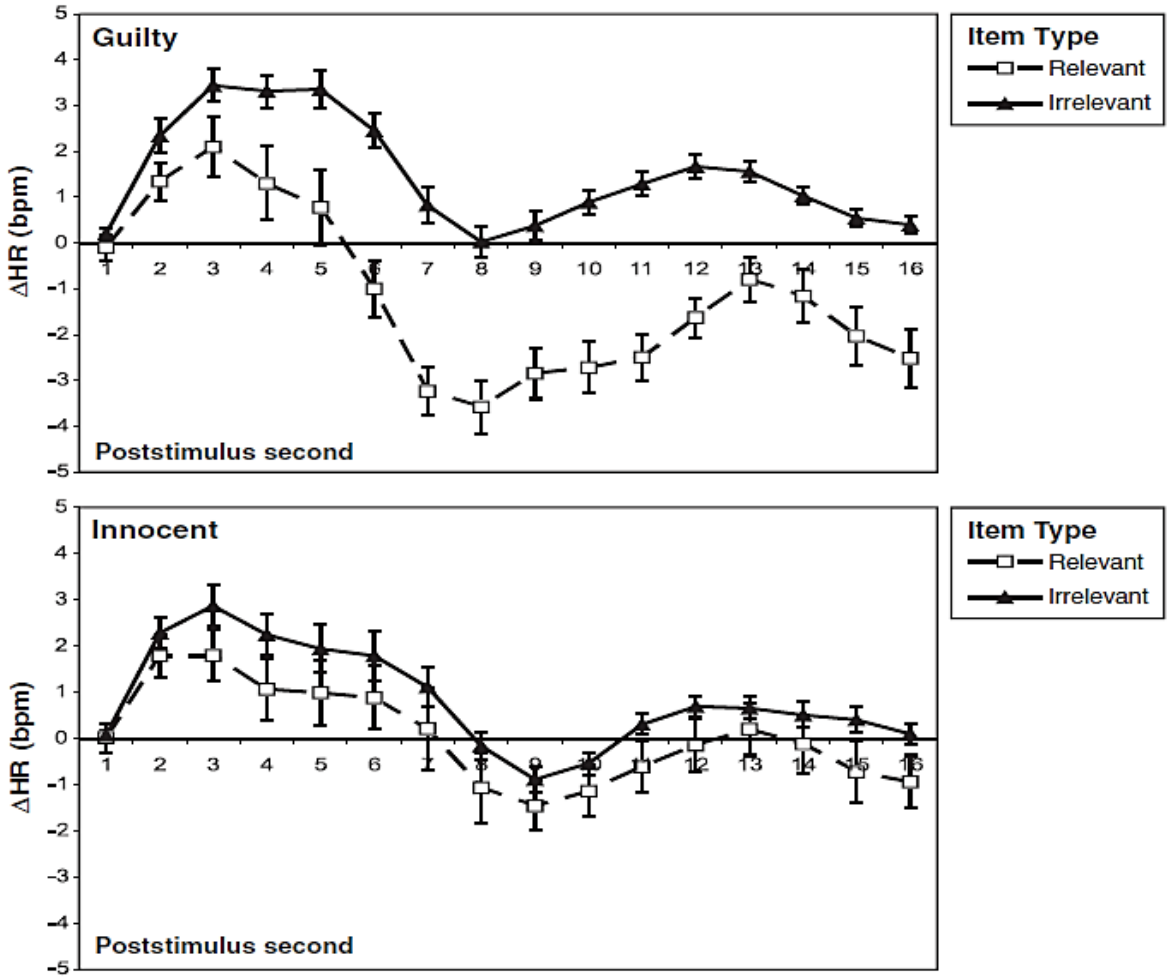
The heart rate and HRV is closely related to the activity of the sympathetic and parasympathetic nervous system (Appelhans & Luecken, 2006; Berntson et al., 2017; Lane et al., 2009; Luque-Casado et al., 2016; Somsen et al., 2004; Thayer et al., 2012; Wu et al., 2019). Since higher heart rate and HRV is linked to better cognitive control

(Gillie et al., 2014; Hansen et al., 2003; Johnsen et al., 2003), and deception is believed to require cognitive control (Vrij, Fisher, et al., 2008), research has explored heart rate and HRV as a cues to deception (Paige et al., 2022).

Gödert el al. (2001) conducted an experimental study in which they examined heart rate under deceptive and truthful conditions in a situation of low emotional involvement and low mental stress in order to elicit the side effects apart from the truth or deception itself. They observed significant changes in phasic heart rate during truthful responses and identified two accelerating (A1, A2) and two decelerating (D1, D2) response components. The deceleration of heart rate was more pronounced in deceptive responses, while in A2 (9-14 seconds after the question) deceptive responses showed a lower acceleration compared to truthful responses, indicating a truthfulness effect (Gödert et al., 2001).

In later studies (Gamer, 2010; Gamer et al., 2006, 2008; Verschuere, Crombez, De Clercq, et al., 2004; Verschuere, Crombez, & Koster, 2004; Verschuere et al., 2009), the decelerations in heart rate were more pronounced than the accelerations as in the study by Gödert et al. (2001). In a CIT, typical deceptive responses showed an initial acceleration in heart rate followed by a deceleration (Gamer et al., 2006). More specifically, only the guilty participants showed different responses between relevant and irrelevant items. A plausible explanation is that the initial acceleration of the heart rate reflects efforts to appear honest, while the deceleration involves controlling the guilty response and gathering information to pass the test. This typical heart rate profile (see Fig. 7, Gamer et al., 2004, p. 82) is considered highly diagnostic for detecting deception (Gamer et al., 2006).

Figure 7: Phasic heart rate (ΔHR) as a function of post stimulus seconds and item type in experimental groups (Gamer et al., 2004, p. 82)



The biphasic heart rate response observed during direct questioning appears to be due to a temporal interplay between non-diagnostic verbalisation and attentional processes that effectively discriminate between guilty and innocent individuals (Gamer, 2011). To further explain this mixed pattern of heart rate, Verschuere et al. (2009) examined the effect of verbalization on heart rate patterns during CIT. The findings showed that during silent conditions (remain silent to all questions), the correct test items elicited greater heart rate deceleration than the incorrect items. The verbalization led to the biphasic heart rate initial increase – for the incorrect items is stronger than for correct items. During verbalization of incorrect items, the sympathetic nervous system causes a sharp heart rate increase, which returns to baseline within 5 – 6 seconds. In contrast, when responding to correct items, parasympathetic activity moderates the initial increase,

leading to a more gradual rise followed by a slowdown after the same period (Verschuere et al., 2009).

rPPG is also gaining interest for the detection of deception (Li et al., 2024; Speth et al., 2021; Vance et al., 2022). It uses advances in signal processing and machine learning to detect changes in heart rate and blood volume associated with deceptive behaviour (Speth et al., 2021). As the technology evolves, researchers are exploring its potential to improve accuracy, particularly when examining multimodal datasets (e.g., Deception Detection and Physiological Monitoring, DDPM, Speth et al., 2021; Vance et al., 2022), where authors provide the collected data to other researchers for further analysis. However, a comprehensive study assessing heart rate or heart rate variability with rPPG that would describe HR or HRV changes as with conventional PPG or ECG methods has not yet been conducted. This represents a significant research gap that goes beyond existing rPPG datasets and remote physiological detection of deception.

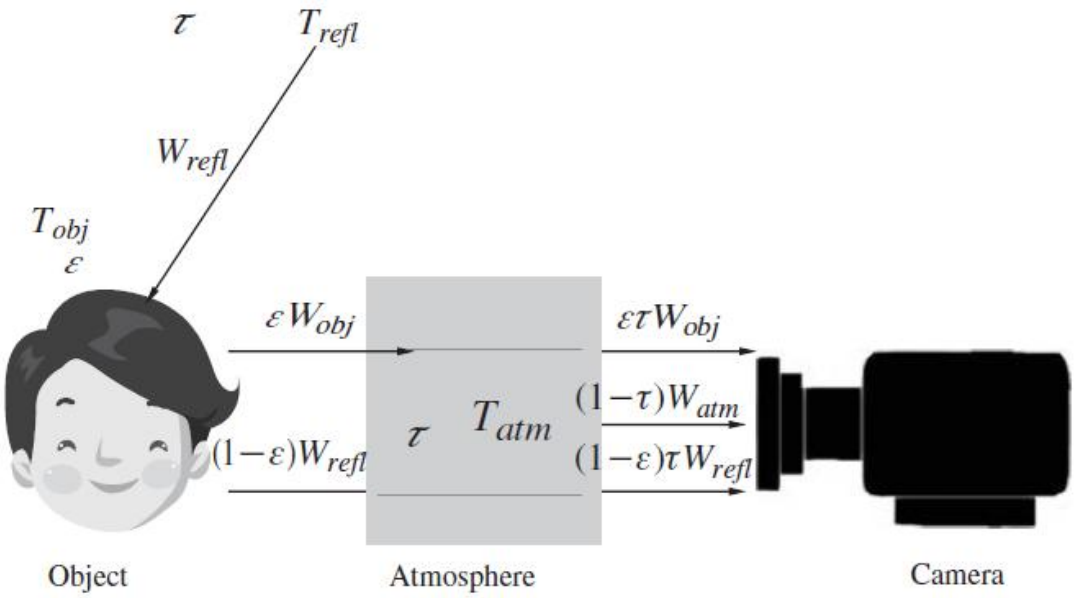
3.4. Functional infrared thermal imaging

fITI, commonly referred to as infrared thermography, is a technique that studies thermal distribution without direct contact with the body (Cardone & Merla, 2017). Thermal cameras works by detecting infrared energy emitted by objects based on their temperature, which is invisible to the human eye (Fluke, 2024). All objects, including humans, emit electromagnetic radiation, influenced by temperature (T) and emissivity (ε), which determines their ability to radiate (Robinson et al., 2012, p. 236):

$$W_{\mathrm{tot}} = \varepsilon\tau W_{\mathrm{obj}} + (1 - \varepsilon)\tau W_{\mathrm{refl}} + (1 - \tau)W_{\mathrm{atm}}$$

Three main components of radiation are collected via fITI: the emission from the object $\varepsilon\tau W_{obj}$ – human emissivity is thought to be 0.98 (Bernard et al., 2013); the emission from any ambient sources $(1 - \varepsilon)\tau W_{refl}$; and the emission from the atmosphere $(1 - \tau)W_{atm}$ as depicted in Fig. 8.

Figure 8: Detecting thermal radiation from the face (Robinson et al., 2012, p. 236)



A thermal imaging camera equipped with an infrared detector captures this radiation and converts it into an electrical output signal (e.g., a voltage output signal) (Cardone & Merla, 2017). Essentially a visual image representing temperature variations (Fluke, 2024). This conversion is based on three main physical laws: (a) *Planck's law* – relationship between the radiance and the wavelength of radiation emitted by a blackbody which absorbs all incident radiations and radiates a continuous spectrum at any temperature, (b) *Stefan-Boltzmann law* – total energy emitted per unit area of a black body during a unit time is proportional to the fourth power of the temperature of the black body, and (c) *Wien's displacement law* – the wavelength of the peak of the radiation spectrum corresponds to the temperature of the black body (Xia et al., 2021). More detailed information on this method and the associated calculation equations, see Xia et al. (2021), Cardone and Merla (2017), Holst (2000), Rogalski (2002, 2010), Vollmer and Möllmann (2018), etc. For additional information on fITI and the physics behind it, visit the Inframet website (https://www.inframet.com/index.html), where not only articles but also e-books on thermography technology are regularly published.

3.4.1. The nature of the thermal print of a face for physiological responses

Thermal imaging provides valuable insights into physiological mechanisms behind psychological states by capturing dynamic thermal responses that are influenced by psychological and physiological factors (Gioia et al., 2023). Specifically, fITI measures facial thermal changes resulting from fluctuations in blood flow caused by different activation of the facial muscles (Clay-Warner & Robinson, 2015) induced by different physical (e.g., Shastri et al., 2009; Ioannaou et al., 2014) or psychophysiological conditions such as deception (e.g., Hypšová et al., 2024; Derakhsan et al., 2020; Moliné et al., 2018; Gálvez-Garcia et al., 2021; Panasiti et al., 2016; Pavlidis et al., 2001; Pavlidis & Levine, 2002; Pollina et al., 2015; Rajoub & Zwiggelaar, 2014). It also records fluctuations in heart rate (Garbey et al., 2007; Nakai et al., 2024), perspiration (Pavlidis et al., 2012; Subhash et al., 2024) or blood flow (Bagavathiappan et al., 2009; Puri et al., 2005; Wang et al., 2022). Therefore, a solid understanding of facial anatomy and the role of the autonomic nervous system in thermoregulation is essential to correctly interpret the thermal responses of the face to emotional or deceptive stimuli.

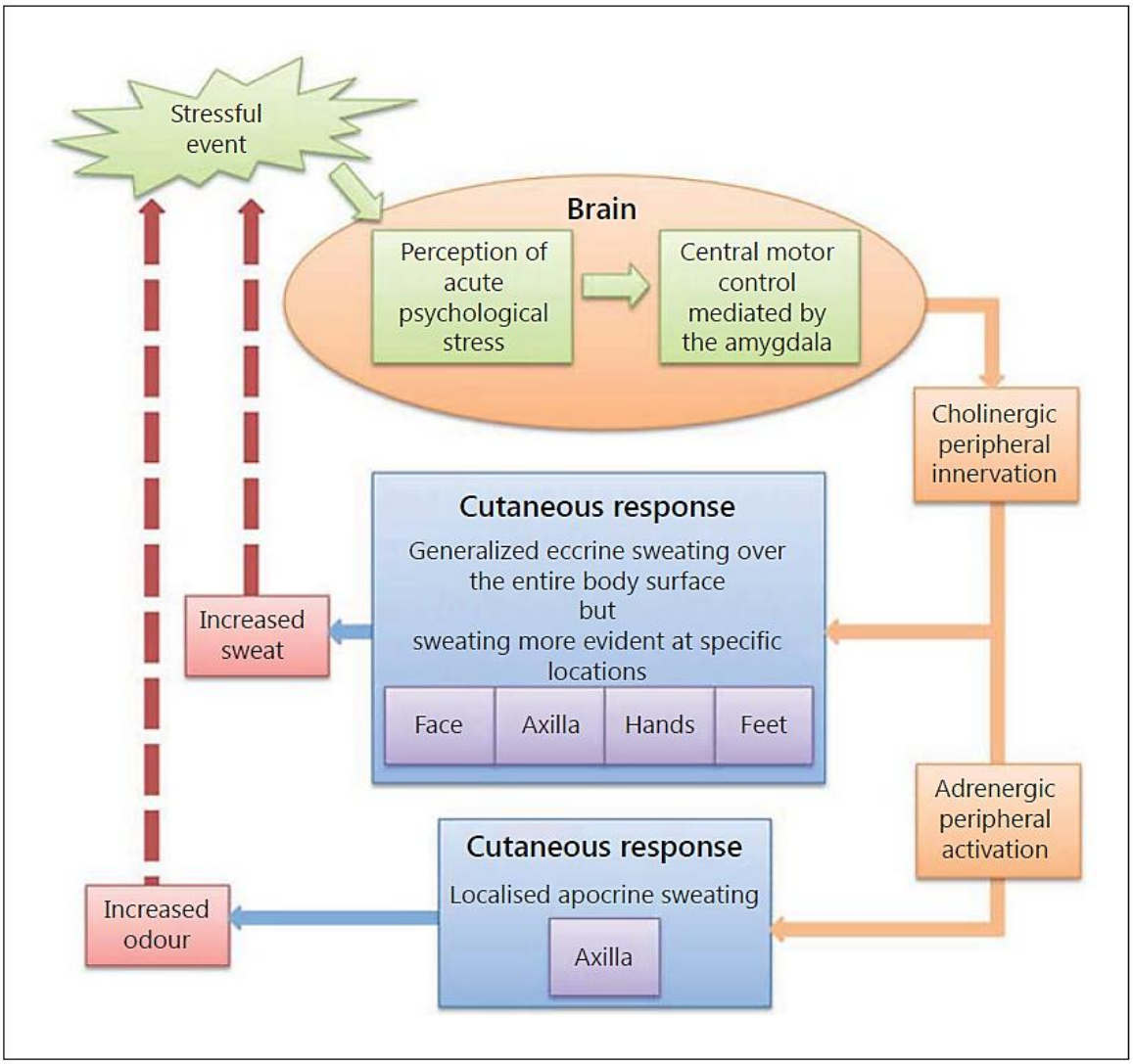
Human temperature and autonomic nervous system activity: A brief summary

Human thermoregulation is controlled by complex neuroregulatory systems (Ioannou, Gallese, et al., 2014) and includes vasomotor control of the skin, metabolic activity and sudomotor control of sweat gland activity (Johnson & Kellogg, 2018). However, we focus on two main mechanisms that reflect emotional imprints on facial temperature: emotional sweating and subcutaneous vasoconstriction. For more information on the physiology of human temperature in general, see Johnson et al., (2014), Johnson and Kellogg (2018).

Emotional sweating occurs in response to an emotional stimulus (e.g., stress, fear, anxiety, etc.) and occurs over the entire body surface, being most prominent on the palms, face, armpits, and soles of the feet (Harker, 2013; Machado-Moreira & Taylor, 2012). It is triggered by the activation of noradrenaline, which is bound to sympathetic preganglionic neurones in the spinal cord. This activation releases acetylcholine in the synaptic cleft, which simulates secretion in the sweat glands (Ioannou, Gallese,

et al., 2014). The amygdala is the main brain area that influences sweat gland function in response to psychological stress. Affective stimuli highly regulate apocrine sweating, which is mediated via the adrenergic peripheral pathway (Harker, 2013). The extent of emotional stimuli that activate emotional sweating depends on the individual and is not uniform across the population (Cacioppo et al., 1998; Harker, 2013). Fig 9. depicts the conceptual model of emotional sweating and the associated cutaneous response (Harker, 2013, p. 97).

Figure 9: Conceptual model of psychological sweating and the associated cutaneous response (Harker, 2013, p. 97)

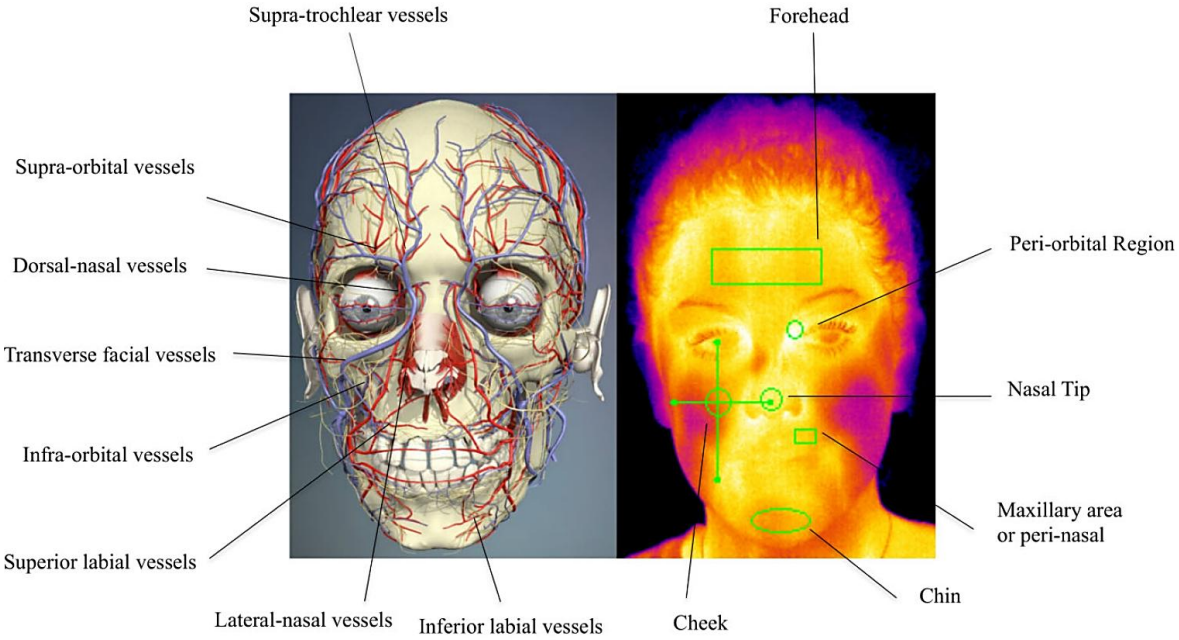


Subcutaneous vasoconstriction is a response to a threat that reduces blood volume in the venous structures under the dermis (Kistler et al., 1998; Pavlidis et al., 2001) and is activated via epinephrine released in the bloodstream (Ioannou, Gallese, et al., 2014).

Although the parasympathetic nervous system acts on endothelial cells, vasomotion in glabrous skin (such as the palms, soles and tip of the nose) is primarily controlled by sympathetic noradrenergic fibres. When these fibres are activated, they cause vasoconstriction leading to a decrease in local temperature (Donadio et al., 2006; Kosonogov et al., 2017; Nhan & Chau, 2010; Westcott & Segal, 2013). In short, vasoconstriction is triggered by stimulation of the sympathetic nervous system, which increases adrenaline levels, while vasodilation is due to reduced activity of the parasympathetic nervous system (Aristizabal-Tique et al., 2023).

The human face and its blood vessels are innervated by both parasympathetic and sympathetic nerves (Drummond, 1994; Matsukawa et al., 2018) that regulate blood flow to the facial muscles. These blood vessels supply the facial muscles with important nutrients via the bloodstream. As a result, there are changes in blood flow to support muscle activity, which in turn alters the heat patterns emanating from the face (Ioannou, Gallese, et al., 2014). The main vessels which influence subcutaneous temperature in the face are shown in Fig. 10 (Berkovitz et al., 2013, In Ioannou, Gallese, et al., 2014, p. 955).

Figure 10: Thermal representation for extraction of regions of interest along with a vascular representation of the major vessels affecting the subcutaneous temperature (Berkovitz et al., 2013, In Ioannou, Gallese, et al., 2014, p. 955)



The affective nature of the facial thermal prints

When a person experiences heightened feelings of different emotions, the autonomic nervous system produces different types of physiological or behavioural responses such as changes in blood flow that cause abrupt changes in local skin temperature (Aristizabal-Tique et al., 2023), especially in the face, which has a very thin layer of flesh (Pavlidis et al., 2001). Existing thermal studies have shown that the type of emotion (Aristizabal-Tique et al., 2023; Clay-Warner & Robinson, 2015; Cruz-Albarran et al., 2017; Ioannou, Gallese, et al., 2014; Marqués-Sánchez et al., 2020; Pavlidis et al., 2012; Salazar-López et al., 2015), or the emotional valence or arousal (Aristizabal-Tique et al., 2023; Cruz-Albarran et al., 2017; Kosonogov et al., 2017; Nhan & Chau, 2010) can be determined by analysing the increase or decrease in facial temperature, especially in the cheeks, periorbital region, nose and forehead.

Nose temperature

The tip of the nose consistently shows a different thermal response due to different emotional activation (Engert et al., 2014; Ioannou, Gallese, et al., 2014). Reason is the absence of underlying muscles that prevent thermal changes due to muscle contractions (Kosonogov et al., 2017) as well as the presence of numerous arteriovenous anastomoses involved in thermoregulation of the body (Johnson et al., 2014). Research has shown that a drop in nasal temperature has been identified as a possible indicator of mental workload in two driving experiments (Or & Duffy, 2007). Participants completed two driving tests – one in a simulator and the other in a real vehicle – while being presented with a mental workload task. The authors found that the higher the mental workload, the greater the decrease in nasal temperature (Or & Duffy, 2007). A similar result was presented by Pavlidis et al. (2012), who analysed the stress level of inexperienced surgeons in comparison to experienced surgeons. The facial temperature of the two groups was observed during the performance of three laparoscopic drillings. The results showed a significantly lower temperature in the perinasal region in the inexperienced surgeons due to the higher stress level of the experienced surgeons (Pavlidis et al., 2012). More recently, Bonyad et al. (2024) found that nasal temperature decreased continuously with increasing mental stress during flight simulations.

Some researchers (e.g., Diaz-Piedra et al., 2019; Kosonogov et al., 2017; Pavlidis et al., 2012; Salazar-López et al., 2015) argue that thermal changes reflect emotional arousal rather than specific positive or negative emotions. This is supported by findings that establish a correlation between the decrease in nasal temperature and central arousal indicators such as the EEG alpha attenuation coefficient (Nozawa & Tacano, 2009). The higher the arousal, the lower the nasal temperature (e.g., Nozawa & Tacano, 2009; Kosonogov et al., 2017; Pavlidis et al., 2001). However, Salazar-López et al. (2015) have shown the opposite. They found that arousal was associated with higher facial temperatures, while negative valence led to a decrease in nasal temperature – the dominant trend of decreasing overall facial temperature with negative valence was also described in the experimental study by Aristizabal-Tique et al. (2023). High arousal associated with higher nasal temperature was also found in Ioannou et al. (2016), Panasiti et al. (2016), Paolini et al. (2016). These contradictory results can be explained by the complex interaction between parasympathetic and sympathetic divisions of the autonomic nervous system, which play a complementary role in the physiological thermal responses to emotional stimuli (Ebisch et al., 2012). Ebisch et al. (2012) also suggested that the reason for the increase in nasal temperature may be due to the residual effect of withdrawal of sympathetic alpha-adrenergic vasoconstrictor effect, while the decrease in nasal temperature may reflect peripheral vasoconstriction due to alpha-adrenergic activity. To summarise, an increase in temperature may occur when the vasoconstrictor effect of the sympathetic nervous system is reduced, while a decrease may occur when this effect is more pronounced and leads to peripheral vasoconstriction (Ebisch et al., 2012).

Periorbital region temperature

Jian et al. (2019) found that the temperature of the periorbital region increased significantly under all measured conditions (low arousal/high valence; high arousal/low valence; low arousal/low valence). They explain this by the connection with the abundance of micro vessels, adipose tissue and soft connective tissue surrounding the periorbital region and by different muscle movements – especially during high arousal/low valence, when the participants' breathing was accelerated and they opened and closed their mouths slightly, an increase in the temperature of the periorbital region and nose was observed

(Jian et al., 2019). Activation of the sympathetic nervous system, particularly in response to startle stimuli, also increases periorbital temperature through increased blood flow (Shastri et al., 2009). Similar results have been reported previously, for example by Pavlidis et al., (2001) or Tsiamyrtzis et al. (2007). In contrast, Gane et al. (2011) observed no significant changes in the mean temperature of the periorbital region during startle stimuli. They pointed out an important comparison with the earlier study by Pavlidis et al. (2001), noting that advances in technology and methodology over the decade are likely factors. In contrast to the continuous temperature data used in the current study, Pavlidis et al. (2001) only recorded single time points before and after the stimulus, without specifying when these were taken. Furthermore, it was unclear whether the intensity values were from a single pixel or an average value for a region, and they did not assess the statistical significance of the temperature differences (Gane et al., 2011). Gane et al. (2011) also explain the contradiction between the theoretical expectations regarding the influence of startle stimuli on the increase in body temperature in the aftermath – since during a fight-or-flight response, most of the blood flow goes to the locomotor system, the additional blood flow to the periorbital region might not be sufficient to significantly change the surface temperature.

Cheek's temperature

The thermal responses of the cheeks to different emotional states are non-specific and vary from person to person (Matsukawa et al., 2018; Murad & Malkawi, 2012; Wang et al., 2019). Previous research shows both increases and decreases in cheek temperature across different emotions. For instance, Matsukawa et al. (2018) found that cheek temperature decreased during positive films (e.g., comedies), while negative films (e.g., horror films) caused a decrease in only a few participants, with wide variation between individuals. In addition, the decrease in cheek temperature correlated significantly with the subjective rating of pleasantness – the higher the subjective pleasantness, the lower the cheek temperature (Matsukawa et al., 2018).

Increased cheek temperature has been observed in response to emotions such as disgust and sadness (Cruz-Albarran et al., 2017), lower levels of positive emotions in general (Robinson et al., 2012) and feelings of embarrassment associated with sympathetic nervous system activity and blushing (Shearn et al., 1990). Blushing serves as

a thermoregulatory mechanism that increases blood flow to the cheeks to dissipate heat more effectively (Ioannou et al., 2017), and can also occur during positive experiences, like being near a loved one (Barbosa Escobar et al., 2021). In addition, higher cheek temperature is associated with social cognition (Ioannou et al., 2016; Ioannou, Morris, et al., 2014; Paolini et al., 2016), and people's attempts to make an impression (Gálvez-García et al., 2021).

Forehead temperature

The supraorbital vessels that supply the corrugator muscle with blood are located in the forehead (Zhu et al., 2007). Increased activity of the corrugator supercilius muscle is thought to be the most important facial muscle indicator of negative affect (Larsen et al., 2003), particularly anger (Cruz-Albarran et al., 2017; Dimberg & Petterson, 2000; Jackson et al., 2000) or in response to unpleasant stimuli (Bradley & Lang, 2000; Codispoti et al., 2001). These findings laid the foundation for the thermographic investigation of forehead temperature as an indicator of negative affective states and stress.

Puri et al. (2005) found that increased blood flow in the forehead vessels correlates strongly with stress. Zhu et al. (2007) suggested that changes in supraorbital signalling reflect prolonged stress from mental effort. In Robinson et al. (2012) study, participants were asked to read a short text on camera and then receive feedback (positive or negative). After receiving the feedback, they completed a questionnaire to rate their emotional response to the feedback. The authors found that the temperature of the forehead, particularly the eyebrows, increased significantly when they received low levels of positive emotion. Interestingly, they found that forehead and cheek temperature showed similar warming patterns in response to negative emotions – however, cheek temperature was more related to positive emotions, while forehead temperature was related to emotional potency (i.e., the strength or intensity of an emotional experience). These results show that forehead and cheek temperature can serve as a reliable indicator of affective reactions during social interactions (Robinson et al., 2012).

3.4.2. Facial temperature and deception detection

Thermal imaging has proven to be a promising tool for capturing psycho-physiological responses, particularly in regions such as the nose, cheeks, periorbital area

and forehead (Abdelrahman et al., 2017; Aristizabal-Tique et al., 2023; Clay-Warner & Robinson, 2015; Engert et al., 2014; Ioannou, Gallese, et al., 2014). These facial areas are sensitive to the activity of the autonomic nervous system, which plays a central role in deception (Ben-Shakhar & Elaad, 2003; Meijer et al., 2016). Deceptive behaviour is typically accompanied by high arousal, negative valence experience (Colwell et al., 2007), and greater cognitive effort (Vrij, Fisher, et al., 2008). It also leads to various spontaneous physiological reactions resulting in changes in subcutaneous temperature (Derakhshan et al., 2020). As thermography is closely associated with emotional states (Ioannou, Gallese, et al., 2014), it has been widely used to detect deception in various contexts (Abdelrahman et al., 2017; Abouelenien et al., 2017; Derakhshan et al., 2020; Gálvez-García et al., 2021; Gołaszewski et al., 2015; Moliné et al., 2017, 2018; Panasiti et al., 2016; Pollina et al., 2015; Rajoub & Zwiggelaar, 2014; Satpathi et al., 2024; Zhu et al., 2007), and in different regions of interest (ROIs), especially: nose (Derakhshan et al., 2020; Gálvez-García et al., 2021; Moliné et al., 2017, 2018; Panasiti et al., 2016), forehead (Derakhshan et al., 2020; Gálvez-García et al., 2021; Zhu et al., 2007), and cheeks (Derakhshan et al., 2020; Gálvez-García et al., 2021).

Pavlidis and Levine (2002) conducted one of the first thermographic studies on deception detection using mock crime scenario[1]. They measured periorbital and forehead temperatures along with two polygraphy tests: the Zone Comparison and the Guilty Knowledge Test. Their aim was to evaluate the fITI as a non-invasive method for detecting physiological changes associated with deception. They found that the temperature of the periorbital region increased during deceptive responses, achieving a correct classification rate of 84%, while the forehead did not provide sufficient signals to discriminate between deceptive and truthful statements. Despite limitations, such as head movements, metabolic factors and facial region selection, their suggestion that thermography could replace polygraphy has helped to increase scientific interest in fITI-based deception detection (Pavlidis et al., 2002; Pavlidis & Levine, 2002).

[1] **Note.** A frequently used paradigm in deception detection research in which participants are instructed to commit or simulate a mock transgression (e.g., theft) in order to create realistic deceptive responses during the interview.

Panasiti et al. (2016) were among the first researchers to conduct a thermography study to investigate the thermal signatures associated with voluntary deception in an ecological setting. They used a card game paradigm (the Temptation to Lie Card Game, TLCG) and measured temperature of the periorbital area, cheeks and nose. The results showed a significant main effect of outcome (self-gain vs. other-gain) on the number of lies told: Participants lied more when the lie benefited themselves than when it benefited others. Thermographic data showed decreased cheek temperature and increased periorbital temperature during the preparation phase of the response, especially when lying for self-gain and under reputational risk. Nasal temperature also increased under these conditions, suggesting activation of the sympathetic nervous system during the decision to lie. When a person's reputation is at stake, they must suppress this sympathetic response in order to behave dishonestly. This downregulation of the sympathetic nervous system has also been previously found in various acts of emotional control (Delgado et al., 2008; Jackson et al., 2000; Sokol-Hessner et al., 2009). In addition, a significant negative correlation was found between Machiavellianism and nasal temperature during the response preparation phase of lying for self-gain, suggesting that individuals with higher manipulative traits showed lower sensitivity to reputational risk when lying. Despite the small sample size (12 participants), the study emphasises the role of sympathetic nervous system and personality in deception and paves the way for future studies on this topic (Panasiti et al., 2016).

In 2017, Moliné et al. (2017) conducted an experimental study in which they investigated the so-called Pinocchio effect of deception. They used the alibi paradigm, in which participants were given the task of creating a fake alibi and then calling their friend/partner and convincing them that the alibi they told was true. During a deceptive phone call, the average nasal temperature decreased by 0.7°C, from 29.60°C to 28.90°C, with 70% of participants experiencing a "*Pinocchio effect*". No other significant changes were observed in the other facial ROIs. The most critical issue in this work is the use of only one image as the baseline condition, taken during the task and after task completion. The use of a single baseline frame for comparison in the thermal analysis may lead to bias as it may artificially inflate the reported thermal changes. A more reliable method would

be to use multiple baseline data or continuous assessment to ensure that the changes are due to the experimental conditions and not the selection of data.

In their other study (Moliné et al., 2018), the thermal changes in the face (especially the nose and forehead) were investigated during deception in two tasks – high mental workload and high anxiety task and low mental workload and low anxiety task. When anxiety and mental workload were high, the deception led to an increase in nasal temperature. When these factors were controlled, nose and forehead temperatures decreased, suggesting that lying may be associated with greater executive control affecting thermal patterns. Combining changes in forehead and nasal temperature to detect lying resulted in 85% accuracy with 25% false alarms. The authors concluded that further research is needed to determine whether the thermal changes during lying are caused by the lie itself, by associated emotions or by cognitive effort. They also called for studies on factors such as mental workload, empathy and stress and suggested combining thermography with other methods to improve accuracy and reduce false alarms (Moliné et al., 2018).

Gálvez-García et al. (2021) tested a trifactorial model of deception detection: cognitive load, subjective arousal and convincing impression. In the first experiment, participants created and gave a fabricated alibi (deceptive condition) and on another day described disturbing pictures (truthful condition, high arousal/negative valence IAPS). Compared to the truth condition, the deceptive condition led to higher cognitive load, higher subjective arousal, a lower sense of conviction, a decrease in nose temperature and an increase in forehead and cheek temperature. In the second experiment, they found that the combination of higher forehead and lower nose temperature gave the best deception detection accuracy (83%). Although this study shows great potential by demonstrating a novel trifactorial model of deception and its thermal imprints, it also has limitations. In particular, as in Moliné et al. (2017), only one baseline recording was used, recorded before and after the tasks, which could compromise accuracy. The study used the same small ROI size (3x3 pixels) for all facial regions, which is problematic. Larger areas, such as the forehead, are more thermally stable, while smaller regions, such as the tip of the nose, may show exaggerated fluctuations. For accurate measurements, ROI sizes should be adjusted to the size of each facial region (Ioannou, Gallese, et al., 2014).

However, researchers claimed that they are developing a deep learning model to analyse all pixels in thermograms and predict illusions, with the aim of improving accuracy by combining it with top-down modelling (Gálvez-García et al., 2021).

Derakhshan et al. (2020) aimed to improve deception detection using artificial intelligence and machine learning in thermography by identifying the best ROIs on the face. They analysed thermography, GSR and PPG data from 41 subjects in two paradigms: a mock crime scenario and a "best friend[2]" scenario, using four machine learning classifiers (Decision Tree, Support Vector Machine with Gaussian and Polynomial Kernels, Linear Discriminant Analysis and K-Nearest Neighbour). Thermography outperformed traditional physiological signals in the mock crime scenario, achieving an accuracy of 83.8% compared to 58% (GSR) and 64.5% (PPG). However, in the best friend scenario, the PPG (79.6%) outperformed thermography (62.9%). Feature selection improved the accuracy of the thermal signals with the LDA classifier to 90.3%. The decision tree classifier was the most successful in this study. It performed consistently better than other models in different scenarios and for different features, especially after feature selection. The study also found that perinasal and chin ROIs were most associated with deceptive anxiety (Derakhshan et al., 2020).

Since the first experiments at the beginning of the 21st century, deception detection using thermography has become increasingly popular. Researchers are now combining psychology, physiology and computer science across different paradigms to improve the classification of deceptive thermal patterns in the face. To provide a broader overview of the main experiments and findings, we summarise selected studies in Table 1.

[2] **Note.** Participants described their best friend truthfully or made deceptively positive comments about someone they do not like.

Table 1: Theoretical overview of selected thermal deception detection research

Authors	Year	Used scenario	Interview methodology	Used Region of Interest	N of subjects	Results specification	Reported accuracy
Pavlidis and Levine	2002	Mock-crime scenario	ZCT and GKT	Periorbital region, forehead	18	Periorbital region heating observed during deception; forehead region not reliable.	Correct classification rate of the thermal analysis 84%; and of the traditional polygraph method 78%
Pollina and Ryan	2004	Mock-crime scenario	ZCT	Mouth, ear, scalp, neck, periorbital region, nose	25	Nose and eye regions showed significant temperature increases during deception. Mouth, neck, ears, scalp did not.	52% (AUC = .92) if nose and periorbital temperature combined with polygraph
Pollina et al.	2006	Mock-crime scenario	CIT	Periorbital region	15	Periorbital warming on the right side after crime-relevant stimulus; no significant change on the left side.	n/a
		Mock-crime scenario	CIT and ZCT	Periorbital region	24	Right periorbital temperature increased during deception; confirms hemifacial differences.	91.7%
Tsiamyrtzis et al.	2007	Mock-crime scenario	Interrogation questions	Periorbital region	39	Significant increase in periorbital temperature during deception.	87.2%

Zhu et al.	2007	Mock-crime scenario	n/a	Forehead	38	Significant increases in forehead temperature during deception.	76.3% (Open-End Snake), 71.1% (Tophat), 68.4% (10% hottest heuristic).
Warmelink et al.	2011	Real-life at the airport about the travel plans	Investigative interview about the travel trip	Whole face, not specified	51	Facial temperature rose during interview for deceivers; remained stable for truth tellers.	64% truth tellers and 69% liars correctly classified; humans without thermal data: 72% and 77%.
Jain et al.	2012	Mock-crime scenario	GKT	Inner and outer edges of eyes and nostrils, tip of the nose, outer edges of the mouth.	16	n/a	83.5%
Park et al.	2013	Mock-crime scenario	CIT	Periorbital region	30	Guilty participants: periorbital increase to relevant questions; innocents: no significant change.	98.89%
Rajoub and Zwiggelaar	2014	Interview about participants lives – they were asked to learn a profile	Questions about participant profile, including items not in profile (spontaneous condition).	Periorbital region	25	Forehead temperature increased significantly during deception.	58–62% (between-person), 86.88% (within-individual).

Pollina et al.	2015	Mock-crime scenario	Crime-relevant and crime-irrelevant questions	Cheeks, carotid and periorbital region	21	Cheek temperature increased significantly; other regions not significant.	76.2%
Panasiti et al.	2016	Temptation to Lie Card Game	n/a	Periorbital area, cheeks and nose	12	Periorbital heating during deception, especially during preparation; nasal tip heating for self-gain lies under reputational risk; cheek cooling during preparation.	n/a
Moliné et al.	2017 (Study 1)	Alibi creation	Lying to a significant person (best friend or partner) via phone call	Tip of the nose, forehead, periorbital region, mouth, cheeks	20	Temperature of the tip of the nose decreased during deception; no significant change in other areas.	70% participants showed a Pinocchio effect
	2017 (Study 2)	Alibi creation + the cold stress test	Lying to a significant person (best friend or partner) via phone call	The tip of the nose and the tip of the finger of the dominant hand	31	Temperature of the tip of the nose decreased during deception.	80%
	2017 (Study 3)	Bibliographical lie (prepared)	ACID system interview procedure	The tip of the nose, the tip of the finger of the non-dominant hand (dorsal part)	20	Temperature of the tip of the nose decreased during deception.	85%

Moliné et al.	2018 (Study 4)	High mental workload and high anxiety task and low mental workload and low anxiety task	Interview with a research assistant	Nose and forehead	20	When anxiety and mental workload were high, deception increased nasal temperature. When these factors were controlled, the temperature in the nose and forehead decreased.	85%
Abouelenien et al.	2019	Best friend, abortion and mock-crime scenario	Interview with a research assistant.	Whole face, forehead, periorbital area, cheeks with the nose and nose only	104	During deception, forehead and periorbital temperatures increased; nasal temperature decreased; cheeks not significant.	Decision tree classifier: 53.8% (Abortion), 50.5% (Best Friend), 59.6% (Mock-crime).
Derakhsan et al.	2020	Mock-crime scenario and best friend scenario	CQT for mock-crime and general topic discussion (best friend scenario).	Forehead, periorbital region, cheeks, maxillary area and chin	40 (mock-crime), 41 (best friend)	Perinasal and chin temperatures increased during deception; other regions less distinctive.	90.1% (Mock-crime), 74.7% (Best Friend).
Gálvez-García et al.	2021 (Study 1)	Alibi creation	Lying to a significant person (best friend or partner) via phone call.	Forehead, cheeks, tip of the nose (main ROIs), middle fingers, chin and maxillary mouth (secondary ROIs)	30	Nose temperature lower during deception; cheeks and forehead higher.	83%

	2021 (Study 2)	Alibi creation + invented burglary interrogation	Interview with a research assistant	Forehead, cheeks, tip of the nose, middle fingers, chin and maxillary mouth	30	Higher forehead and lower nose temperature during deception.	80%
Satpathi et al.	2024	Mock-crime scenario and friendly interaction	Interview with a research assistant	Forehead and periorbital region	33	Higher forehead and periorbital temperature during deception.	89.28% (Support Vector Classification)
Hypšová et al.	2024	Work and study related interview	Work- and study-related interview with both rehearsed and spontaneous questions	Forehead, nose, cheeks	15	No significant differences between deception and truth telling.	n/a

Note. ZCT – *Zone Comparison Test*; GKT – *Guilty Knowledge Test*; CIT – *Concealed Information Test*; CQT – *Control Question Test*; n/a – *not specified*. **Source:** Author of the thesis.

The table shows that 87% of the studies used the periorbital region as the key ROI and consistently found significant temperature increases during deception. For example, the studies by Pavlidis and Levine (2002), Pollina and Ryan (2004), Tsiamyrtzis et al. (2006) and Park et al. (2013) all reported periorbital warming, with accuracy rates ranging from 84% to 98.89%. About 47% of the studies also examined the forehead, with mixed results. Studies such as Zhu et al. (2007) and Rajoub and Zwiggelaar (2014) found an increase in forehead temperature during deception and achieved accuracy rates between 58% and 76%. However, Pavlidis and Levine (2002) reported that the forehead is unreliable for detecting deception. The nose was used in 53% of studies, with Moliné et al. (2017, 2018) and Gálvez-García et al. (2021) demonstrating a significant drop in temperature during deception, supporting the "*Pinocchio effect*", with these studies reporting accuracy of up to 85%. About 33% of studies, such as Pollina et al. (2015) and Panasiti et al. (2016), investigated cheek temperature and reported various findings, with some showing an increase and others a decrease during deception. In addition, 13% studies, like Derakhshan et al. (2020), identified the perinasal and chin region as strong predictors, achieving a high accuracy of 90.1%. In summary, the periorbital region (87%), forehead (47%) and nose (53%) were the most commonly studied ROIs, with mixed findings on temperature changes during deception, highlighting future challenges in deception detection research using thermography.

While these results suggest that certain facial regions, particularly the periorbital region, nose and forehead, are promising for identifying thermal patterns associated with deception, the variability in results between studies highlights a crucial issue: the lack of methodological consistency. Differences in environmental conditions, ROI selection, baseline measurements and technical settings can significantly affect thermal results. Therefore, the accuracy and reproducibility of fITI findings depend heavily on strict adherence to validated protocols. The following section outlines the main challenges researchers face when using thermal imaging to measure facial temperature and discusses the key factors that need to be controlled to ensure reliable results.

3.4.3. The main challenges of using thermal imaging to measure human facial skin temperature

Due to the complexity of factors involved in heat measurement, it is crucial to control conditions that can be influenced by the experimenters to minimise bias in thermographic assessments (Moreira et al., 2017). Fernández-Cuevas et al. (2015) categorised factors influencing the use of fITI in humans:

a) *Environmental:* room size, ambient temperature, relative humidity, atmospheric pressure and source radiation
b) *Individual:*
    i. *Intrinsic:* gender, age, anthropometry, height, weight, circadian rhythm, hair density, skin emissivity, medical history, metabolic rate, skin blood flow, genetics and emotions
    ii. *Extrinsic:*
        - *intake factors:* consumption or intake of medications or drinks
        - *application factors:* application of things on the skin – ointments and cosmetics, water, sunlight
        - *therapies:* electrotherapy, ultrasound, heat treatment, cryotherapy, massage, acupuncture
        - *physical activity*
c) *technical:* validity, reliability, protocol, camera features, ROI selection, software, statistical analysis.

Many researchers do not report the specific conditions under which the fITI technologies were applied (Costello et al., 2012), making it essential to implement and follow a strict protocol when performing thermographic measurements. Although several checklists have been proposed (Ammer, 2008; Ring & Ammer, 2012; Zhou et al., 2020), none of them was standardised, except the *Thermographic Imaging in Sports and Exercise Medicine* (TISEM, Moreira et al., 2017), which contains 15 items approved by 24 experts in physiology, physiotherapy, medicine and sports science from 13 countries worldwide. The questions cover three groups of information: participant

demographics, camera/room set-up and recording/analysis, to be marked 'yes', 'no' or 'unclear'. To give an example of the most important points: (a) At least four hours before the fITI assessment, participants should especially refrain from alcoholic beverages, smoking, caffeine, large meals, ointments, cosmetics, showering and sunbathing, (b)There should be an acclimatisation or rest period – at least 15 – 20 minutes before the experiment, (c) The rest period must take place in the same room in which the measurement is carried out (Fernández-Cuevas et al., 2015; Moreira et al., 2017), (d) The room temperature must be specified and the humidity of the room should be measured, and (e) Researchers should also carefully describe and maintain the distance between the camera and the participant – ideally, they should use exactly the same distance in all cases. The full checklist points can be found in Moreira et al. (2017, p. 159). In addition, all shiny objects, direct sunlight through windows, heat-emitting monitors in close proximity to the participants' face must be covered to avoid over- or underestimation of thermal changes (Fernández-Cuevas et al., 2015; Ioannou, Gallese, et al., 2014; Moreira et al., 2017; Ring & Ammer, 2012). Wearing glasses should also be avoided as glass is opaque to infrared light – if participants are asked to remove their glasses, sufficient time is needed to adjust the temperature of the facial area under the glasses (Gane et al., 2011).

An important issue is the selection of an appropriate baseline period (Ioannou, Gallese, et al., 2014). Two types of baselines are usually used: the resting baseline and the baseline opposite to the measured condition. The “*resting*" baseline, where participants are asked to relax and sit quietly for a few seconds or minutes, however it does not reflect a natural emotional situation. The *opposite state to the one measured* where the opposite emotion to the one studied (e.g., sadness or anger when studying happiness). Sometimes the baseline state is not measured at all, which is problematic as there is no contrast between the measured states (Ioannou, Gallese, et al., 2014) or researchers use a single shot recorded at the beginning and after the task as a baseline (Gálvez-García et al., 2021; Moliné et al., 2017, 2018). There is no single golden standard for baseline recordings, but authors must clearly describe how baselines are selected and measured (Ioannou, Gallese, et al., 2014).

Last but not least, it is important to select the right region for the analysis, for which there is also no standard. Therefore, researchers should indicate the inter-rater reliability in the selection of ROIs or describe exactly how the selection of ROIs was done (Fernández-Cuevas et al., 2015). To overcome the problems of manual ROI selection, researchers should focus on developing automatic and objective methods for selecting and recognising ROIs. Although the use of fITI may seem challenging, following the right protocols and procedures can provide valid and highly reliable data for various purposes, both in research and in practise (Moreira et al., 2017). This is especially true when adhering not only standardised protocols such as TISEM, but also the manufacturer's guidelines.

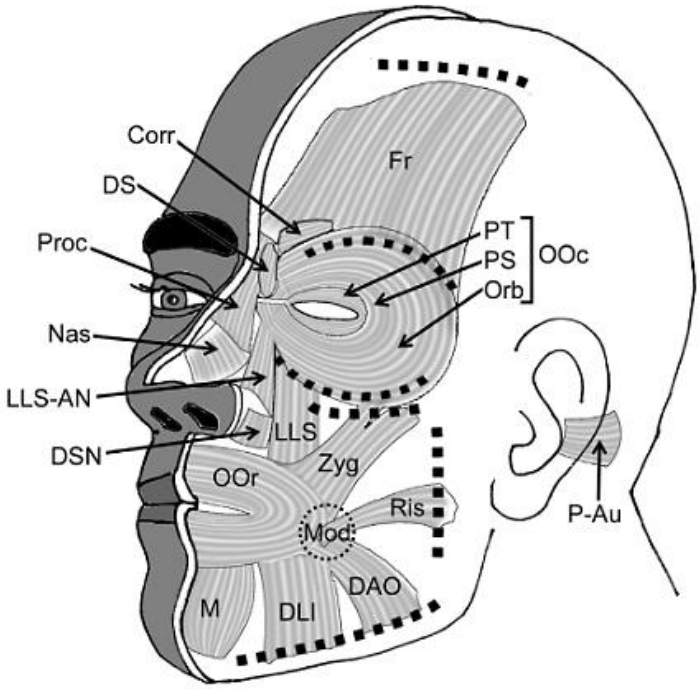
4 FACIAL EMOTION (MICRO)EXPRESSIONS AND DECEPTION DETECTION

Emotions cannot be defined as a simple phenomenon. For a comprehensive understanding, three key components must be considered: (a) the subjective experience of the emotion, (b) the physiological and neural processes that underlie it, and (c) its external expression (Izard, 2013). This chapter focuses on the third component, facial expressions, which are key to social functioning (Dong et al., 2022). They are often used as cues to deception with long and controversial history (Ekman, 2009; Ekman & Friesen, 1969; Hurley & Frank, 2011; Porter & ten Brinke, 2008). Critics claim they are unreliable and unpredictable, while proponents believe they contain important information about the cues to deception (Zlotenaou, 2020). Before exploring emotional expressions in deception, it is important to understand the facial motor system, the AUs and their role in the expression of emotions. A solid understanding of these mechanisms is crucial for analysing how emotions are expressed and how they can be manipulated or misinterpreted in deceptive behaviour. Without this foundation, any study of emotion and deception is incomplete.

4.1. Facial motor system, action units and emotion expressions

The facial muscles are innervated by nerves, in particular by the seventh cranial nerve (CN VII) in the brain, which is divided into five branches: temporal (innervating the frontalis, corrugator supercilii, depressor supercilii and orbicularis oculi), zygomatic (innervating the orbicularis oculi and zygomaticus), buccal (innervating the buccinators, orbicularis oris and the remaining orbicularis muscles), marginal mandibular (innervating the lower lip and chin muscles) and cervical (innervating the platysma) (Drake et al., 2010). For better visualisation, see Fig. 11, which shows the most important facial muscles (Cattaneo & Pavesi, 2014, p. 136).

Figure 11: Schematic representation of the facial muscular system (Cattaneo & Pavesi, 2014, p. 136)



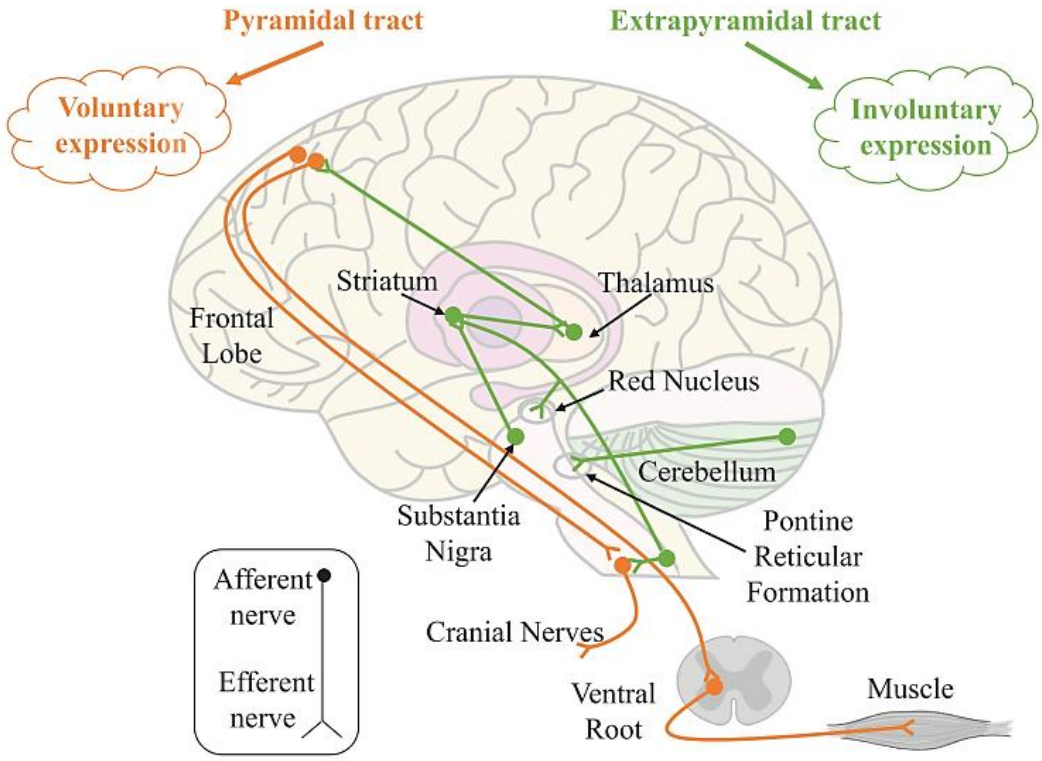
Note. Corr – *Corrugator*; Fr – *Frontalis*; Proc – *Procerus*; Nas – *Nasalis*; DS – *Depressor supercilii*; OOc – *Orbicularis oculi*; PT – Pretarsal; PS – Preseptal; Orb – Orbital; LLS-AN – *Levator labii superioris alaeque nasi*; LLS – *Levator labii superioris*; DSN – *Depressor septi nasi*; Zyg – *Zygomaticus major and minor*; Ris – *Risorius*; M – *Mentalis*; DLI – *Depressor labii inferioris*; DAO – *Depressor anguli oris*; P-Au – *Posterior auricularis*; Mod – *Modiolus*.

These muscles control facial movements and expressions (Dong et al., 2022), by the facial nerve originating from the nucleus facialis (Dong et al., 2022). This nerve is part of a highly complex facial motor system composed of specialised cortical areas that rely on several parallel systems, including voluntary and involuntary motor functions, emotional processes and visual inputs (Cattaneo & Pavesi, 2014).

In a nutshell, it can be said that both the somatic and the emotional motor system must be activated for the expression of emotions. The somatic motor system controls both voluntary and involuntary movements of the skeletal muscles, with voluntary movements originating in the cortical centres of the brain and being consciously controlled, while involuntary movements, such as trembling, occur spontaneously without conscious control. Voluntary facial expressions are transmitted via the pyramidal pathway,

while involuntary expressions utilise the extrapyramidal pathway, as shown in Fig. 12 (Dong et al., 2022, p. 7).

Figure 12: The somatic motor system (Dong et al., 2022, p. 7)



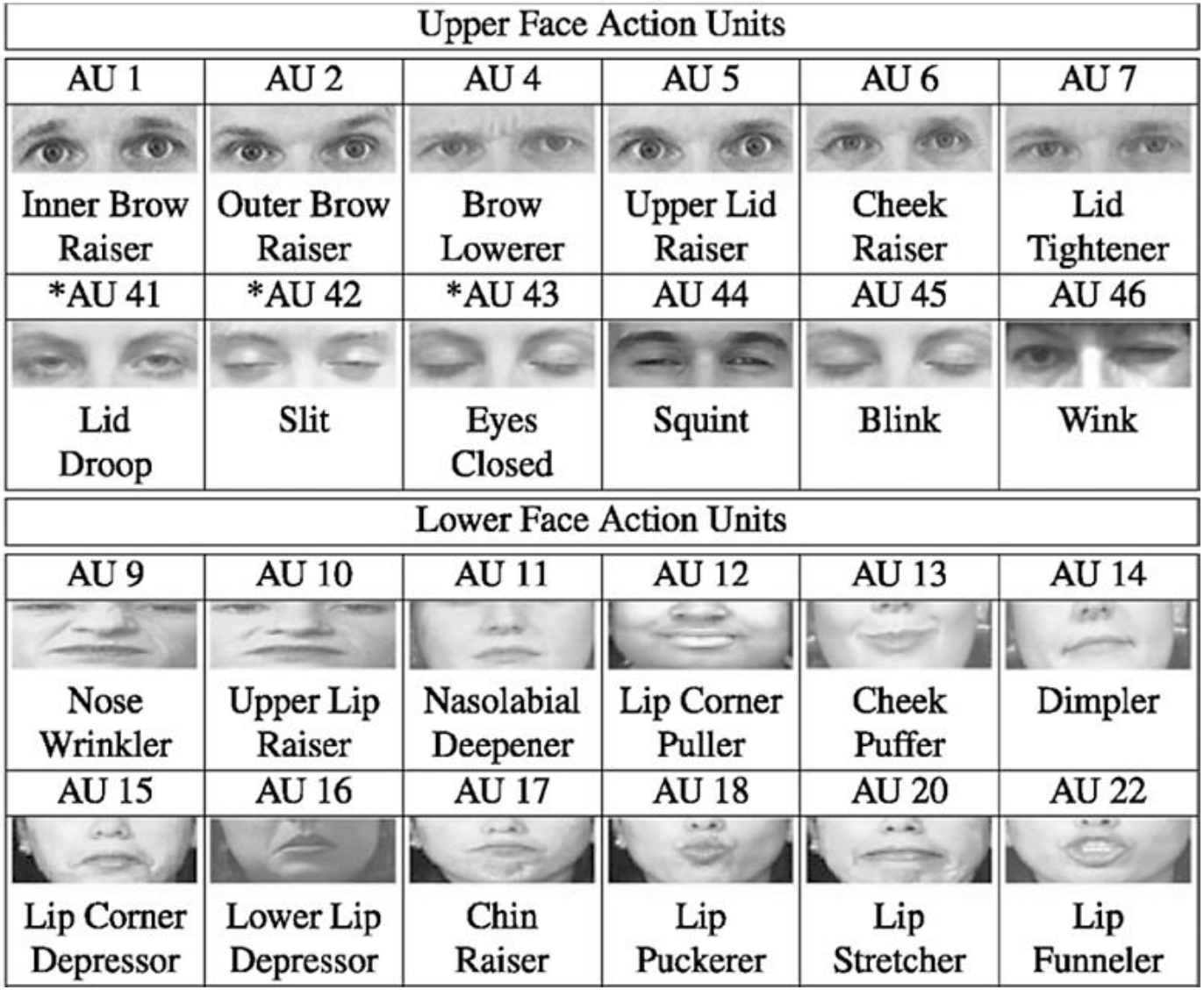
The emotional motor system originates in the grey matter around the striatum, amygdaloid nucleus and lateral hypothalamus and controls facial expressions in response to emotions. It operates independently of the voluntary motor system at the level of the brainstem and projects to the motor neurons of the face to control facial movements (Holstege, 2002). A case study of traumatic facial paralysis (Bouras et al., 2007), supports the idea that genuine emotional expressions cannot be generated voluntarily but require emotional stimuli (Dong et al., 2022). This concept underpins the famous 'leakage' theory of emotional micro-expressions as a cue to deception, where involuntary emotions, such as fear of being caught out, may reveal themselves despite efforts to conceal them (Ekman & Friesen, 1969). To examine these expressions, facial movements are categorised into AUs, the smallest observable facial movements associated with emotions (Cohn et al., 2007).

AUs can consist of one or more facial muscles, the activation and combination of which leads to a variety of expressions (Dong et al., 2022). The most commonly used

system for objectively describing facial movements, the Facial Action Coding System[3] (FACS, Ekman & Friesen, 1978), describes 46 AUs, each categorised according to the facial region in which they occur. Each AU is assigned both a numerical and a verbal label based on its anatomical basis with one or more facial muscles (Cohn et al., 2007). AUs are activated in characteristic patterns during different emotional states. For example, surprise is characterised by the simultaneous occurrence of AU1 (Inner Brow Raiser), AU2 (Outer Brow Raiser), and AU5 (Upper Lid Raiser). In sadness, AU1 and AU4 (Brow Lowerer) combine to form an oblique eyebrow shape. Embarrassment typically involves AU12 (Lip Corner Puller), AU24 (Lip Pressor) and head movements (AU51+54) (Cohn et al., 2007; Ekman & Friesen, 1978). Fig. 13 shows the commonly used AUs with their numerical designations (Ekman et al., 2002, In Zhi et al., 2020, p. 1069).

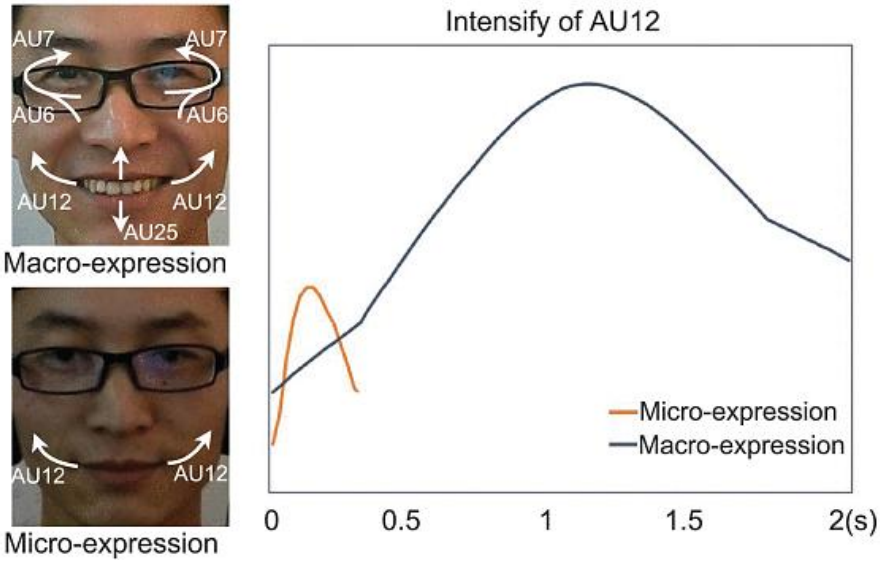
[3] **Note.** In addition to the most commonly used Facial Action Coding System, FACS (Ekman & Friesen, 1978), other systems have been developed, such as The Facial Expression Coding System, FACES (Kring & Sloan, 2007), Maximally Discriminative Facial Movement Coding System (Izard & Weiss, 1979) or the Face Animation Parameters (Pandzic & Forchheimer, 2002). Besides these systems, machine learning and deep learning approaches have been used to recognise the AUs and then detect emotional expressions and micro-expressions (Chang et al., 2017; Chu et al., 2017; Khorrami et al., 2015; Liu et al., 2014).

Figure 13: Selected upper and lower face AUs (Zhi et al., 2020, p. 1069)



The facial expressions can be divided into micro and macro expressions (Dinges et al., 2024). Micro-expressions are the expressions lasting fractions of a second (usually less than 500 milliseconds) that reflect the genuine emotional state (Ekman, 2009; Ekman & Friesen, 1969). Macro-expressions are regular facial movements that represent observable muscle activation of different AUs and last significantly longer than micro-expressions, usually 0.5 seconds to 4 seconds (Dinges et al., 2024). Macro-expressions involve multiple AUs of varying intensity (Ekman & Friesen, 1978; Matsumoto et al., 2008), whereas micro-expressions involve fewer muscles (usually one or two) and have a very low intensity. Moreover, macro-expressions can be controlled to a certain extent by will, while micro-expressions occur spontaneously, usually in situations where people try to hide their emotions, and thanks to this they are short, fragmented and subtle (Dinges et al., 2024; Zhao et al., 2023). An example can be seen in Fig. 14 (Zhao et al., 2023, p. 2).

Figure 14: An example of the macro-expression and micro-expression (Zhao et al., 2023, p. 2)



Since micro-expressions can sometimes be low-intensity AUs and it is often difficult to categorise them to a single basic emotion or neutral state in real-life situations, researchers use continuous regression of valence and arousal values as an alternative or complementary method (Dinges et al., 2024; Posner et al., 2005). This approach follows the circumplex model (Russell, 1980), which offers a more flexible and nuanced representation of emotions than macro-expressions (Posner et al., 2005). Instead of categorising emotions into clear and rigid categories (as with macro-expressions),

two dimensions are used: valence (pleasant to unpleasant) and arousal (activation to deactivation), which allows mixed emotions, different intensities and the subtleties of emotional experience to be captured. It is also more in line with neuroscience as it captures overlapping emotional and physiological states (Posner et al., 2005).

4.2. The emotion-based approach towards deception detection

In deception detection, psychological theories explain how liars unintentionally give themselves away through non-verbal cues such as facial expressions. Explaining these theories is crucial as many researchers select features without an adequate theoretical basis, resulting in less effective deception detection methods, especially with new classifiers (Delmas et al., 2024).

4.2.1. Theoretical foundation of facial expressions and deception detection

In the current literature on deception detection, four main theoretical approaches are being pursued: the leakage theory, four-factor theory, self-presentational theory and interpersonal deception theory (Bond et al., 2014). Recently, theories have been classified into two branches: mental processes theories, and social psychological approaches. Mental processes theories suggest liars undergo both emotional (e.g., leakage theory) and cognitive processes (e.g., cognitive load theory), with the four-factor theory bridging the two. Social psychological approaches focus on the social context of deception, highlighting the influence of interpersonal dynamics and situational factors, as seen in interpersonal deception theory, self-presentational theory, and moral psychology theory (Vrij et al., 2019).

Mental processes theories: Emotions

The leakage theory (Ekman & Friesen, 1969) and Inhibition hypothesis

The rationale behind the leakage theory can be dated to Darwin's theories on the universality of emotional facial expressions (Ekman, 2009). Darwin theorised that human emotions have evolved to reorganise physiological priorities for certain actions associated with emotions (Frijda, 2010), such as flight in the case of fear or aggression/attack in the case of anger, necessitating the communication of these intentions to enhance social

interaction and reduce conflict (Solbu et al., 2024). Darwin further argued that these emotional states of basic emotions are primarily signalled by involuntary facial expressions (Ekman, 2009), which are driven by 'nervous force', meaning that they are difficult to inhibit – the so-called inhibition hypothesis (Ekman, 2009; Ekman & O'Sullivan, 2006; Hurley & Frank, 2011; Porter & ten Brinke, 2008). If a deception evokes a certain emotion – e.g., the fear of being caught – it will manifest ('*leak*') in an unintentional facial micro-expression, regardless of the liar's attempts to conceal it (Ekman & Friesen, 1969). Ekman and Friesen expected that there are three emotions related to lying – fear, guilt and duping delight – however the link is not that straightforward. For example, truth tellers may also experience fear, such as the fear of being falsely accused, which leads to facial expressions similar to those of liars (Zlotenaou, 2020).

The four-factor theory (Zuckerman et al., 1981)

The four-factor theory provides a hypothetical bridge between emotional and cognitive theories, as it also includes cognitive elements (Delmas et al., 2024). It states that deception is not directly related to specific behaviours, but to four factors that increase behavioural differences between liars and truth tellers (Bond et al., 2014). The first factor, labelled '*emotions*', focuses on certain emotions that liars may experience, particularly fear of being caught and guilt – similar to leakage theory – which may lead to negative emotion expressions (Zuckerman et al., 1981). The second factor, '*arousal*', reflects the notion that deception is physiologically arousing and may also manifest itself in behaviours such as increased eye blinking or more head movements (Bond et al., 2014; Delmas et al., 2024; Zuckerman et al., 1981). The third factor relates to the *cognitive effort* which liars have to make in order to appear honest, which leads, for example, to fewer gestures or fewer head movements – in contrast to when they feel fear and experience greater arousal (Delmas et al., 2024; Sporer & Schwandt, 2007). The final factor relates to *attempted behavioural control to conceal the lie* by displaying behaviours they believe to be honest, typically resulting in being stiff and overly controlled or displaying a discrepancy between body movements (Bond et al., 2014; Zuckerman et al., 1981). Although this theory accounts for broader cognitive and emotional factors, it is less frequently applied to face recognition systems than the leakage hypothesis (Delmas et al., 2024). Due to its inconsistent results,

particularly in relation to facial features (Sporer & Schwandt, 2007), it is worthy of further investigation (Delmas et al., 2024).

Mental processes theories: Cognition

Cognitive load theory

The core of cognitive load theory lies in the assumption that lying is (in some cases) more cognitively demanding than telling the truth (Vrij, Fisher, et al., 2008, 2017). The reasons include (a) inventing a detailed lie requires imagination (Vrij et al., 2019), (b) lies can be easily refuted if the interviewer has information that contradicts the liar's story (Nahari et al., 2014a), (c) liars do not take their credibility for granted, whereas truth tellers do – this results in truth tellers simply talking about an event (Kassin, 2005) whereas liars have to work harder to be credible, and (d) deception is more intentional than truth (Walczyk et al., 2003). A key advantage of this theory is based on the idea that investigators can enhance the differences between verbal and nonverbal cues that reflect the cognitive load of truth-tellers and liars by using strategies that result in the liar's tasks being more mentally demanding. This approach includes three techniques to differentiate between truth tellers and liars: (1) increasing cognitive load, (2) encouraging the interviewee to provide more details, and (3) asking unexpected questions. If these strategies are effective, they should result in liars providing more revealing cognitive cues, making deception easier to detect (Vrij, Fisher, et al., 2008, 2017; Vrij, Mann, et al., 2008; Vrij, Meissner, et al., 2017; Vrij & Granhag, 2012).

Strategic models

Partly, they draw on the classic Decision-Making Model of Confessions (Hilgendorf & Irving, 1981), which emphasises that rational decisions to confess are influenced by factors such as stress and police authority (Hilgendorf & Irving, 1981; Ofshe & Leo, 1996). The strategic models assume that liars consciously plan and calculate to control how they appear in the interaction – liars engage in a psychological "game" in which they adjust their behaviour according to how they believe they will be perceived by their audience (Vrij et al., 2019). Liars focus on suppressing cues that they believe indicate deception, such as signs of nervousness, while consciously try to appear more credible. This strategic behaviour requires careful attention to both verbal and non-verbal cues, making it a cognitively demanding task. Similar to cognitive load theory, deception

detection can be facilitated if interviewers use the right techniques aimed at making lying more challenging, such as the verifiability approach (Nahari, 2018; Palena et al., 2021), the strategic use of evidence (Granhag & Hartwig, 2014) or cognitive credibility assessment (Vrij, 2018; Vrij, Meissner, et al., 2017).

Interpersonal and contextual theories

Interpersonal deception theory

This theory was introduced by Buller and Burgoon in 1996 and it claims that deception is a dynamic interaction between senders and receivers depending on the interactivity in the context of communication (Buller & Burgoon, 1996). The sender's communication, whether truthful or deceptive, is shaped by his or her expectations, goals, knowledge and skills. In deception, the sender uses deliberate strategies to make the lie convincing, but also displays unintended behaviours that could reveal the truth. The receiver evaluates the sender's initial behaviour, may become suspicious and change their own behaviour as a result. Throughout the interaction, both the sender and receiver are constantly observing each other and adapting their actions to manage the situation (Vrij et al., 2019). The success or failure of deception depends on the context of the interaction, social cues, immediacy and spontaneity (Buller & Burgoon, 1996). Despite the 18 theoretical proposals offered by this theory, it is controversial and has been criticised for its inability to provide testable hypotheses and its lack of conceptual development (Bond et al., 2014; DePaulo et al., 1996).

Self-presentational theory

DePaulo (1992) presented a theory based on earlier findings by Erving Goffman on self-presentation, in terms of expressive behaviours that can be deliberately controlled to create a particular impression – life is like a theatre in which people act like actors on stage (Goffman, 1959, In DePaulo, 1992). This assumption can be applied to deception by assuming that both liars and truth-tellers pursue the same goal: to appear truthful (Vrij et al., 2019). According to DePaulo (1992), everyone uses self-presentation strategies to make a good impression and be viewed favourably. DePaulo (1992) focused on the similarities between liars and truth tellers, but highlighted a key difference – the deception discrepancy – truth tellers tend to be more relaxed and natural in their behaviour as they do not have to deal with contradictions between what they know and what they say.

In contrast, liars must actively manage their behaviour in order to appear honest, which can lead, for example, to more conscious control of facial expressions and body language, often resulting in a stiffer and less natural presentation (DePaulo, 1992). This theory has a stronger empirical and theoretical basis than Interpersonal deception theory, but provides little guidance on how to improve deception detection (Bond et al., 2014).

Moral psychology theory

The moral psychology deception theory was highlighted in a meta-analysis by Bond and DePaulo (2006). It emphasises the moral element of the deception and its judgement. They established two perspectives on the morality of lying: (a) what people think when they lie themselves, and (b) what people think when they are lied to (Bond & DePaulo, 2006). Liars often generalise justifications, are more pragmatic and come to terms with the importance and necessity of lying (Bond & DePaulo, 2006). In contrast, people think morally when they consider the lies of others (Saxe, 1991). Combining this theory with Ekman's (2009) claim that the emotions we feel when lying reflect what we think we should feel, we often justify lies pragmatically to maintain a moral self-image (Vrij et al., 2019). This is consistent with self-concept maintenance theory (Mazar et al., 2008) and moral hypocrisy theory (Monin & Merritt, 2012), which shed a light on how people rationalise deceitful behaviour. While moral psychology theory offers a new approach to understanding deception, it needs to be further explored by deception researchers (Vrij et al., 2019).

4.2.2. An overview on facial expressions as cues to deception: insights and future directions for improving deception detection

The use of facial expressions for deception detection is controversial and has led several researchers to claim that deception detection research should shift from non-verbal cues to more cognitive approaches (Sporer, 2016). This decision should not be definitive as it negates the role of emotions in deception. Rather than calling for a moratorium on emotional cues to deception, one should critically evaluate the emotional approach and integrate a broader perspective that considers both involuntary emotional cues and the strategic use of facial expressions in communication (Zlotenaou, 2020). In this chapter, we provide an overview of the main findings from the literature on emotion micro-expressions for deception detection and address limitations and future challenges

to improve the reliability of nonverbal methods for deception detection. We focus exclusively on studies that are not older than 10 years (from the publication date) and that examine facial features related to AUs as well as facial measures such as duration, presence, intensity, and the dimensions valence and arousal as depicted in Tab. 2. A broader range of features and measures discussed in the existing literature can be found in Delmas et al. (2024).

Table 2: Theoretical overview of selected non-verbal deception detection research

Authors	Year	Used theory	Used dataset	N of analysed videos	N of subjects	Used AUs or expressions	Facial measures	Reported accuracy (ACC) or effectiveness (Area under the ROC curve, AUC)	Results specification
Avola et al.	2019	n/a	Public trial hearings dataset (Pérez-Rosas et al., 2015).	121 (61 lie, 60 truth)	56 (21F, 35M)	AU1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26, 28, 45	intensity, presence	Logistic Regression: 54.86%, Random Forest: 58.42%, SVM (Linear): 65.56%, SVM (Sigmoid): 71.99%, SVM (RBF): 76.84%	Significant differences in AU4, AU5, AU10, AU12, and AU14 between truthful and deceptive behaviour.
Carissimi et al.	2018	n/a	Public trial hearings dataset (Pérez-Rosas et al., 2015).	118 (59 lie, 59 truth)	56 (21F, 35M)	AU1, 2, 4, 45, 7, 23, 25, 26, 28	intensity, presence	ACC for AUs and other modalities (i.e., gaze, head movement, hand gestures): SVM: 63%, LMKL: 67%, MVL: 75%.	n/a
Hasan et al.	2019	Leakage theory	UR Lying dataset (Sen et al., 2018)	n/a	n/a	AUs unspecified; affect features	intensity, presence	Weighted Fusion Model: 70%, SVM: 61%	n/a
Jaiswal et al.	2016	Leakage theory	Public trial hearings dataset (Pérez-Rosas et al., 2015).	100 (50 lie, 50 truth)	n/a	AU1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26, 28	presence	Individual modality accuracy analysis: 67.20%	n/a

Mathur & Matarić	2020	Leakage theory; Four factor model of valence and arousal	Public trial hearings dataset (Pérez-Rosas et al., 2015).	108 (55 lie, 53 truth)	47 (n/a)	facial affect, AU1, 2, 5, 15, 17, 26, 45	intensity, presence, valence, arousal	SVC: **(a)** Unimodal models of facial affect AUC 0.80, AUs AUC 0.83; **(b)** facial affect and AUs AUC 0.86 (early fusion); **(c)** facial affect and AUs AUC 0.83 (soft hybrid fusion); **(d)** facial affect and AUs AUC 0.87 (adaptive boost).	Liars higher SD in facial valence (M = 0.14) and arousal (M = 0.12) compared to truth-tellers (M = 0.11 and M = 0.09); AU1 and AU45 top model contributors.
Mathur & Matarić	2021	n/a	Public trial hearings dataset (Pérez-Rosas et al., 2015).	108 (55 lie, 53 truth)	47 (n/a)	AUs unspecified	intensity, presence	AUs unimodal subspace alignment: AUC 0.59, ACC 0.64.	n/a
			UR Lying dataset (Sen et al., 2018)	107 (63 lie, 44 truth)	29 (n/a)	AUs unspecified	intensity, presence	n/a	n/a
Monaro et al.	2022	Leakage theory, cognitive load theory	Recalling past holidays dataset (Monaro et al., 2020a).	62 (30 lie, 32 truth)	62 (43F, 19M)	AU1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26, 28, 45	intensity, presence	SVM AUC: 0.72 (no cognitive load), 0.78 (with load); LSTM AUC: 0.72 (with load); C3D AUC: 0.64 (no load), 0.75 (with load).	n/a
Rill-Garcia et al.	2019	Leakage theory	Public trial hearings dataset (Pérez-Rosas et al., 2015).	n/a	58 (n/a)	AUs unspecified	intensity, presence	SVM (Linear SVC): AUC 0.699 for binary AU presence.	n/a

		Leakage theory	Spanish Abortion/Best Friend dataset (developed by authors).	42 (21 lie, 21 truth)	11 (n/a)	AUs unspecified	intensity, presence	Linear SVC: AU intensity AUC not provided; binary AU presence performed poorly (AUC not provided).	n/a
Shen et al.	2021	Leakage theory	Game show "The moment of truth" (2018)	32 (16 lie, 16 truth)	16 (8F, 8M)	AUs related to fear: AU1, 2, 4, 5, 20, 26	intensity, presence, symmetry	Random Forest: 86.90%, KNN IBK: 85.11%, Bagging: 86.15%.	AU20 duration shorter in lies (507 ms) vs. truth (692 ms); facial movements more asymmetrical in lies (coherence = 0.71 vs. 0.81).
Thannoon et al.	2018	Leakage theory	Control/relevant question dataset (developed by authors).	400 (200 lie, 200 truth)	43 (23F, 20M)	AU5, 6, 7, 10, 12, 14, 23, 28	intensity	VG-RAM WNN: 84% (overall), 90% (males), 85% (females).	Key AUs: AU5, AU6, AU7, AU10, AU12, AU14, AU23, AU28.
Matsumoto & Hwang	2018	Leakage theory	Simulated security interview dataset (developed by authors).	77 (40 lie, 37 truth)	77 (38F, 39M)	MEs, AUs not analysed	duration of micro-expressions	MEs ≤0.40s: 63.2% (d = 1.21), ≤0.50s: 68.4% (d = 1.02), ≤1.00s: 77.6% (d = 1.43).	Negative MEs (anger, contempt, disgust, fear, sadness) ≤0.40s and ≤0.50s more frequent during deception.
Abdulridha & Albaker	2024	n/a	MMDD (Hugenberg et al., 2017)	320 (n/a)	80 (40F, 40M)	35 analysed AUs not specified	intensity, presence	Random Forest (visual features, not only AUs): 90.55%.	n/a

		n/a	Public trial hearings dataset (Pérez-Rosas et al., 2015).	121 (61 lie, 60 truth)	56 (21F, 35M)			Random Forest (visual features, not only AUs): 98.83%.	n/a
Yildirim et al.	2023	Leakage theory	Dataset developed by authors.	n/a	15 (7F, 8M)	MEs and MaES of 6 basic emotions plus neutral	intensity, presence	CNN: 74.17% accuracy.	Shift from neutral to happy was the most significant deception cue.
Nam et al.	2023	Leakage theory	Public trial hearings dataset (Pérez-Rosas et al., 2015).	104 (54 lie, 50 truth)	n/a	AU1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26, 28, 45	intensity, presence	FacialCueNet with spatial-temporal attention: 88.45% accuracy (AUC = .954).	Key deception AUs: AU14, AU23, AU45; fewer blinks and mouth movements indicated lying.
		CIT polygraph paradigm	DDCIT dataset (Concealed Information Test, developed by authors).	630 (210 lie, 420 truth)	105 (54F, 51M)		intensity, presence	FacialCueNet with spatial-temporal attention: 70.79% accuracy.	

Note. F – *Female*; M – *Male*; SVM – *Support Vector Machine*; RBF - *Radial Basis Function*; LMKL - *Localized Multiple Kernel Learning*; MVL - *Multiview Learning*; SVC - *Support Vector Classifier*; LSTM - *Long Short-Term Memory*; C3D - *Convolutional Neural Networks*; KNN IBK - K-*nearest neighbours IBK*; VG-RAM WNN - *Virtual Generalizing Random Access Memory Weightless Neural Network*; CNN - *Convolutional Neural Network*; MEs – *Micro-expressions*; MAEs – *Macro-expressions*; MMDD - *Miami University Deception Detection Database*. **Source.** Author of this thesis.

53% studies focussed on the leakage theory, with 6% combining it with cognitive load or four-factor theory, 6% using the CIT polygraph paradigm and 29% reporting no theory. This emphasis on the leakage hypothesis risks neglecting other concepts and oversimplifying mimicry without a link to broader psychological insights. Furthermore, some systems lack a clear theoretical basis. They rely on raw data or superficial associations between facial movements and deception without integrating these results into a coherent understanding of the underlying emotional or cognitive processes (Delmas et al., 2024).

71% of studies used secondary datasets for training and testing purposes, while only 29% developed their own. The most commonly used dataset was the real-life trials dataset (Pérez-Rosas et al., 2015). Although different studies reported different numbers of videos from this dataset – studies noted issues with poor video quality and face visibility, making certain videos unanalysable (e.g., trial – lie 45, 53 and trial – truth 41; Carissimi et al., 2018). However, other studies (e.g., Abdulridha & Albaker, 2024) did not mention this issue, raising concerns about potential bias in results. Furthermore, the use of secondary data sets, especially with regard to real life trial data, implies a critical point – ensuring ground truth (Delmas et al., 2024). Usually the ground truth is either the trial result (Pérez-Rosas et al., 2015) or the result of the polygraph tests (Shen et al., 2021), which is problematic, since a high probability of false confessions during trials (Bradford & Goodman-Delahunty, 2008; Gudjonsson, 2003; Kassin, 2005, 2014; Kassin & Gudjonsson, 2004). In addition, the ground truth established by the polygraph examination results in the Shen et al. (2021) dataset poses a further risk – as polygraphs simply do not achieve 100% accuracy in detecting deception. In this sense, when analysing facial expressions (or other modalities), one should strive to use one's own data sets with a clear ground truth. Otherwise, the results reported using secondary datasets may not reflect the accuracy or effectiveness of deception detection itself, but more or less the predictability of the decisions of courts or polygraph examinations.

About 90% of the cited studies used a number of these AUs: AU1, AU2, AU4, AU5, AU6, AU7, AU9, AU10, AU12, AU14, AU15, AU17, AU20, AU23, AU25, AU26, AU28 and AU45, which primarily correspond to six basic emotions and facial movements in the form of eyebrow raising, cheek raising, or mouth movements. About 29% of the studies

focused on unspecified AUs and only 2 studies also focused on affect features in the form of valence and arousal. About 12% of the studies focused on macro- and micro-expressions, either without a precise specification of AUs or emphasising basic emotions. The most commonly used measures of facial features were intensity and presence (approximately 89%), while the duration of micro-expressions was explicitly specified and analysed in only one study (6%). We argue that relying on micro- and macro-expressions for deception detection is problematic because it forces emotions into fixed categories that are usually based on basic emotions. Instead, the dimensional approach of the circumplex model of affect could offer a more nuanced prediction of deceptive behaviour, although it has not received as much attention as micro-expressions and macro-expressions. Another problem is coarse measurement, such as using a low frequency per video (one per minute of video) (Vrij et al., 2019), or relying on the naked human eye (Bond & DePaulo, 2006; Curci et al., 2019; Pérez-Rosas et al., 2015; Porter & ten Brinke, 2008).

Micro expression performance for deception detection varied by time interval (63.2% accuracy for expressions ≤0.40s; 68.4% accuracy for expressions ≤0.50s; and 77.6% accuracy for expressions ≤1.00s). Five of the 17 studies provided specific results on AUs and their relationship to deception. The remaining studies were labelled as "n/a", meaning that results related to AUs or facial expressions for deception detection were not specified. Key indicators focused on specific facial AUs, duration and symmetry of micro expressions, and changes in emotional valence and arousal. The most effective AUs identified for deception detection included: AU5, AU6, AU7, AU10, AU12, AU14, AU23, AU28. It should be noted that these features and their ideal combination might be tailored to the specific types of lies and truths in the training data, meaning that they might not apply well to other datasets. This problem could be exacerbated by the fact that many classifiers have been developed with limited datasets (Delmas et al., 2024).

Several authors have attempted to use artificial intelligence to automatically recognise deception (e.g., Monaro et al., 2020; Monaro, Gamberini, et al., 2017; Monaro, Spolaor, et al., 2017), and train machine learning models to distinguish fake from real emotions (Abouelenien et al., 2017; Avola et al., 2019, 2021; Monaro et al., 2022; Pérez-Rosas et al., 2015; Su & Levine, 2016). Their results consistently show that artificial intelligence performs significantly better than humans (Monaro et al., 2022; Pérez-Rosas

et al., 2015; Wu et al., 2018). Among the studies reviewed, Support Vector Machines (SVMs) were the most commonly used classifiers, appearing in nine studies. Their performance varied depending on the kernel and feature sets used, with classification accuracy ranging from 61% to 76.84% and area under the curve (AUC) values ranging from 0.699 (when using binary AUs) to 0.87 (when using adaptive boosting with fusion models). Convolutional Neural Networks (CNNs) also performed strongly with reported accuracy of up to 88.45% and AUC values of up to 0.954. Four studies used Random Forest classifiers, with accuracies ranging from 58.42% to 98.83%, usually using AU data in combination with other features. Other machine learning models included logistic regression (54.86% accuracy), K-nearest neighbours (IBK, 85.10%), VG-RAM WNN (84% overall accuracy, with 90% for men and 85% for women) and a bagging classifier (86.14%). Monaro et al. (2022) suggested that despite the potential of machine learning to improve the identification of facial features associated with deception, future studies should prioritise improving the interpretability of machine learning algorithms over replication of results.

Although not explicitly mentioned in our review, most of the studies cited were published in the field of computer science or engineering and not in the social sciences. In line with Delmas et al. (2024), we argue that this trend highlights a gap in the solid theoretical foundation of deception detection based on facial features and an overemphasis on technical justifications for machine or deep learning methods. This emphasises the need to increase multidisciplinary collaboration, as deception detection has been extensively researched by both psychologists and computer scientists, but often in isolation. Building bridges between these disciplines could lead not only to stronger theoretical foundations in psychology and psychophysiology, but also to improved data processing techniques from computer science. This represents a major challenge and opportunity to advance deception detection research across different modalities.

In summary, investigated studies on facial expressions in deception detection reveal highly heterogeneous results, characterised by the theoretical framework, methodological limitations and the type of datasets used. While most studies are based on leakage theory, only a minority include affective models such as valence and arousal. AUs commonly associated with deception include AU5, AU6, AU7, AU10, AU12, AU14, AU23, and AU28, with several studies reporting increased expressive intensity or asymmetry in lying.

However, the generalisability is undermined by the inconsistent quality of the data sets, the unclear ground truth and the different selection of AU. In particular, dimensional emotion measures (e.g., valence/arousal) are still not sufficiently utilised, although they have the potential to provide more differentiated findings. Most classifiers, especially SVMs and CNNs, outperformed human judgement, but the lack of theoretical integration and over-reliance on technical metrics limit broader psychological interpretation. Overall, the results suggest that while facial expressions hold promise for deception detection, current approaches are often fragmented, dataset-specific, and lack interdisciplinary synthesis.

5 EYE-TRACKING AND DECEPTION DETECTION

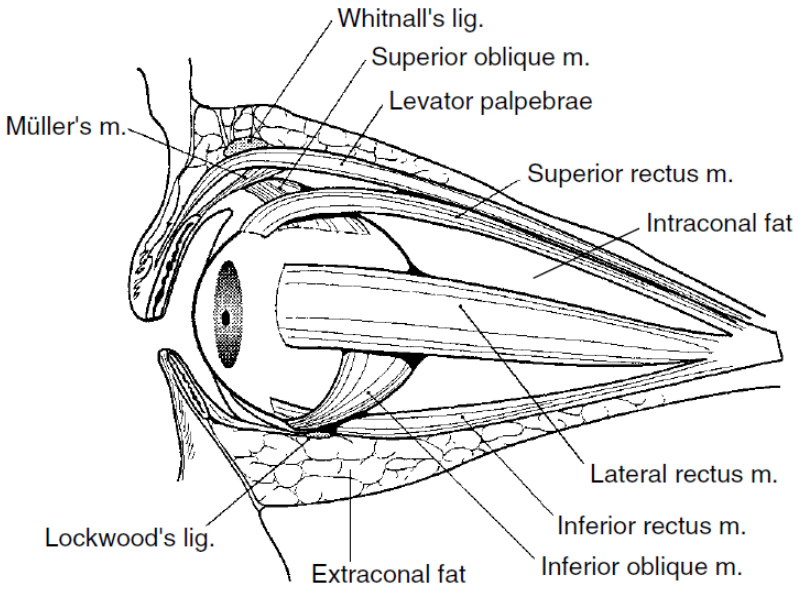
Recent studies suggest that it is not enough to rely solely on non-verbal cues to accurately recognise deception. Instead, a more comprehensive examination of several behavioural and physiological indicators is recommended (Abouelenien et al., 2019; Belavadi et al., 2020; Sen et al., 2022; Vrij, Granhag, et al., 2010). In the context of non-invasive deception detection, this includes not only thermal patterns and facial expressions, but also eye-related measures such as oculometry and pupillometry, which have shown consistent differences between deceptive and truthful behaviour (Proudfoot et al., 2016).

5.1. Anatomy and physiology behind oculometry and pupillometry

5.1.1. Oculomotor system

The oculomotor system is essential both for the stabilisation of vision and for the coordination of eye movements (Land & Furneaux, 1997). It comprises two main components: the efferent limb of the visual system and the vestibular system (Wade & Jones, 1997). The vestibular system provides the brain with important sensory information about head position, movement and spatial orientation, supporting motor functions such as posture, balance and stability during movement (Day & Fitzpatrick, 2005; Wade & Jones, 1997). The efferent limb is responsible for maintaining eye position and executing various types of eye movements (Mahanama et al., 2022). This is accomplished through the coordination of six extraocular muscles (Müller's muscle, superior oblique, superior rectus, lateral rectus, inferior rectus, and inferior oblique), suspensory ligaments, and surrounding orbital fat (Wright, 2006). The fat on the back of the orbit helps to push the eye outwards, while the four rectus muscles, which attach in front of the equator of the eye, pull the eye backwards. In contrast, the two oblique muscles attached behind the equator, exert a force forward. As the tension in the rectus muscles increases, the eye is pulled further back into the orbit, resulting in enophthalmos and a narrowing of the eyelid opening as shown in Fig. 15 (Wright, 2006, p. 25).

Figure 15: The lateral view of the extraocular muscles (Wright, 2006, p. 25)

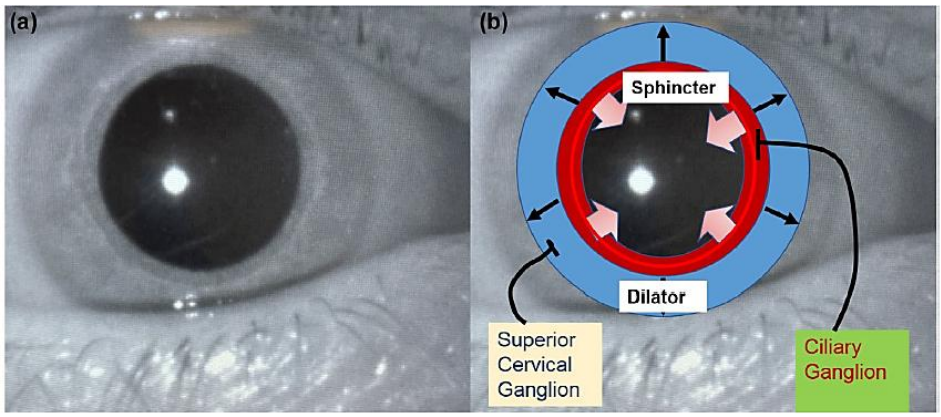


The oculomotor system comprises five types of eye movements: two for gaze stabilisation – the vestibulo-ocular reflex (VOR) and opto-kinetic nystagmus (OKN) – and three for gaze orientation – saccadic, smooth pursuit and vergence (Duchowski, 2017). *Gaze stabilisation movements* are fixations that stabilise the retina over a stationary object of interest, characterised by a tiny movements such as tremor, drift and micro-saccades (Martinez-Conde & Macknik, 2015). Nystagmus movements are synchronised eye movements characterised by a time-series signal pattern, where optokinetic nystagmus combines smooth pursuit with saccades to balance the movements of the target object across the retina (Duchowski, 2017). *Gaze orientation* comprises three eye movements: (a) smooth pursuit, a slow and accurate movement to pursue moving targets, generated in the occipital, parietal and temporal cortex (the right cortex controls movements to the right and the left cortex to the left); (b) saccades, rapid movements to pursue fast targets or to shift focus, controlled contralaterally by the frontal lobes (stimulation of the right frontal lobe leads to a saccadic movement to the left and vice versa). Interestingly, they cannot be controlled voluntarily, although they can be initiated voluntarily (Duchowski, 2017; Wright, 2006); and (c) vergence, which focuses both eyes on distant objects (Duchowski, 2017). Fixations, smooth pursuit and saccades provide valuable insights into visual attention, with fixations indicating the desire to maintain gaze and saccades indicating the intention to shift focus (Duchowski, 2017).

5.1.2. Pupillometry

The pupil is a transparent centre of the eye that normally appears black. The coloured area around the pupil is called the iris and contains the smooth muscles responsible for controlling pupil size (Mathôt, 2018). The activity of the pupil is bidirectional – it can enlarge or shrink (approx. 2-10 mm in humans) – the enlargement depends on the dilator pupil muscle, the reduction on the sphincter pupil muscle, as shown on Fig. 16 (Steinhauer et al., 2022, p. 2).

Figure 16: Bidirectional activity of the pupil (Steinhauer et al., 2022, p. 2)



These two main groups of smooth muscles interact and are responsible for changes in the pupil that are not only due to psychological states but also to external environmental changes, particularly in relation to light control. Pupil size is controlled by two neuronal pathways: the sympathetic dilation pathway and the parasympathetic constriction pathway (Mathôt, 2018). The dilator muscle is activated by noradrenaline via the sympathetic nervous system and can be relaxed by blocking the alpha-adrenergic receptors. The sphincters are controlled by the parasympathetic nervous system and cause the pupil to constrict when activated (Mathôt, 2018; Steinhauer et al., 2022). Although the pathways of constriction and dilation are largely separate, they interact via at least three mechanisms: (1) the locus coeruleus (LC) causes pupil dilation by activating the sympathetic pathway and inhibiting the parasympathetic pathway of constriction in the Edinger-Westphal nucleus (EWN) (Mathôt, 2018), which may be the primary mechanism for pupil dilation in response to arousal and mental effort (Steinhauer et al., 2004); (2) the superior colliculus (iSC) inhibits the EWN and thus contributes to rapid dilation during the orienting response (Wang & Munoz, 2015); and (3) light both directly triggers pupil constriction

and indirectly promotes dilation by activating the wakefulness pathways via parts of the hypothalamus (specifically the suprachiasmatic nucleus (SCN) and the dorsomedial hypothalamus (DMH)) (Mathôt, 2018).

5.2. Cognitive and affective influences behind the eye

Several research showed that pupil size is related to stress (Alshanskaia et al., 2024; Alshanskaia & Martynova, 2023; Sabatino DiCriscio et al., 2018; Simonovic et al., 2018), arousal (Bradley et al., 2008; Kinner et al., 2017; Partala & Surakka, 2003; Sabatino DiCriscio et al., 2018; Unsworth & Robison, 2015), cognitive load and mental effort (Ahmad et al., 2023; Franzen et al., 2022; He et al., 2012; Krejtz et al., 2018; Menekse Dalveren & Cagiltay, 2018; Prabhakar et al., 2020; Ruiz Puentes et al., 2023; Wu et al., 2022; Yoo et al., 2021). Additionally, saccades, fixations, or blinks represent another indicator of cognitive load (Calancie et al., 2022; De Rivecourt et al., 2008; Diaz-Piedra et al., 2017; Gegenfurtner et al., 2011; Isbilir et al., 2018; Kan et al., 2021; Keskin et al., 2020; Kim et al., 2022; Menekse Dalveren & Cagiltay, 2018; Sciaraffa et al., 2021; Vine et al., 2014; Wilson et al., 2011).

Regarding pupil size, it has been repeatedly found that when experiencing higher stress, the pupil diameter increases (Alshanskaia et al., 2024; Alshanskaia & Martynova, 2023; Pedrotti et al., 2014; Ren et al., 2013). Pedrotti et al. (2014), studied pupil dilation during a simulated driving lane change test under stress conditions, such as sound alerts. They found that pupil size increased significantly in participants exposed to stress, while pupil diameter decreased in the control group without stress stimuli, probably due to habituation (Pedrotti et al., 2014). Similar patterns were also reported by Bradley et al. (2008), Kinner et al. (2017), Partala and Surakka (2003), and Sabatino DiCriscio et al. (2018). In general, the higher the load is, the bigger the pupil size (Ahmad et al., 2023; He et al., 2012; Krejtz et al., 2018; Menekse Dalveren & Cagiltay, 2018; Palinko et al., 2010; Prabhakar et al., 2020; Wu et al., 2022). In the study by Krejtz et al. (2018), participants completed arithmetic tasks of varying difficulty while pupil diameter was measured. Self-reports confirmed a higher cognitive load for difficult tasks. Two pupil indicators were analysed: *inter-trial change in pupil diameter* (BCPD; baseline-corrected pupil dilation) and *intra-trial change of pupil diameter* (CPD; pupil dilation during the task, not baseline-

corrected). Both showed greater pupil dilation during the difficult task compared to the easy task (Krejtz et al., 2018, p. 15). However, the BCPD significantly predicted task difficulty, with larger coefficients for both difficult (β = 2.47) and easy tasks (β = 1.43), indicating greater sensitivity to task difficulty. In contrast, the intra-trial CPD was less predictive, with a small negative coefficient for difficult tasks (β = -0.09) and a significant decrease for easy tasks (β = -0.58). The BCPD explained 16% of the variance, compared to 7% for the CPD, making it a better indicator of cognitive load. This suggests that the BCPD is more sensitive to task difficulty, which is likely due to the fact that it uses the mean pupil diameter during a control task as a baseline (Krejtz et al., 2018). This is also in line with Mathôt and Vilotijević (2022), who explicitly recommend that pupil size should also be measured during a baseline condition in which participants ideally do nothing.

Fixations are another significant indicator of cognitive load, especially when the level of experience is taken into account (Skaramagkas et al., 2023), as shown in studies on surgical environments (Diaz-Piedra et al., 2017; Menekse Dalveren & Cagiltay, 2018; Vine et al., 2014). In particular, novices tended to fixate on different objects more frequently and for longer than experienced surgeons (Menekse Dalveren & Cagiltay, 2018), reflecting the high ability of experienced surgeons to use their gaze control effectively (Vine et al., 2014). In addition, novices tended to divide their time by focusing on tool tracking and targets (Wilson et al., 2011), whereas experts were more flexible and effective at dividing their attention, resulting in less fixation duration (Gegenfurtner et al., 2011). Several studies also showed that gaze control training can enhance surgeons' performance and improve computerised simulation training (Causer et al., 2014; Gegenfurtner et al., 2017; Wilson et al., 2011). In the geographic environment, novices showed longer fixation times, indicating a higher cognitive load as they needed more time to process the information. In contrast, experts had shorter fixation durations, as they were able to process the visual information faster and with less mental effort due to their experience (Keskin et al., 2020). In another study, in which the operation of a military landing platform was simulated, the authors found that under normal conditions no significant differences were found between experts and novices (Isbilir et al., 2018). However, there was a significant difference in fixation duration when responding to error messages. Experts increased their fixation duration after an error message, indicating that they were focussing

their attention more on solving the problem. In contrast, fixation duration decreased for novices, indicating more scanning behaviour, likely due to confusion or lack of familiarity with the error message (Isbilir et al., 2018).

When cognitive tasks become more difficult, people tend to avert their gaze from the faces of others, likely to reduce distractions and focus on internal cognition (Abeles & Yuval-Greenberg, 2017; Doherty-Sneddon et al., 2002; Doherty-Sneddon & Phelps, 2005) or to save additional resources for internal cognitive processes such as problem solving, memory retrieval, etc. by minimising individual external factors (Salvi & Bowden, 2016). In a recent study by Servais et al. (2023), the authors investigated gaze averting during memory retrieval and showed that gaze averting occurred predominantly in the access phase of memory retrieval, indicating higher cognitive effort or vivid memory retrieval. They proposed to redefine averted gaze as visual disengagement from external information, consistent with the cognitive load hypothesis (Servais et al., 2023).

Eye tracking – specifically the measurement of pupil responses and eye movements, including the number and duration of fixations – has become a popular approach for assessing cognitive load, arousal and mental workload due to its promising results. Therefore, several publicly available datasets now provide eye-tracking data on these topics to support further research. Notable examples include: EMOtional attention dataset (Fan et al., 2018), MAMEM Phase I (Nikolopoulos et al., 2017), EYEC3D (Hanhart & Ebrahimi, 2014), COLET (Ktistakis et al., 2022), DOVES (Bovik et al., 2009), UT Multi-view (Sugano et al., 2014), etc.

5.3. Selected cues to deception from eye-tracking studies: an overview

Eye-tracking has become a popular tool for deception detection due to several reasons: (a) it can be used for data collection without the need for direct physical contact, (b) it provides automatic calibration, (c) it is suitable for data collection in different environments, (d) it enables covert data collection, and e) it allows the use of shorter and more efficient interaction formats than traditional contact polygraphs (Proudfoot et al., 2016). For the detection of deception using eye tracking, the most commonly used

indicators are gaze aversions or fixations (Borza et al., 2018; Cook et al., 2012; Gallardo-Antolín & Montero, 2021; Hypšová et al., 2024; Mann et al., 2013; Millen & Hancock, 2019; Mirsadikov & George, 2023; Proudfoot et al., 2016; Twyman et al., 2014; Webb, Hacker, et al., 2009), pupil dilation variations (Cook et al., 2012; Hochman et al., 2016; Kim et al., 2019; Trifiletti et al., 2020; Wang et al., 2010), saccadic movements (Borza et al., 2018; Proudfoot et al., 2016; Speth et al., 2021; Twyman et al., 2014; Vrij et al., 2015), and blinks (Borza et al., 2018; Leal & Vrij, 2010; Marchak, 2013; Peth et al., 2013; ten Brinke & Porter, 2012).

Given the complexity of eye-related variables in deception, we provide a brief overview of recent findings on eye tracking in deception detection, focussing on studies from the last 10 years. We focus primarily on the number and duration of fixations, but also address pupil dilation, saccadic movements, and eye blinks to gain a broader understanding for our future research goals.

Table 3: Theoretical overview of selected eye-tracking deception detection research

Authors	Year	Used scenario	Interview methodology	Used dataset	Used eye-tracking metrics	N of subjects	Results specification	Accuracy (ACC) or effectiveness (AUC)
Twyman et al.	2014	Mock-crime with IED; ASK system; measured twice over 2 days	CIT	data gathered during experiment	Initial saccade direction; avoidance of relevant stimuli; fixation on irrelevant stimuli	136	Guilty: avoided relevant objects, fixated more on irrelevant ones (defensive reaction); orienting response not significant.	AUC 0.69 (day 1) and 0.70 (day 2) based on the defence reaction
Proudfoot et al.	2015	Mock-crime involving IED construction	CIT	data gathered during experiment	pupil diameter	116	Guilty: larger pupil diameters; non-exposed group: greater pupil decreases than innocent and exposed groups.	n/a
Vrij et al.	2015	Structured opinion interview with 3 phases: questionnaire, interview, post-interview	Opinion discussion: 1 truth, 1 prepared lie, 1 spontaneous lie	data gathered during experiment	saccadic eye movements represented as eye movement rate (EMR)	30	Spontaneous lies led to higher EMR than truths; no differences between spontaneous vs. planned lies or truths vs. planned lies.	n/a
Proudfoot et al.	2016	Mock-crime involving IED construction	CIT	data gathered during experiment	pupil diameter, eye gaze dwell time	114	Faster pupil dilation decreases for guilty participants (no exposure); centre	Model sensitivity: 73.9%.

							gaze dwell time increased for exposed guilty group.	
Hochman et al.	2016	Flexible dot task with deceptive incentives for higher pay out.	No interview; decision-making in perceptual task with incentivized false answers	data gathered during experiment	pupil diameter, gaze behaviour	46	Pupil dilation increased during beneficial errors; gaze shifted from helpful info to self-benefiting choices during cheating.	n/a
Borza et al.	2018	Eye-tracking-based deception detection algorithm; validated on 3 public datasets	No data collection	SFD (Radlak et al., 2015): truth/lie about geometric shapes	Blink rate (NBRD); gaze direction; saccadic eye movements	101	No significant correlation between saccades and deception; no clear blink rate differences reported.	NBRD + Decision Stump classifier: 96.15% accuracy.
Kim et al.	2019	Mock-crime scenario	CQT	data gathered during experiment	pupil diameter	33	Guilty: greater pupil dilation to crime-relevant questions in audio-visual condition; innocents: more dilation to comparison questions.	n/a
Millen & Hancock	2019	Face recognition task: deny known, reject unknown, identify known target	CIT (Three-Stimulus Protocol)	data gathered during experiment	eye fixations of the presented faces; average fixation duration;	48	Guilty: longer fixation and fewer eye fixations on familiar vs. unfamiliar faces;	Avg. Fixation Duration AUC: 0.67 (guilty), 0.74 (CM); First Fixation Duration AUC:

					number of eye fixations		effect held despite countermeasures.	0.69 (guilty), 0.66 (CM); Inner face fixations AUC: 0.61 (guilty), 0.80 (CM); Eyes AUC: 0.87 (guilty), 0.48 (CM).
Trifiletti et al.	2020	Truth or lie to white/black partners; participants believed remote interaction	Interview with yes/no questions	data gathered during experiment	pupil dilation	40	Greater pupil dilation in deception than truth; also, more dilation when answering to white partners vs. black; no interaction effect.	n/a
Gallardo-Antolín & Montero	2021	No data collection	No data collection.	Bag-of-Lies dataset (Gupta et al., 2019): image description with truth/lie freedom	FPOGX, FPOGY, LPD, RPD	35	No pupil dilation results reported.	LSTM: AUC 67.37% (segment - focussing on smaller parts of the interaction), 72.09% (turn - with regard to the entire interaction); SVM: AUC 55.67% (segment), 57.86% (turn).

Speth et al.	2021	Mock-crime scenario	Interview: experiential, travel screening, and superlative questions	DDPM dataset developed by authors	EMR for eye saccades	70	EMR increased during lying vs. truth during response phase; no differences in question or combined phases.	Saccadic EM: 54.5% accuracy (threshold classifier).
Hypšová et al.	2024	Work and study related interview	Work/study interview with rehearsed and spontaneous responses	data gathered during experiment	eye fixations of the interviewers' eyes	15	More eye fixations in prepared lies vs. truth; fewer fixations in spontaneous lies than spontaneous truths; overall lower in spontaneous vs. prepared scenarios.	n/a

Note. ASKS – *Automated Screening Kiosk System*; IED – *Improvised explosive device*; CIT – *Concealed Information Test*; DDPM – *Deception Detection and Physiological Monitoring*; EMR – *Eye Movement Rate*; NBRD - *Normalized Blink Rate Difference*; CM – *Countermeasures*; LSTM – *Long Short-Term Memory*; SVM – *Support Vector Machines*; NBRD – *Normalised Blink Rate Deviation*; FPOGX – *Horizontal Fixation Point-Of-Gaze*; FPOGY – *Vertical Fixation Point-Of-Gaze*; LPD – *Left Pupil Diameter*; RPD – *Right Pupil Diameter*; SFD – *Silesian Face Database*.
Source. Author of the thesis.

41.76% studies used mock crime scenarios in which participants either constructed an IED (Proudfoot et al., 2015, 2016; Twyman et al., 2014), participated in an illegal task, such as packing a suitcase with predetermined props (Speth et al., 2021) or stealing money and deleting the webcam footage (Kim et al., 2019). 8.33% studies used the opinion-based scenarios (Vrij et al., 2015). More interactive interview was used in Hypšová et al. (2024). Trifiletti et al. (2020) added also an exploration of racial dynamic. 33.33% studies used some form of a visual task, such as the dot task with an incentive for deceptive answers (Hochman et al., 2016), or tasks requiring a deceptive or truthful description of visual stimuli or presented images (Borza et al., 2018; Gallardo-Antolín & Montero, 2021; Millen & Hancock, 2019).

Regarding interview methodology, several studies have utilised polygraphy paradigms, in particular the CIT (Millen & Hancock, 2019; Proudfoot et al., 2015, 2016; Twyman et al., 2014) and the CQT (Kim et al., 2019). Twyman et al. (2014) and Millen and Hancock (2019) specifically tracked eye fixations of relevant and irrelevant objects or familiar and unfamiliar faces. Guilty participants tended to avoid relevant objects or had longer fixation durations on familiar faces during concealment (Millen & Hancock, 2019). Pupil dilation also increased in guilty participants when exposed to crime-relevant stimuli in CIT (Proudfoot et al., 2015) or CQT (Kim et al., 2019). The authors hypothesise that guilty individuals showed increased arousal or cognitive load when avoiding relevant information, which is consistent with research linking pupil dilation to cognitive load and arousal. Interestingly, Proudfoot et al. (2016) observed that pupil dilation decreased faster in guilty participants who did not see relevant stimuli, which is likely due to lower cognitive engagement when avoiding crime-related objects as a defence mechanism (Proudfoot et al., 2016). From these studies, it appears that pupil dilation may be an important cue for deception, however, other factors may have also influenced these results. According to Mathôt and Vilotijević (2022), when studying pupil dilation for cognitive purposes, it is important to follow the Hillyard principle, i.e. to equalise experimental conditions and control visual stimulus properties such as brightness and contrast to avoid confounding factors. In studies with visual stimuli (e.g. relevant/irrelevant images, familiar/unfamiliar faces), brightness, contrast and visual saliency should be controlled and reported, as pupil responses are very sensitive to even small visual changes (Mathôt, 2018;

Mathôt & Vilotijević, 2022). None of the cited studies controlled for the properties of the stimulus. We suggest that future research should re-examine pupil dilation changes to ensure that they are not influenced by external conditions.

Other authors mainly used the yes/no response format (Trifiletti et al., 2020; Vrij et al., 2015), open answers format (Hypšová et al., 2024; Speth et al., 2021), or asked participants to respond to visual task (Borza et al., 2018; Hochman et al., 2016). In deceptive tasks participants diverted their gaze away from relevant information that could contribute to truthful decisions and instead focused on options that maximised financial gain, indicating distorted information processing during deception (Hochman et al., 2016). In addition, people often try to appear more convincing through direct eye contact (DePaulo et al., 2003; Griffin & Oppenheimer, 2006; Mann et al., 2013). However, the opposite was observed in spontaneous deception, with participants being less fixated on the interviewer's eyes (Hypšová et al., 2024), likely due to the increased cognitive load associated with spontaneous lying, which requires considerable executive control (Warmelink et al., 2019; Yin et al., 2016). In a prepared deception with lower cognitive demands, participants maintained more eye contact (Hypšová et al., 2024). Participants under deceptive conditions showed higher saccadic eye movement rates during spontaneous lies, indicating increased cognitive load, but no difference was found between truths and prepared lies (Vrij et al., 2015). Notably, the study did not include prepared truth conditions, as it assumed that truth tellers do not prepare (Vrij et al., 2015). We suggest that researchers control for all conditions when comparing rehearsed and spontaneous scenarios to fully assess their effects on various physiological and behavioural measures.

Borza et al. (2018) and Gallardo-Antolín and Montero (2021) applied machine learning techniques to detect deception from eye tracking metrics. In the study by Borza et al. (2018), a simpler feature-based approach with the decision stump classifier achieved 96.15% accuracy by using the normalised blink rate deviation. On the other hand, Gallardo-Antolín and Montero (2021) focused on different metrics related to fixations and pupil diameter with a more sophisticated ML architecture: the LSTM network for the sequential nature of their data – the use of LSTMs is an important contribution as it allowed to capture how the eye-tracking metrics change over time, particularly over the course of a deceptive interaction. The LSTM model outperformed traditional classifiers such as Support Vector

Machines (SVMs), achieving an AUC of 67.37% at the segment level and 72.09% at the turn level. The authors emphasised that LSTMs excel at processing sequential data because they can learn long-term dependencies, making them well suited to detect deceptions in dynamic, temporally evolving eye behaviour (Gallardo-Antolín & Montero, 2021). Apart from the different ML classifiers, the high accuracy of Borza et al. (2018) in NBRT can be attributed to a single and highly discriminative eye metric, whereas Gallardo-Antolín and Montero (2021) combined a broader range of eye metrics, which may result in slightly lower accuracy.

83.33% of cited studies used their own data gathered within their experiments (Hochman et al., 2016; Hypšová et al., 2024; Kim et al., 2019; Millen & Hancock, 2019; Proudfoot et al., 2015, 2016; Trifiletti et al., 2020; Twyman et al., 2014; Vrij et al., 2015). Two studies used a secondary dataset, such as The Silesian Face Database (Borza et al., 2018) or the Bag-of-Lies dataset (Gallardo-Antolín & Montero, 2021). Speth et al. (2021) developed their own publicly available dataset DDPM. Using the primary datasets is of a crucial importance, especially in terms of ground truth establishment (Delmas et al., 2024).

In summary, the above research findings suggest that pupil dilation, gaze behaviour, blinking and saccadic eye movements can serve as a cue to deception. Studies using ML strategies have achieved high accuracy of up to 96.15% (Borza et al., 2018) or have shown that the use of more complex models such as LSTM can serve as an indicator of the temporal dynamics of gaze behaviour (Gallardo-Antolín & Montero, 2021). Despite the promising results, there are limitations, such as the lack of control over external factors that can influence pupil response. In addition, some authors did not control for prepared truth (Vrij et al., 2015) or used a small sample (Hypšová et al., 2024) when investigating the differences between prepared and spontaneous scenarios. Given the complexity of eye-tracking metrics, future research should address these challenges in order to better generalise the results.

6 MODERATION BETWEEN ATTACHMENT AVOIDANCE, DECEIVER'S BEHAVIOUR AND PHYSIOLOGY

Building on previous chapters, in which various non-invasive methods for detecting deception were described, it becomes clear that neither behavioural nor physiological indicators can be fully understood without taking into account the underlying psychological characteristics of the person. Recent behavioural and psychophysiological research on deception detection has shown that individuals differ in their behaviour and physiological responses when they lie or tell the truth. These differences are not only a product of the situational context in which the deception occurs, but are also shaped by stable individual characteristics. This suggests that there is increasing recognition in the literature of the role that personality and emotional regulation play in deceptive behaviour. Specifically, two key questions arise: "*Why are some people better able to cope with stressful situations while others have difficulty doing so?*" (Berant et al., 2001) and "*Do people differ in how they regulate their emotions in general?*" (Gross & John, 2003).

Attachment theory (Ainsworth, 1978; Bowlby, 1982) and emotion regulation theory (Gross, 2015; Gross & John, 1998, 2003) provide a valuable framework for addressing this issue. Emotion regulation refers to the processes by which people influence their emotional experiences and expressions. Based on Gross's process model of emotion regulation (Gross & John, 2003), two widely studied strategies are cognitive reappraisal and expressive suppression. *Cognitive reappraisal* is an antecedent-focused strategy in which an emotional situation is reinterpreted in order to change its effects, whereas *expressive suppression* is a response-oriented strategy in which the outward expression of emotions is inhibited when they are already underway (Gross & John, 1998, 2003). These strategies differ not only in timing but also in their psychological, social, and well-being outcomes, with reappraisal generally associated with better adaptability (Gross, 2015; Liu et al., 2010) and suppression with emotional inauthenticity, lower social connectedness, and poorer well-being outcomes (Aldao et al., 2010; Gross, 2015; Gross & John, 2003; Ioannidis

& Siegling, 2015). Attachment theory is being seen as an innate behavioural system, which serves in itself as "*an emotion regulation device*" (Mikulincer & Shaver, 2007, p. 190). On a broad evolutionary level, it serves to ensure survival by promoting closeness to protective others, however its more immediate function is to regulate fear and insecurity. In the presence of a threat, this system is activated and motivates individuals to seek the closeness and support of significant others. Once safety is restored and emotional equilibrium is achieved, the system is usually deactivated, allowing the individual to refocus on non-defensive goals (Seitl et al., 2023).

Despite the normative functions of the attachment system, much of the literature has focused on individual differences in attachment orientations (Seitl et al., 2023). These differences are thought to stem from early interactions with primary caregivers and manifest as trait-like tendencies that influence emotion regulation throughout life (Gillath et al., 2010; Mikulincer & Shaver, 2019). Specifically, adult attachment has been commonly categorised as secure, anxious, avoidant and fearful-avoidant (Bartholomew & Horowitz, 1991). Securely attached individuals generally experience and report emotionally fulfilling relationships based on trust and mutual support. In contrast, people with an anxious attachment orientation often show increased dependence on others, accompanied by fears of abandonment and a constant concern for the security of their relationships. People with an avoidant attachment style typically favour emotional independence and tend to distance themselves from close attachments. A disorganised attachment pattern is characterised by contradictory behaviours in which the person concerned simultaneously seeks proximity and behaves in an avoidant manner, leading to ambivalence and instability in relationships (Bartholomew & Horowitz, 1991).

Currently, the attention is shifted towards dimensional models, because they offer a more nuanced understanding of these attachment patterns (Mikulincer & Shaver, 2007). Brennan et al. (1998) proposed a two-dimensional framework in which attachment orientations are positioned along the axes of anxiety and avoidance. These dimensions are strongly associated with certain emotion regulation strategies (Mikulincer & Shaver, 2007). Secure attachment is associated with more effective regulation of both positive and negative emotions (Cooper et al., 1998; Wei et al., 2005). Anxious attachment individuals typically rely on hyperactivating strategies, which involve heightened sensitivity

to threat, persistent distress, and excessive efforts to gain reassurance and closeness (Mikulincer et al., 2002). On the other hand, avoidantly attached individuals tend to deactivate their attachment system (Seitl et al., 2023), distancing themselves emotionally and cognitively from distress (Mikulincer & Shaver, 2019), which may be leading to reduction or masking not only verbal but also nonverbal expressions of emotions (Clear et al., 2020; Mikulincer & Shaver, 2007).

Given the central role that both emotion regulation and attachment orientation play in shaping interpersonal behaviour, it is not surprising that these factors also play a role in the context of deception. Emotional suppression, physiological arousal and the processing of interpersonal impressions – all of which are relevant to lying (Ekman, 2009; Porter et al., 2011, 2012) – are closely linked to a person's attachment-related emotion regulation tendencies. Moreover, avoidant attachment has been associated with a higher tendency towards inauthenticity and dishonesty in both self-report and behavioural studies (Gillath et al., 2010). Although this emphasises a motivational link between avoidance and dishonesty, it leaves open the question of how avoidant individuals behave and react physiologically during deception. In particular, little is known about how their characteristic suppression of emotional expression and physiological arousal influence their bodily responses when lying.

With this in mind, we will focus exclusively on attachment avoidance, as it presents a paradox: Although avoidant individuals strive to suppress the expression of emotions and maintain their balance (Clear et al., 2020; Mikulincer & Shaver, 2007) , research shows that their physiological systems can nevertheless exhibit heightened arousal under emotional or stressful conditions (Diamond et al., 2006; Dias et al., 2011; Vrtička et al., 2012). This discrepancy between internal arousal and external control makes avoidance behaviour particularly relevant for understanding how individual differences shape both the behavioural and physiological aspects of deception. To date, however, no studies have directly investigated the moderating role of attachment avoidance in the expression of physiological and behavioural responses during deception compared to truth-telling.

6.1. Existing research on emotion regulation and deception in avoidant individuals

Avoidant-attached individuals rely on deactivating emotion regulation strategies that suppress the expression of emotions and inhibit approaching behaviours, especially in stressful situations (Frías et al., 2014; Holmberg et al., 2011; Mikulincer & Shaver, 2019; Pascuzzo et al., 2013; Shallcross et al., 2014). Behavioural evidence shows that avoidant individuals show lower intensity of emotional facial expressions, especially for positive emotions such as happiness, when exposed to emotionally charged situations (Seitl et al., 2023). This effort to limit emotional expression may also lead to reduced visibility of deception-related behavioural cues, such as expressive valence (Mathur & Matarić, 2020) or stronger intensity of emotional micro expressions (Matsumoto & Hwang, 2018). While their behaviour may appear calm or neutral, this emotional suppression requires cognitive and regulatory effort, especially in situations where the stakes are high or emotionally stressful, such as lying.

It has been shown that deception is often more cognitively demanding than telling the truth, especially when the individual tries to control both the content and delivery of a lie (Vrij, Fisher, et al., 2008, 2017). In this context, avoidant individuals may be exposed to increased cognitive load as they must simultaneously suppress their emotional expression and cope with the demands of deception. This dual burden is further illustrated in a recent study by Uccula et al. (2022), who used eye-tracking methodology to investigate attention and decision-making in avoidant individuals in distress. Although all participants initially fixated on comforting (care-related) images, avoidant-attached individuals chose these images significantly less often, opting instead for neutral or unrelated alternatives such as food. This discrepancy between attention and behaviour suggests that avoidant individuals perceive emotionally supportive cues as threatening and strategically avoid them at the decision-making level, even when they perceptually process these cues. These findings support the broader view that attachment avoidance involves not only the suppression of emotional expression, but also the attentive and motivational avoidance of relational cues – a strategy that may be especially vulnerable to breakdown under cognitive or emotional stress (Uccula et al., 2022). In addition, research suggests that under

prolonged stress, avoidant individuals may show a strong negative affect or even a loss of emotional control, indicating not only increased cognitive effort but also increased physiological arousal (Berant et al., 2001). Taken together, these factors suggest that avoidant individuals may be especially prone to behavioural inconsistency and physiological reactivity when the demands of deception exceed their regulatory capacity.

From a physiological perspective, one might assume that their suppressed emotionality would lead to muted physiological responses, but studies instead show a discrepancy between what avoidant individuals report and how their bodies respond under stress (Diamond et al., 2006). For example, in an early study by Mikulincer (1998), he found that when he experimentally induced anger, the avoidant subjects showed significant heart rate reactivity, but when asked about their subjective rating of the experience of anger, they did not report it. This suggests that avoidance behaviour is more likely to be characterised by disassociations between physiological and subjective manifestations of reactivity (Diamond et al., 2006). Moreover, Diamond et al. (2006) observed that during stress-inducing tasks, avoidantly attached individuals displayed heightened skin conductance responses, suggesting increased sympathetic nervous system activation. Similar result was reported also in a study by Dias et al. (2011). These findings suggest that attachment avoidance is associated with a physiological stress response pattern consistent with repressive coping, in which exposure to tasks that evoke negative thoughts or emotions leads to increased and sustained activation of the sympathetic nervous system, even in the absence of subjective distress (Diamond et al., 2006). In terms of cardiovascular measures, Kim (2006) reported that avoidant attachment was associated with increased diastolic blood pressure during stress-inducing interactions, indicating a pronounced cardiovascular reactivity. Ehrenthal et al. (2011) extended these findings by demonstrating that avoidantly attached individuals not only had elevated blood pressure in response to stress, but also showed impaired recovery following the stressor, indicating persistent physiological arousal. In addition, Maunder et al. (2006) found a negative correlation between attachment avoidance and HRV, with lower HRV reflecting reduced parasympathetic regulation and a reduced ability to effectively modulate stress responses.

At the neural level, avoidant attachment is associated with increased activation of regions related to cognitive control and emotion regulation. In a fMRI study conducted by Vrtička et al. (2012), the authors found that that avoidantly attached individuals exhibited heightened activity in the dorsolateral prefrontal cortex (DLPFC) and anterior cingulate cortex (ACC) when processing negative social stimuli. These areas are crucial for implementing cognitive control strategies and modulating emotional responses. Notably, the DLPFC and ACC have also been implicated in deception processes (Christ et al., 2009).

The above results confirm the previously discussed paradox: despite their calm outward appearance, avoidantly attached individuals exhibit underlying physiological markers of increased stress and effort. This internal and external incongruence may have a significant impact on the detection of deception. While their restrained expressivity makes the behavioural cues of deception less obvious, the physiological indicators of stress and cognitive load may serve as more reliable markers that can “reveal" their lies. Therefore, attachment avoidance should be investigated as a possible moderator in multimodal deception detection methods that integrate both behavioural observations and physiological measures.

7 ETHICAL ASPECTS OF DECEPTION DETECTION RESEARCH

Areas such as law, security, personnel selection and even everyday settings are looking for accurate ways to recognise deception (Vrij & Ganis, 2014). Due to the challenges in accurately assessing truthfulness by humans, many have turned to more objective technological methods (Luber et al., 2009), reaching from traditional polygraphs (Ginton, 2017; Iacono & Ben-Shakhar, 2019; Oksol & O'Donohue, 2004; Raskin & Kircher, 2014) to modern non-invasive methods such as fITI (Gálvez-García et al., 2021; Hypšová et al., 2024; Moliné et al., 2017, 2018; Pavlidis & Levine, 2002), rPPG (Li et al., 2024; Speth et al., 2021; Vance et al., 2022), or eye tracking (Hypšová et al., 2024; Kim et al., 2019; Proudfoot et al., 2015, 2016; Trifiletti et al., 2020). Although these methods have improved the accuracy of deception detection, their application raises significant ethical concerns. Psychological research follows the APA Code of Ethics (APA, 2017), but there are no specific guidelines for deception detection research. This chapter addresses this gap by summarising the key elements and exploring ethical considerations in laboratory settings, as deception detection in real life raises broader legal issues that are beyond the scope of this thesis. For legal concerns, particularly regarding the use of polygraphs, see National Research Council (2003), the Daubert v. Merrell Dow (*Daubert v. Merrell Dow Pharmaceuticals, Inc., 509 U.S. 579 (1993)*, n.d.), or the American Polygraph Association (APA, 2024).

Physiological deception detection raises moral and philosophical concerns about the "protection of the human soul and the unconscious and involuntary". In contrast to traditional interviewing, physiological approaches examine not only spoken statements, but also those that are made involuntarily without the person being able to control this (Fischer, 2020). The protection of human autonomy in deception detection was a central concern, especially in the German legal debate of the 1950s on human dignity, which was later incorporated into the case law of the Federal Constitutional Court (Fischer, 2020). This argues that people must not be degraded to objects and must be

“protected” from technology that could measure their unconscious emotions, as it could violate their freedom to decide and exercise their will (§ 136 a stPO, In Fischer, 2020). Therefore, in 1954, the Federal Constitutional Court argued that the use of such devices to analyse the human soul or unconscious emotions violated personal autonomy (Fischer, 2020). After the 1954 decision, German courts increasingly focussed on the tension between human dignity and the use of polygraphs. Initially, the polygraph was seen as a violation of personal autonomy because it tapped into unconscious emotions, but in the 1980s discussions evolved to emphasise the device’s technical ability to measure body signals rather than the soul. In 1998, in an important judgement, the polygraph was seen as a tool that improved the judgement of experts by making unconscious reactions visible, which led to a potential acceptance of the device in scientific terms, while ethical concerns receded, although some are still necessary (Fischer, 2020). Nevertheless, the fundamental ethical problem remains: These technologies can violate personal autonomy by revealing inner states that the individual has not voluntarily disclosed. This issue applies not only to polygraphs, but also to modern non-invasive methods such as fITI, eye tracking and rPPG. Therefore, any use of these technologies, whether in research or in application, must actively compensate for this interference with autonomy through strict ethical guidelines, including transparency, informed consent and clear communication about the limitations of the method.

Given the legal and philosophical emphasis on protecting the dignity and autonomy of the individual, it is critical that the technologies used are not viewed as definitive tools for detecting deception, but as methods for observing responses that could shed light on behaviour. Ensuring that participants understand this difference will help to maintain transparency and protect their autonomy and privacy. Researchers need to clearly explain how these involuntary physical responses will be measured to reassure participants about the study methods. When deception detection research in the laboratory attempts to replicate real-life scenarios to increase ecological validity (Iacono & Ben-Shakhar, 2019), researchers must carefully consider the ethical implications of such realism, especially when it comes to how participants handle manipulations that aim to mimic real-life situations. Researchers need to find a balance between scientific rigour and the well-being of participants, particularly through the careful use of informed consent

(Iacono & Ben-Shakhar, 2019). According to the Ethical Principles for Psychological Research and Publication, obtaining informed consent in research is essential. It includes fully informing participants about the study purposes, the procedures, the risks, the benefits, and their right to withdraw at any time. Researchers must explain the limits of confidentiality, available incentives, contacts for questions, and details about experimental treatments, group assignments, alternatives, and costs. Participants should have the opportunity to ask questions and receive clear answers (APA, 2017).

In accordance with APA (2017, Section 9.06: "Interpreting Assessment Results"), psychologists consider various factors such as test conditions and personal differences that may affect their assessments. Despite extensive research, there is no gold standard that technologies used for deception detection can consistently rely on (Vrij, Granhag, et al., 2010), which raises ethical concerns about the replicability of technological deception detection. As technological approaches are not yet able to distinguish truth tellers from liars with absolute accuracy and lack scientific validity, it should be limited to use in the laboratory and should not be admitted as evidence in court (Meijer et al., 2016). Furthermore, deceptive behaviours are often indirectly inferred from physiological or neural responses rather than directly measured, raising ethical questions about the conclusions drawn from these measurements (Bogaard, Meijer, Vrij, et al., 2014; Kassin, 2014; Kassin et al., 2013). These challenges require greater attention to the ethical implications, particularly in relation to informed consent, and the importance of protecting the rights of participants in these studies (Meijer et al., 2016).

Another ethical issue related to technological deception detection is the use of video recordings for the upcoming analyses, which are essential for methods such as fITI, eye-tracking and facial analysis. While this provides an important amount of information for deception detection, it also poses ethical risks such as privacy, confidentiality and the potential misuse of these recordings. According to APA Ethical Standard 4.01 (Maintaining Confidentiality), researchers must keep the recordings secure, restrict access to them, and fully inform participants about their use as part of the consent process (as in APA Standard 8.03: Informed Consent for Recording Voices and Images in Research).

Since deception detection designs are often designed to answer more or less sensitive questions, participants must be able to withdraw their consent at any point during the experiment. It is beneficial to offer participants the opportunity to withdraw their consent and request the deletion of the data, even a few days after the experiment. This gives them time to review the process and ensure that they are comfortable with their data to be used. In addition, if researchers need to show some illustrative images in their publications, additional consent or a statement from each participant must be obtained so as not to violate APA Ethical Standard 8.05 (Dispensing with Informed Consent for Research) or APA Standard 3.04 (Avoiding Harm).

Last but not least, APA Ethical Standard 8.08 (Debriefing) requires researchers to explain the true purpose and nature of the research to participants at the conclusion of data collection, particularly if deception or misleading information was used during the study. This ensures that participants are fully informed and can understand the context of their participation. It is also in line with APA Ethical Standard 3.04 (Avoiding Harm), which states that participants should leave the study without lasting discomfort or confusion.

Deception detection research involves a number of ethical considerations that not only help to improve the reliability of results, but also increase the ecological validity of the research by bringing it closer to real-life scenarios (Iacono & Ben-Shakhar, 2019). To maintain the ethical standards, we believe it is necessary for researchers to first obtain Institutional Review Board approval, as outlined in APA Standard 8.01 (Institutional Approval). This ensures that all ethical criteria and potential challenges are adequately addressed from the beginning of the research.

EMPIRICAL PART

8 THE RESEARCH PROBLEM AND RESEARCH OBJECTIVES

Deception is often necessary part of human communication. While many lies are harmless or sometimes even prosocial to maintain social relationships or protect other's feeling (Vrij & Ganis, 2014), there are lies which carry significant interpersonal, legal or societal consequences (DePaulo et al., 1996). From law enforcement to personnel selection to security screening, the ability to accurately detect deception has long been considered a scientific and practical challenge (Granhag et al., 2015; Vrij, Granhag, et al., 2010). In the past, researchers have attempted to overcome this challenge by identifying observable physiological and behavioural markers associated with lying (Meijer & Verschuere, 2014). However, traditional methods such as polygraphs are increasingly criticised for lacking ecological validity and being susceptible to countermeasures (Gamer, 2010; Synnott et al., 2015; Vrij & Ganis, 2014). Furthermore, these techniques are often contact-based, which may limit the duration and nature of the interview and increase subject's anxiety, which in turn may affect the accuracy and reliability of the results (Cardone & Merla, 2017; Derakhshan et al., 2020). In this vein, a growing body of work (e.g., Abdulridha & Albaker, 2024; Borza et al., 2018; Curci et al., 2019; Derakhshan et al., 2020; Gálvez-García et al., 2021; Hypšová et al., 2024; Li et al., 2024; Millen & Hancock, 2019; Mirsadikov & George, 2023; Moliné et al., 2017, 2018; Panasiti et al., 2016; Shen et al., 2021; Speth et al., 2021; Vance et al., 2022) has begun to explore a non-invasive approach using various technologies such as fITI, rPPG, facial expression analysis and eye-tracking to detect various behavioural and physiological cues that may indicate deception in a more flexible, less intrusive and more accurate way.

In particular, fITI has proven to be a promising and effective tool for detecting deception, especially when focussing on nasal temperature (Derakhshan et al., 2020; Gálvez-García et al., 2021; Moliné et al., 2017, 2018). However, existing fITI remains inconsistent: baseline measurements are often inconsistently reported, ROI definitions and sizes vary, and experimental paradigms often lack ecological validity – most studies rely on

laboratory scenarios in which crime is faked, overlooking basic conversational exchanges that are more representative of everyday social interactions. In addition, statistical analyses often fail to account for inter-individual variability, which can mask subtle effects associated with deception. The lack of standardised protocols for the collection and pre-processing of fITI data is also striking. Few studies use validated protocols (such as Fernández-Cuevas et al., 2015; Moreira et al., 2017), and most rely on ad hoc methods. In addition, there is currently no widely used software solution for automated processing of fITI data that can account for different ROI sizes – such as the inherently smaller nasal region compared to the forehead – and large, representative primary datasets are generally not used. Taken together, these limitations highlight the need to use well-defined baseline conditions in future studies, include natural conversation as experimental stimuli, apply statistical models that can handle variability (e.g., mixed-effects models), apply standardised protocols for data collection and processing, and provide open-source or reproducible software frameworks to enable consistent analysis across different datasets. Furthermore, context matters. It is recognised that the type of deception (e.g., spontaneous or rehearsed) has a significant impact on deception detection (Granhag & Vrij, 2005; Hypšová et al., 2024; Vrij, Mann, et al., 2008; Vrij, Meissner, et al., 2017; Warmelink et al., 2012, 2019). Spontaneous lies usually trigger greater cognitive load, higher arousal and greater activation of the autonomic nervous system, whereas rehearsed lies can be more regulated and cognitively efficient. However, there are few studies that have systematically compared deception under these conditions with employing fITI.

In addition, criticism has been pointed towards the use of facial expression analysis. While some studies report promising results when using AUs, emotional valence or arousal (see Delmas et al., 2024 for extensive systematic review), others emphasise the limited usefulness of micro-expressions due to their low frequency, cultural variability and context dependency (Zlotenaou, 2020). However, a more critical problem with analysing facial expressions is the reliance on secondary datasets, many of which have no reliable ground truth or use problematic ground truths such as study or polygraph results (Abdulridha & Albaker, 2024; Borza et al., 2018; Carissimi et al., 2018; Gallardo-Antolín & Montero, 2021; Zhu et al., 2007). These methodological issues point to the need for

research that collects primary data that has a clearly defined ground truth and a dimensional rather than categorical approach to affective expression.

The collection of primary datasets with fully established ground truths is also a challenge in deception detection with rPPG (Li et al., 2024; Speth et al., 2021; Vance et al., 2022). As the technology evolves, researchers are exploring its potential to improve accuracy, particularly when investigating various datasets (e.g., Deception Detection and Physiological Monitoring, DDPM, Speth et al., 2021; Vance et al., 2022), where authors make the collected data available to other researchers for further analysis. However, to our knowledge, a comprehensive study evaluating heart rate with rPPG under different deceptive and truthful scenarios and taking into account cognitive load and individual differences is lacking. This therefore opens the space for a preliminary use of rPPG to describe heart rate and highlights its potential for further analyses and research.

Last but not least, eye tracking has also proven to be a promising tool for detecting deception (Gallardo-Antolín & Montero, 2021; Hochman et al., 2016; Hypšová et al., 2024; Millen & Hancock, 2019; Proudfoot et al., 2015; Speth et al., 2021; Trifiletti et al., 2020; Vrij et al., 2015). However, its current application for deception detection has several limitations. Many studies use non-ecologically valid scenarios or visual stimuli that lack real-world social context, and few examine how gaze behaviour evolves during natural interpersonal interactions. While eye-tracking data, particularly fixations on socially relevant areas such as the eyes, have been associated with deception, findings also show that such behaviour is influenced by cognitive load (Hypšová et al., 2024). For example, spontaneous lying, which involves a higher executive demand, has been associated with less fixation on the interlocutor's eyes and increased background fixation, patterns that are reversed during rehearsed lying (Hypšová et al., 2024). However, there are few studies that systematically compare spontaneous and rehearsed lies, and even fewer studies that use rehearsed truths as a basis for analysing the effect of rehearsal itself. This raises the question of whether differences in fixation are really a sign of deception or merely reflect cognitive effort. As far as we know, there are very few eye-tracking studies that use cognitively sensitive deception paradigms or compare spontaneous and rehearsed conditions in both truth and lie scenarios. This conceptual and methodological gap limits our ability to interpret gaze behaviour as a reliable indicator of deception. Future research

should address this problem by employing cognitively sensitive paradigms that compare all combinations of spontaneity and veracity, to help clarify whether gaze cues are associated with deception itself or with the mental effort required to achieve it.

While understanding deception through non-invasive technologies and different cognitive load conditions is crucial, an equally important but under-researched aspect is how individual differences, such as attachment avoidance can influence deceptive behaviour and its detection. Avoidantly attached individuals are characterised by deactivating emotion regulation strategies. They suppress the expression of emotions, avoid intimacy and strive for autonomy, especially in stressful or emotionally charged situations (Mikulincer & Shaver, 2019). While this pattern of regulation may outwardly manifest as calmness or emotional neutrality, physiological studies have shown that such individuals actually experience increased internal arousal under stress, including increased heart rate, blood pressure and skin conductance (e.g., Diamond et al., 2006; Kim, 2006; Dias et al., 2011). Despite the strong theoretical rationale, attachment avoidance has yet to be systematically examined as a moderator in non-invasive deception detection paradigms. Avoidant individuals may confound conventional detection strategies by masking behavioural indicators while displaying measurable physiological arousal.

Taken together, the primary aim of this thesis is twofold: (1) To evaluate the individual predictive value of four non-invasive modalities (fITI, rPPG, facial expression analysis and eye-tracking) in distinguishing between truthful and deceptive responses; and (2) to investigate how different levels of cognitive load (rehearsed truth, rehearsed lie, spontaneous truth, and spontaneous lie) influence deception detection accuracy for each modality. In addition to these primary objectives, a secondary aim is to develop and test a customised software tool for pre-processing thermal data and to explore future possibilities to improve its application in the context of deception detection. Finally, the study investigates whether attachment avoidance moderate the relationship between behavioural and physiological responses and deception detection accuracy, separately assessing moderation effects for each modality. Although all measurements were conducted in controlled laboratory environment, the setting was designed to resemble everyday interpersonal communication, reflecting the thesis's focus on the applicability of non-contact methods in realistic social contexts.

9 METHODS AND CONDUCTED STUDIES

In order to address the research gaps identified in Chapter 8 and to fulfil the stated research objectives, this thesis used a combination of one case study, two pilot studies and one main study. The research followed a stepwise process that began with an initial case study that formed the basis for two pilot studies aimed at refining experimental procedures and validating measurement instruments. The findings from these pilot studies were then integrated into the final design of the main study. In all studies conducted (with the exception of the case study), a standardised protocol developed by Moreira et al. (2017) for the use of fITI in human participants was strictly adhered to. In each study, the ground truth (i.e., determining where the participants were telling the truth) was established after the experimental interview by having the participants themselves fill out a short form on which they directly wrote which information was completely true and which was completely deceptive.

9.1. Ethics

All participants received clear instructions and gave written informed consent before taking part in the study. In addition, all individuals mentioned in this thesis gave written consent for the publication of the case details. All studies adhered to the Ethical Principles for Psychologists and the Code of Conduct of the American Psychological Association (APA, 2017). Ethical approval was obtained from the Institutional Review Board (IRB) of Palacký University, specifically the FF UP Ethics Panel for Research, under reference number 03/2023.

9.2. Case study

As a first step towards the application of behavioural and physiological analysis in deception research, a case study was conducted and published in Hypšová and Seitl (2022). The study involved two within-subject laboratory experiments with a selected participant (a 26-year-old woman) to test the feasibility of combining fITI, rPPG, and automatic facial expression analysis in FaceReader software. The primary aim was

to calibrate the technical setup and evaluate the physiological and behavioural responses under different deceptive conditions.

Participant took part in both rehearsed and spontaneous truth and lie scenarios while interacting with a simulated interviewer represented by high-resolution facial photographs showing either a pleasant or unpleasant expression. This approach allowed for standardisation while excluding confounding factors such as tone of voice and non-verbal behaviour. Despite the limitations in ecological validity, the simulated setup ensured control over environmental and procedural variables.

Data was collected using a Fluke Ti450 PRO thermographic camera and a Canon 4K video camera. Heart rate was measured using rPPG and emotional facial expressions were analysed using FaceReader. Temperature changes in three facial regions (nose, cheeks, forehead), heart rate, and emotion expression of basic emotions were recorded under five conditions: baseline condition[4], rehearsed truth, rehearsed lie, spontaneous truth and spontaneous lie. For conditions explanation, see Hypšová and Seitl (2022).

The results showed consistent patterns: deception – especially spontaneous – was generally associated with lower nasal temperatures and a slight increase in heart rate. Cheek temperature also increased during lies, possibly due to emotional arousal or to an attempt at impression control. Neutral facial expressions decreased slightly during the rehearsed deception, while emotions such as fear and surprise increased slightly, consistent with previous research on emotional "*leakage*" during deception.

Crucially, this study highlighted important methodological challenges. Manual processing of the thermal images – including the selection of facial regions of interest – was time-consuming (over 20 hours per participant) and did not account for head movement, leading to data loss. These limitations prompted the development of automated pre-processing tools in pilot studies.

Although the results were descriptive, this case study successfully demonstrated the technical and conceptual feasibility of integrating fITI, rPPG and behavioural analysis

[4] **Note.** In this study, a baseline was employed as the resting state.

in deception research and directly influenced the design of subsequent pilot studies with larger samples and advanced data processing.

9.3. Pilot study 1

The first pilot study, funded by the Czech Ministry of Education (IGA_FF_2022_035) and published in Hypšová et al. (2024), aimed to empirically evaluate the feasibility of combining fITI and eye-tracking for deception detection in simulated interviews. Using a within-subject design with 15 participants, the study investigated differences in physiological (facial temperature) and behavioural (eye fixations) responses across two conditions of varying cognitive load: rehearsed truth and lie and spontaneous truth and lie. This approach built directly on the earlier case study and was designed to overcome its methodological limitations, including the development of an automated thermographic pre-processing framework.

Participants facial temperature was monitored using a Fluke Ti450 Pro thermal imaging camera and eye fixations were recorded using a Tobii Pro Spectrum 300 eye tracker. Automated ROI selection, developed using ArcGIS Pro and Python, enabled standardised temperature analysis despite head movements – a significant improvement over manual processing in the case study.

Results showed no significant difference in facial temperature between truth and lie but spontaneous responses were associated with significantly higher forehead and cheek temperatures, likely reflecting increased cognitive load. Nasal temperature did not vary significantly between conditions. However, the behavioural data showed strong effects: Participants fixated the interviewer's eyes more frequently during rehearsed deceptive responses than during spontaneous responses, supporting the idea that liars intentionally use gaze to control impressions (DePaulo et al., 2003; Griffin & Oppenheimer, 2006; Mann et al., 2013) when cognitive resources are available (Vrij & Granhag, 2012). Spontaneous lies, which involve greater executive demands, led to lower eye contact, which is consistent with the hypothesis that cognitive load inhibits gaze behaviour (Doherty-Sneddon & Phelps, 2005). A significant interaction between scenario and veracity on gaze behaviour also indicated that behavioural cues to deception are highly context-dependent and influenced by cognitive availability (Hypšová et al., 2024).

While physiological markers were less sensitive to veracity than expected, gaze patterns proved to be a more reliable indicator of deception, especially in cognitively demanding situations. The study highlighted the importance of spontaneous responses as a diagnostic condition and emphasised the need to consider ecological validity – leading to the use of real face-to-face interactions with interviewers in subsequent studies. Finally, the study laid a crucial technical foundation by developing and testing automated tool for thermal data pre-processing.

9.4. Pilot study 2

The second pilot study, which was conducted under the research grant IGA_FF_2023_035 from the Czech Ministry of Education, was designed to extend the earlier results by increasing the ecological validity and improving the procedures for analysing thermal data. It is currently under review and is summarised here to contextualise its contribution to the main study of this dissertation.

In contrast to the previous pilot study, this study utilised a real interviewer to simulate job interviews, creating a more high-stakes and socially authentic environment – in this case a personnel selection simulation. Using a within-subjects experimental design, the study examined the effects of faking (truth vs. lie), rehearsal (rehearsed vs. spontaneous) and the interaction between all conditions including baseline[5] on facial thermal responses in four key regions: nose, forehead, and left and right cheek. Three hypotheses were tested for each effect:

- *Effect of faking:* Based on previous research on thermal deception (Gálvez-García et al., 2021; Moliné et al., 2017; Pollina et al., 2015; Zhu et al., 2007), we expected higher forehead and cheek temperature and lower nasal temperature in deceptive responses compared to truthful responses.
- *Effect of rehearsal:* It was hypothesised that rehearsed responses, which were assumed to reduce cognitive load and stress (Hartwig et al., 2007; Vrij, Fisher, et al., 2017), would lead to lower cheek and forehead temperatures and higher nasal temperatures than spontaneous responses.

[5] **Note.** In this study, a baseline was employed as the resting state.

- *Interaction effects:* Spontaneous lies were expected to elicit the strongest changes in nasal temperature (due to anxiety and cognitive effort), while rehearsed lies would elicit moderate or minimal changes, especially in the forehead and cheek areas.

Participants (N = 27; 74% women) were recruited from the general population via digital outreach and posters. Participants completed a deception task structured as a simulated job interview. Each participant prepared two answers in advance (one truthful and one deceptive; 7 days before the experiment) and spontaneously answered two additional questions during the interview. The instructions as to whether they should answer truthfully or deceptively were delivered in sealed envelopes.

The thermal videos were taken with the Fluke Ti450 Pro camera in a controlled laboratory environment. To incentivise believable lying, participants were told that the best 'candidate' (as judged by the interviewer) would receive a reward of €158. After a 20-minute acclimatization, the interviews began with rehearsed responses followed by spontaneous questions that mirrored the previous designs (Hypšová et al., 2024; Hypšová & Seitl, 2022) and reflected the mental representations of the interview (Warmelink et al., 2019).

Three linear mixed models[6] in R Studio version 4.4.1, changes in facial temperature were analysed under five conditions (baseline, rehearsed truth, rehearsed lie, spontaneous truth, spontaneous lie). ROIs and conditions were treated as fixed effects and participant ID as a random effect. Bonferroni correction was applied to control for multiple comparisons and effect sizes were calculated using partial eta squared (η_p^2).

Mixed model analysis showed no significant overall effect of faking, $F(1, 398) = 3.40$, $p = .066$, $\eta_p^2 = .008$. However, there was a significant main effect of rehearsal, $F(1, 398) = 13.09$, $p < .001$, $\eta_p^2 = .032$, and a significant interaction between all conditions and ROI, $F(12, 494) = 1.934$, $p < .05$, $\eta_p^2 = .045$. Pairwise comparisons revealed significant

[6] **Note.** Three tested models: *Model 1* examined the effect of rehearsal and ROI using the formula: Temperature ~ Rehearsal * Region + (1 | ID); *Model 2* focused on faking across ROIs: Temperature ~ Faking * Region + (1 | ID); *Model 3* integrated the full factorial design, testing the joint effects of veracity, rehearsal, and ROI while maintaining baseline as fifth condition: Temperature ~ All conditions * Region + (1 | ID). All models included participant ID as a random intercept.

interaction effects, particularly in nasal temperature responses. Nasal temperature was significantly higher at baseline than during spontaneous truth (M_{diff} = 0.361, *SE* = 0.066, $p < .001$), and higher in both rehearsed lie (M_{diff} = 0.272, *SE* = 0.066, $p < .001$) and rehearsed truth (M_{diff} = 0.318*, SE* = 0.066, $p < .001$) compared to spontaneous truth. Spontaneous lies also showed higher nasal temperature than spontaneous truths (M_{diff} = 0.193, *SE* = 0.066, $p < .05$), indicating the nasal region's sensitivity to cognitive and emotional demands in spontaneous responses. In forehead and cheeks, no significant differences were found between any conditions, including rehearsed and spontaneous responses.

While we found no significant overall effect of faking on facial temperature, our results showed that, particularly nasal temperature, was more closely related to task demands and cognitive load than to deception per se. This is consistent with the literature (for e review see e.g., Synnott et al., 2015) suggesting that both liars and truth tellers may experience heightened arousal in evaluative contexts, making the detection of deception based on physiological markers inherently complex.

Crucially, by using linear mixed models, we were able to control individual variability better than with traditional repeated measures ANOVA, which may explain the discrepancies with previous studies reporting significant deception effects. For more information on the benefits of using LMMs in deception detection studies, see Zloteanu and Vuorre (2024).

Our findings on the variability of nasal temperature in spontaneous and rehearsed responses suggest that spontaneous responses – whether truthful or deceptive – elicit greater thermal reactivity, possibly due to increased uncertainty or anxiety (Gálvez-García et al., 2021; Moliné et al., 2017; Zhu et al., 2007). Interestingly, increased physiological responses were observed in spontaneous honest responses, not in deceptive ones. This suggests that the fear of not being believed may have triggered stronger autonomic responses than faking – patterns observed in polygraph CQT, where innocent individuals sometimes respond more strongly to relevant questions (National Research Council, 2003). In contrast to previous thermographic studies that mainly compared deception to truth or baseline (Abouelenien et al., 2019; Derakhshan et al., 2020; Gálvez-García et al., 2021;

Moliné et al., 2017, 2018), our findings emphasise the need to investigate variability within truthful responses as a significant source of thermal change.

An important step forward in this pilot study was the development of another framework for processing thermal data in MATLAB, which allowed us to overcome the limitations identified in pilot study 1. In contrast to the previous ArcGIS-based tool, the new framework enables continuous extraction of thermal features across the entire video sequence and automates the selection and tracking of ROIs despite head movements. The temperature metrics – mean, median, standard deviation and dispersion – could be calculated for each image within predefined ROIs, increasing accuracy and reducing data loss. In addition, the framework allows thermal data to be stored and exported in a proprietary raw format so that researchers can use their own preferred metrics and statistical analyses.

To summarise, this study provides important methodological and theoretical insights into the complexity of using fITI for deception detection. While deception alone did not elicit consistent thermal effects, nasal temperature changes were more closely related to cognitive load and emotional arousal, especially during spontaneous honest responses. This novel finding challenges the traditional comparison between deception and truth and suggests that the fear of not being believed may be just as, if not more, pronounced physiologically. By applying linear mixed models, we were better able to account for individual variability than previous work and provided a more robust analytical approach. Furthermore, by switching from a simulated to a real interviewer, we significantly improved ecological validity by capturing more authentic interpersonal dynamics. Finally, the thermal data processing framework developed here, capable of tracking facial ROIs across movements, proved reliable and was utilised in the main study.

9.5. Main study

The main study was conducted on the basis of the case study described above and the subsequent pilot studies. It utilised a within-subjects experimental design with real interviewers and two different "missions" assigned to participants prior to the experimental procedure. These tasks were intended to increase ecological validity

by encouraging authentic engagement in both truthful and deceptive responses. Three main objectives with three effects were operationalised, each of which includes several research questions and hypotheses.

9.5.1. Aims and hypotheses

Aim 1

To evaluate the individual predictive value of four non-invasive modalities (fITI, rPPG, facial expression analysis and eye-tracking) in distinguishing between truthful and deceptive responses.

Effect of deception (i.e., veracity)

RQ1: Do the mean values of the dependent variables, as separately measured by each technology ($RQ1^{fITI}$, $RQ1^{FaceReader7}$, $RQ1^{Eye\text{-}tracker}$) differ between periods when participants are lying and telling the truth?

Infrared thermal imaging

H1.1a (nasal temperature): Nasal temperature will significantly decrease during deceptive responses compared to truthful conditions.

- The nose, which lacks large muscles (Kosonogov et al., 2017) and contains arteriovenous anastomoses (Johnson et al., 2014), has been shown to be highly sensitive to such changes in previous studies of deception (Abouelenien et al., 2019; Gálvez-García et al., 2021; Moliné et al., 2017). Therefore, we hypothesised that nasal temperature would decrease during deception, reflecting peripheral vasoconstriction commonly associated with increased stress, arousal or cognitive load (Abouelenien et al., 2019; Gálvez-García et al., 2021; Moliné et al., 2017).

H1.1b (forehead temperature): Forehead temperature will significantly increase during deceptive responses compared to truthful conditions.

[7] **Note.** All research questions related to FaceReader include both facial expression analysis and rPPG, as the software provides continuous measurements of emotional valence, arousal and heart rate, the latter being derived from the rPPG implemented in FaceReader.

- We predicted an increase in temperature during deceptive responses, which is consistent with findings linking increased forehead temperature to negative affect, cognitive effort, and stress-induced vasodilation in the supraorbital region (Puri et al., 2005; Robinson et al., 2012; Zhu et al., 2007).

H1.1c (cheek temperature): Cheek's temperature will significantly increase during deceptive responses compared to truthful conditions.

- An increased cheek temperature was to be expected, as the temperature of the cheeks is often influenced by social-emotional processes such as IM and embarrassment – factors that are likely to play a role in deceptive communication (Cruz-Albarran et al., 2017; Gálvez-García et al., 2021; Ioannou et al., 2016). Although cheek responses are generally more variable from person to person (Matsukawa et al., 2018; Murad & Malkawi, 2012; Wang et al., 2019), previous findings suggested that their elevated temperature is still relevant in deceptive contexts (Panasiti et al., 2016).

FaceReader

H1.2a (heart rate): Heart rate will significantly increase during deceptive responses compared to truthful conditions.

- We expected this trend based on previous research that has consistently shown that heart rate increases under emotional stress and arousal (Kop et al., 2011; Y. Wu et al., 2019), and that deceptive behaviour can trigger both an initial heart rate acceleration and a subsequent deceleration – reflecting cognitive effort and IM (Gamer, 2010; Gamer et al., 2006; Verschuere et al., 2009).

H1.2b (emotional arousal): Emotional arousal will be significantly higher during deceptive responses compared to truthful conditions.

H1.2c (emotional valence): Emotional valence will be significantly lower (i.e., more negative) during deceptive responses compared to truthful conditions.

- Reasoning for H1.2b and H1.2c was grounded in theories of deception that emphasize the emotional and cognitive demands of lying. According to the four-factor theory (Zuckerman et al., 1981), and leakage theory (Ekman & Friesen, 1969), deception elicits internal emotional states – particularly fear, guilt, and anxiety – that may manifest as heightened arousal and negatively valenced emotional expressions.

Eye-tracking

In contrast to traditional assumptions about gaze avoidance during deception (Vrij, Akehurst, et al., 2006), recent evidence suggests that deceivers increase their visual attention to the interlocutor's face – especially the eye region – as a compensatory strategy to appear credible and monitor the interlocutor's reactions (Griffin & Oppenheimer, 2006; Hypšová et al., 2024; Mann et al., 2013). Therefore, we operationalised the eye-tracking hypotheses as follows:

- **H1.3a (upper face):** Participants will fixate the interviewer's upper face (e.g., eye region) significantly more during deceptive responses compared to truthful conditions.
- **H1.3b (lower face):** Participants will fixate the interviewer's lower face (e.g., mouth and jaw region) significantly less during deceptive responses compared to truthful conditions.
- **H1.3c (background):** Participants will fixate the background (i.e., avoidant gaze behaviour) significantly less during deceptive responses compared to truthful conditions.

Aim 2

To investigate how different levels of cognitive load (rehearsed truth, rehearsed lie, spontaneous truth, and spontaneous lie) influence deception detection accuracy for each modality (fITI, rPPG, facial expression analysis, and eye-tracking).

Effect of rehearsal

RQ2: Do the mean values of the dependent variables, as separately measured by each technology ($RQ2^{fITI}$, $RQ2^{FaceReader}$, $RQ2^{Eye\text{-}tracker}$) differ across rehearsed and spontaneous responses?

Infrared thermal imaging

H2.1a (nasal temperature): Nasal temperature will be significantly higher during rehearsed responses compared to spontaneous responses.

- Previous findings indicated that nasal temperature decreases in response to increased cognitive load and stress (Bonyad et al., 2024; Or & Duffy, 2007; Pavlidis et al., 2012), suggesting that spontaneous responses – requiring spontaneous on-the-spot formulation without the possibility of preparation – would elicit greater activation of the sympathetic nervous system and thus a decrease in nasal temperature.

H2.1b (forehead temperature): Forehead temperature will be significantly higher during spontaneous responses compared to rehearsed responses.

- The forehead temperature has been associated with stress-related vascular changes (Puri et al., 2005; Robinson et al., 2012; Zhu et al., 2007). Although the forehead has been described as relatively thermally stable under moderate stress, it appears to be more sensitive under conditions of sustained cognitive load – such as spontaneous responding.

H2.1c (cheek temperature): Cheek temperatures will be lower during rehearsed responses compared to spontaneous responses.

- Cheek temperature has been associated with affective arousal, social cognition (Ioannou et al., 2016; Ioannou, Morris, et al., 2014; Paolini et al., 2016), IM (Gálvez-García et al., 2021), or feelings of embarrassment (Shearn et al., 1990). When people have to answer spontaneously and without prior preparation, they are more likely to experience increased cognitive load, stress and social discomfort, especially due to the pressure

to give convincing answers immediately (Vrij, Mann, et al., 2008; Warmelink et al., 2019). These factors, triggered by increased activation of the sympathetic nervous system, are expected to make spontaneous responses more salient than rehearsed responses, which can lead to increased cheek temperature.

FaceReader

We hypothesised that heart rate (H2.2a) and emotional arousal (H2.2b) would be significantly higher during spontaneous responses, reflecting increased sympathetic nervous system activity and mental effort associated with producing spontaneous responses (Appelhans & Luecken, 2006; Gamer et al., 2006). In contrast, rehearsed responses allow participants to plan and regulate their behaviour in advance, which is likely to result in a lower heart rate and a lower level of arousal. In addition, spontaneous responding, especially under pressure, may evoke stress, anxiety, or even embarrassment – emotions typically associated with lower (i.e., negative) valence (H2.2c) (Ekman, 2009; Frank & Ekman, 2004).

- **H2.2a (heart rate):** Heart rate will be significantly lower during rehearsed responses compared to spontaneous responses.
- **H2.2b (emotional arousal):** Emotional arousal will be significantly lower during rehearsed responses compared to spontaneous responses.
- **H2.2c (emotional valence):** Emotional valence will be significantly higher (i.e., more positive) during rehearsed responses compared to spontaneous responses.

Eye-tracking

Previous research has shown that looking at socially relevant areas – especially the eyes rather than background – is more likely when the person feels in control and is trying to appear credible (Hypšová et al., 2024). In contrast, we expect the opposite with spontaneous responses. This pattern is supported by cognitive load theory and recent research showing that people tend to avert their gaze from faces during demanding tasks in order to reduce distractions and focus on internal cognition (Abeles & Yuval-Greenberg, 2017; Doherty-Sneddon et al., 2002; Doherty-Sneddon & Phelps, 2005), or to enhance

cognitive processes such as problem solving or memory retrieval (Salvi & Bowden, 2016). Therefore, we hypothesise the following:

- **H2.3a (upper face):** Participants will fixate more on the interviewer's upper face (e.g., eye region) during rehearsed responses compared to spontaneous responses.
- **H2.3b (lower face):** Participants will fixate less on the interviewer's lower face (e.g., mouth and jaw region) during rehearsed responses compared to spontaneous responses.
- **H2.3c (background):** Participants will fixate the background (i.e., display avoidant gaze behaviour) significantly less during rehearsed responses compared to spontaneous responses.

Interaction effect

RQ3: Is there an interaction between all conditions (i.e., small talk, rehearsed lie, rehearsed truth, spontaneous lie, spontaneous truth) and dependent variables measured separately by the different technologies ($RQ3^{fITI}$, $RQ3^{FaceReader}$, $RQ3^{Eye\text{-}tracker}$)?

Infrared thermal imaging

In fITI, spontaneous lying is expected to lead to a significant decrease in nasal temperature (H3.1a), reflecting increased stress and cognitive effort (Pavlidis et al., 2012; Bonyad et al., 2024), while forehead temperature is thought to rise due to mental workload and stress-related vascular changes (H3.1b) (Zhu et al., 2007; Robinson et al., 2012). Cheek temperature is predicted to increase during both types of lies, but more so during spontaneous deception (H3.1c), which is due to IM, arousal and emotional stress (Ioannou et al., 2016; Gálvez-García et al., 2021).

- **H3.1a (nasal temperature):** Nasal temperature will significantly decrease during spontaneous lies, with a smaller decrease observed during rehearsed lies. Small talk and both rehearsed and spontaneous truths will elicit higher nasal temperature.
- **H3.1b (forehead temperature):** Forehead temperature will significantly increase during spontaneous lies, but will remain stable during rehearsed lies and other conditions.

- **H3.1c (cheek temperature):** Cheek temperature will increase during both rehearsed and spontaneous lies, with a more pronounced rise observed during spontaneous deception.

FaceReader

Spontaneous lies are hypothesised to elicit higher heart rate and increased emotional arousal (H3.2a, H3.2b), which can be attributed to cognitive processing and the emotional stress of lying without preparation (Gamer et al., 2006; Appelhans & Luecken, 2006). Emotional valence is expected to be more negative under these conditions (H3.2c), as spontaneous lying may trigger fear of detection or guilt, which is consistent with theories of emotional leakage and four factor theory (Ekman, 2009; Zuckerman et al., 1981).

- **H3.2a (heart rate):** Heart rate will be significantly higher during spontaneous lies than during rehearsed lies, truth-telling, and small talk.
- **H3.2b (emotional arousal):** Emotional arousal will be significantly higher during spontaneous lies than during rehearsed lies, truthful responses, and small talk.
- **H3.2c (emotional valence):** Emotional valence will be significantly more negative during spontaneous lies, while small talk, rehearsed lies and truthful responses will show more neutral or positive valence.

Eye-tracking

For eye-tracking (H3.3a–c), participants are expected to maintain more direct eye contact during rehearsed lies than during spontaneous lies (H3.3a), as they have a greater capacity for IM (Vrij et al., 2015; Hypšová et al., 2024). In contrast, fixation on the lower face decreases during spontaneous lying (H3.3b) and background fixation increases (H3.3c), which is consistent with the hypothesis of cognitive load and visual disengagement during mental effort (Doherty-Sneddon & Phelps, 2005; Servais et al., 2023).

- **H3.3a (upper face):** Fixation on the interviewer's upper face (e.g., eyes) will be significantly higher during small talk and rehearsed lies than during spontaneous lies, and rehearsed truth will also elicit more upper-face fixation than spontaneous truth.

- **H3.3b (lower face):** Fixation on the interviewer's lower face (e.g., mouth and jaw) will decrease significantly more during spontaneous lies than during small talk, rehearsed lies, rehearsed truths, or spontaneous truths.
- **H3.3c (background):** Background fixation (i.e., gaze aversion) will increase significantly during spontaneous lies compared to all other conditions, while small talk, rehearsed lies and both truth conditions will show more stable, face-directed gaze behaviour.

Aim 3

To investigate whether attachment avoidance, as measured by the Czech version of the Experiences in Close Relationships (ECR) questionnaire, moderates the relationship between behavioural responses (i.e., emotional valence, arousal, and eye fixations), physiological responses (i.e., facial temperature and heart rate) and deception detection accuracy, with moderation effects assessed separately across conditions for each modality.

Moderation effect

RQ4: Does attachment avoidance moderates the relationship between all experimental conditions measured separately by different technologies ($RQ4^{fITI}$, $RQ4^{FaceReader}$, $RQ4^{Eye\text{-}tracker}$)?

Infrared thermal imaging

Avoidant individuals show increased sympathetic activation under stress (e.g., skin conductance, heart rate and blood pressure), even if they subjectively report that they are not under stress (Diamond et al., 2006; Dias et al., 2011). Facial temperature is an indicator of such autonomic reactivity (Gioia et al., 2023; Ioannou, Gallese, et al., 2014; Shastri et al., 2009), and is expected to reflect this heightened physiological response. During deception, especially spontaneous lies, the dual regulatory demands of emotional suppression and lying can lead to greater changes in facial temperature in avoidant individuals, which is why we hypothesise the following:

- **H4.1a:** Higher levels of attachment avoidance will be associated with increased facial temperature in all ROIs, regardless of condition.

- **H4.1b:** Attachment avoidance would interact with condition, such that individuals high in avoidance would show a greater increase in temperature under certain conditions – particularly those requiring more spontaneous or deceptive responses – reflecting higher physiological arousal when emotional or social demands are heightened.

FaceReader

Avoidantly attached individuals tend to suppress outward emotional expressions (Frías et al., 2014; Holmberg et al., 2011; Mikulincer & Shaver, 2019; Pascuzzo et al., 2013; Shallcross et al., 2014). However, this emotional suppression is not reflected in their physiological responses, which tend to show increased reactivity – including an increased heart rate (Kim, 2006; Mikulincer, 1998). We assume that this discrepancy is most pronounced during spontaneous deception, revealing a moderating effect of attachment avoidance on physiological and behavioural reactivity:

- **H4.2a:** A higher level of attachment avoidance will be associated with an increased heart rate under all conditions.
- **H4.2b:** A higher level of attachment avoidance will be associated with lower emotional valence across all conditions.
- **H4.2c:** A higher level of attachment avoidance will be associated with lower emotional arousal across all conditions.
- **H4.2d:** Attachment avoidance would interact with condition, such that individuals high in avoidance would show a greater increase in heart rate under certain conditions – particularly those requiring more spontaneous or deceptive responses – reflecting higher physiological arousal when emotional or social demands are heightened.
- **H4.2e:** Attachment avoidance would interact with conditions, such that individuals high in avoidance would show lower valence under certain conditions – particularly those requiring more spontaneous or deceptive responses – indicating increased deactivation strategies when emotional or social demands are heightened.
- **H4.2f:** Attachment avoidance would interact with conditions, such that individuals high in avoidance would show lower emotional arousal under

certain conditions – particularly those requiring more spontaneous or deceptive responses – indicating increased deactivation strategies when emotional or social demands are heightened.

Eye-tracking

Avoidant individuals avoid paying attention to relational cues such as faces, favouring neutral or unrelated stimuli (Uccula et al., 2022). However, we argue that this pattern is reinforced in interpersonally ambiguous or emotionally charged situations such as spontaneous conversations. Conversely, in structured tasks (e.g., a rehearsed deception), the demands of the task can temporarily reduce avoidance behaviour, leading to context-dependent gaze behaviour, which is why we hypothesise the following:

- **H4.3a:** A higher level of attachment avoidance is associated with increased background (i.e., gaze avoidance) and upper face (i.e., scanning not connecting) fixations and decreased lower face fixation in all conditions.
- **H4.3b:** Attachment avoidance will moderate the relationship between the type of condition and gaze behaviour across ROIs, such that the avoidant gaze pattern (i.e., increased fixation on the background and upper face and decreased fixation on the lower face) is more pronounced in small talk and spontaneous deceptive conditions and is attenuated in rehearsed deceptive and truthful conditions.

9.5.2. Participants

Participants were selected from the general population using a non-probability convenience sampling method. Interested individuals signed up using a registration form that was distributed via social media platforms such as Instagram and LinkedIn, as well as via QR codes on printed posters in public places such as bus stations and university corridors. The data for this study was collected over a one-year period beginning on June 28, 2023 until October 04, 2024. The length of this data collection has reflected the complexity of conducting within-subject experimental design, where participants had to spend ~ 90 up to 120 minutes in a laboratory. In total, our experiment included 100 participants from the general population, 64% (*n* = 64) were women aged from 18 to 35 years (*M* = 21,09 years, *SD* = 4.02 years), and 33% (*n* = 33) were men aged from

18 to 35 years (*M* = 22.42 years, *SD* = 4.99 years), and 3% (*n* = 3) participants did not fill any demographic information and were excluded from upcoming analyses. However, because the main study was conducted using three different technologies, each with its own measurement protocols which need to be followed, the final number of participants for thermographic, FaceReader and eye-tracker analysis differed. The final sample[8] for each technology consisted of following:

- *Thermographic analyses[9]:* 96 participants, of whom 61.74% (*n* = 63) were women aged from 18 to 35 years (*M* = 21.06 years, *SD* = 4.05 years), and 31.36% (*n* = 33) were men aged from 18 to 35 years (*M* = 22.55 years, *SD* = 5.12 years).
- *FaceReader analyses:* 97 participants, of whom 65.97% (*n* = 64) were women aged from 18 to 35 years (*M* = 21,09 years, *SD* = 4.02 years), and 34.03% (*n* = 33) were men aged from 18 to 35 years (*M* = 22.42 years, *SD* = 4.99 years).
- *Eye-tracking analyses[10]:* 55 participants, of whom 61.82% (*n* = 34) were women aged from 18 to 35 years (*M* = 21.12 years, *SD* = 3.81 years) and 38.18% (*n* = 21) were men aged from 18 to 35 years (*M* = 22.57 years, *SD* = 5.20 years).

9.5.3. Materials and equipment

ECR. Attachment avoidance was measured using the Czech version of the Experiences in Close Relationships (Lečbych & Pospíšilíková, 2012), a 36-item instrument designed to measure two dimensions of attachment: Attachment Anxiety (ANX) and Attachment Avoidance (AVO). Each subscale comprises 18 items, which are rated on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). In the present study, internal consistency was high, with Cronbach's alpha coefficients of α = .834 for the avoidance subscale and α = .876 for the anxiety subscale. In order to fulfil the operationalised aims, only the ECR_AVO was used in the following analyses.

[8] **Note.** Our sample size for each technology has adequate power for detecting within-subject effects, assuming a medium effect size (f = 0.25, equivalent to $\eta_p^2 \approx 0.059$), with α = 0.01 (Bonferroni corrected) and a power of 0.95, according to calculations using G*Power 3.1.

[9] **Note.** Data from one participant could not be included because the participant did not meet the criteria specified in the methodological checklist by Moreira et al. (2017). The final sample for the fITI analyses therefore consisted of 96 participants.

[10] **Note.** For the eye-tracking analyses, the sample was notably smaller (n = 55) due to the availability of the hardware. The eye-tracking system was only accessible for a limited part of the data collection period, which restricted the number of participants for whom valid eye-tracking data could be recorded.

The Fluke Ti450 PRO thermographic camera with increased sensitivity was used to visualize temperature differences. The device has a thermal sensitivity (NETD) of ≤ 0.025 at a target temperature of 30°C (25 mK). Emissivity was configured to 0.98, reflecting the standard value for human skin (Bernard et al., 2013). The autofocus function of the camera was activated for all recordings. The thermal images were recorded with a resolution of 320 × 240 pixels and a frame rate of 20 frames per second when autofocus was activated. The camera was mounted on a tripod 110 cm from the participant's face and adjusted in height to ensure that only the facial area was captured. To ensure a non-invasive setup, no chin rest or hand grip were used. Thermal data was processed using Fluke SmartView Classic software and with our developed framework described below.

The Noldus FaceReader 9.0 software was used to analyse the video recordings made while the participants answered the experimental questions. This software allows the assessment of basic emotions, custom-defined emotional states, emotional valence, arousal levels, and non-contact measurements of heart rate variability using rPPG at a frequency of 26 Hz. Using a model based on the FACS (Ekman et al., 2002), the software identifies emotions and their intensity in real time. In this study, the data on emotional arousal, emotional valence, and the heart rate values were used. The analyses with FaceReader 9.0 were performed on a Dell Precision 3560 laptop that met the system requirements. Prior to the analyses, the videos were recorded with the Canon Legria GX10 4k camera at a system frequency of 50 Hz. To ensure high quality of the rPPG signal, the entire experiment was conducted under constant lighting conditions. The camera was set up on a tripod at the same distance as the thermographic camera.

Eye-tracker Tobii Pro Spectrum 300. Eye fixations were recorded using the Tobii Pro Spectrum 300 Eye Tracker, which operates at a sampling frequency of 300 Hz with an RMS precision of 0.01° and an accuracy of 0.3°. The stimuli were displayed on the device's native 23.8-inch screen (EIZO FlexScan EV2451) with a resolution of 1920×1080. The eye tracker was positioned on a table 65 cm away from each participant to ensure that the average eye position remained centred within the device's field of view. No head stabilisation was used during the experiment. Data analysis was performed using Tobii Pro Lab 1.194 software.

Small-talk condition. Before the main interview began, a short small talk segment was conducted as a separate baseline condition. The purpose of this interaction was to help participants relax, build rapport, and collect baseline physiological and behavioural data in a neutral conversational context. The interviewer asked a standardised series of friendly, informal questions (e.g., "*How do you feel?*", "*Did you find the building easily?*", "*How did you hear about the experiment?*"). In addition, the small talk condition was only included in the interaction models that examined the combined effects of all experimental conditions (i.e., small talk, rehearsed truth/lie, spontaneous truth/lie) on the dependent variables. It was intentionally excluded from the main effect analyses of veracity and rehearsal, as these comparisons aimed to isolate the core effects of deception and cognitive load without introducing variance through a neutral interaction. However, the inclusion of small talk in the interaction models provided an extended approach for interpreting task-related changes in a broader social context.

Rehearsed truth and lie scenario. For the rehearsed conditions, participants were given two questions that were intentionally designed to reflect frequently asked questions in general conversations. Participants had 7 days to prepare answers to these questions, one of which was completely truthful and the other completely deceptive. This seven-day timeframe was intentionally set based on the pilot study 1 (Hypšová et al., 2024). The participants were free to decide how much time they wanted to spend preparing their answers within this 7-days period. The only condition was that written notes could not be used during the experimental session.

Spontaneous truth and lie scenario. In this task, participants underwent two short missions an hour before the actual experiment. In the first task, participants were instructed to visit four predetermined locations near the Upper and Lower Squares in Olomouc, where they were required to photograph a specific landmark or object according to prior instructions. In the second task, participants sat in a laboratory where they spent about 15-20 minutes putting together simple puzzles which, when completed, revealed a short narrative. Neither of these tasks was recorded. Following these activities, participants were asked to sit in front of the designated technical equipment for a structured interview. In this interview, they were asked to answer two questions about the tasks – one that required a completely honest answer and one that required

a completely deceptive answer. This design was developed based on previous research (Deeb et al., 2022, 2023, 2024) to ensure that the events discussed in the "honest answer" condition were recent and anchored in participants' memory, minimising the risk of memory decay or confabulation for events that occurred further back in time. To decide whether the response should be honest or deceptive, participants had to open an envelope lying in front of them, where they had the instruction.

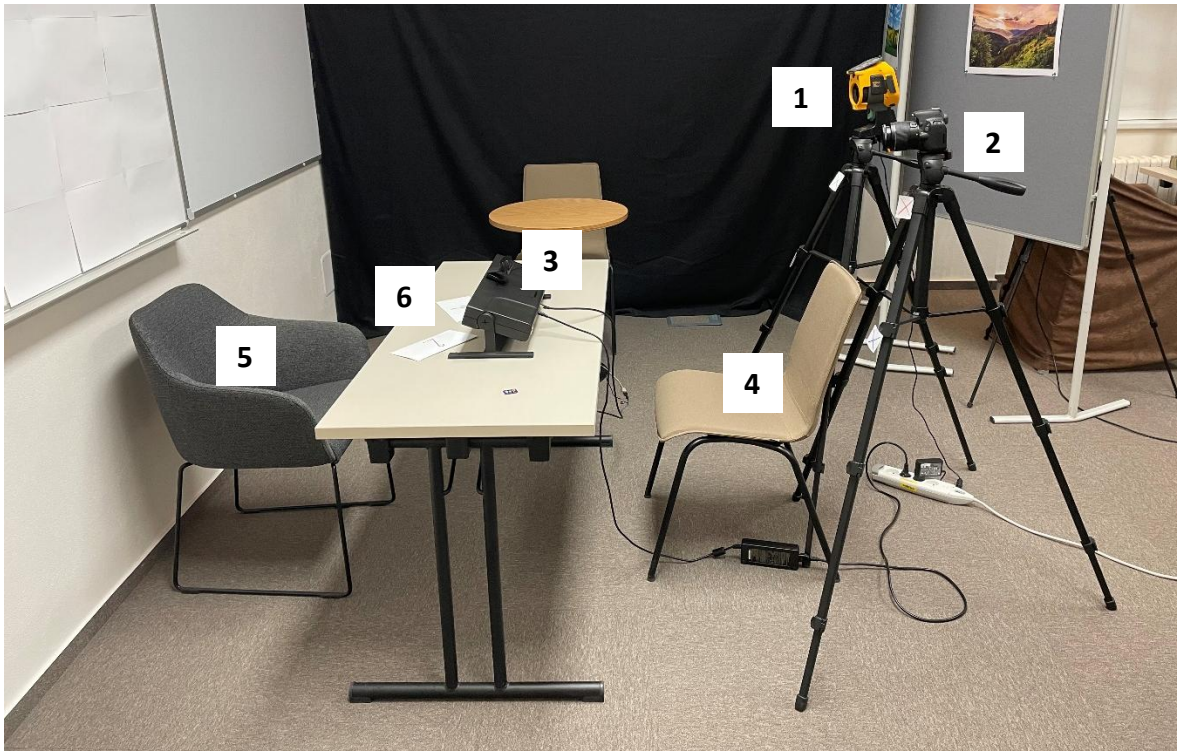
9.5.4. Procedure

The main study used a within-subject experimental design in which participants interacted face-to-face with a real interviewer. The independent variables were baseline (small talk), veracity (truth vs. lie) and scenario (rehearsed vs. spontaneous). The dependent variables included:

- *Thermography:* temperature changes of the forehead, nose, and cheeks
- *FaceReader:* raw heart rate, emotional valence and arousal
- *Eye-tracking:* the number of the eye fixations of the interviewer's eyes during the experimental procedure
- *Personality:* Attachment avoidance

The experiment took place in a 35 m² laboratory (20.5 °C). The thermal imaging camera, the 4k camera and the eye tracker were placed in the centre of the lab, directly opposite the participant. The cameras were mounted on a tripod and adjusted in height so that they only captured the entire face of the participant, as shown in Figure 17.

Figure 17: Laboratory setting for the main study



Note. (1) – *Infrared thermal camera*; (2) – *4k camera*; (3) – *Eye-tracker*; (4) – *Interviewer spot*; (5) – *Interviewee spot*; (6) – *Envelopes with instructions for spontaneous conditions*

Seven days before the experiment, participants received instructions for the rehearsed scenario and online link to complete the ECR questionnaire with demographic information. On the day of the experiment, participants were invited to the experimenter's office, where they signed a consent form and received a sealed envelope containing information for the first mission – the walk around the main squares in Olomouc. Participants were asked to take this envelope and fulfil the task as a first step before the actual experiment. Once this was done, participants were asked to enter a laboratory where they had to solve a second task: putting together a puzzle to solve a story. The second task was limited to exactly 20 minutes and also served as an acclimatization procedure. Neither the first nor the second task was recorded.

After the second task was completed, the experimenter asked an interviewer to enter the lab and asked the participants to sit in front of the technologies to calibrate the eye tracker and set up the remaining technologies. Once the set-up was complete, the experimenter activated the device, left the room and the interview began. All interviewers were female (N = 6) and between 24 and 28 years old. Only one gender

was considered in order to maintain relative standardisation and avoid the introduction of potential confounding variables related to gender dynamics in the interviewer–participant interaction. Prior to data collection, interviewers were trained on how to conduct the interview while maintaining a neutral and consistent demeanour. To ensure standardisation and counterbalance, each interviewer received a printed script containing the exact wording and order of the questions. Each participant was interviewed by only one interviewer.

The interviewer greeted the participants and introduced a short small talk segment. This small talk served as a distinct baseline condition to build rapport with the participants and to get them in the mood for the upcoming experimental interview. The interview itself had the same structure as in the second pilot study: first, the interviewer asked questions from the rehearsed scenario and then informed the participants that they should answer two additional questions about two missions, which served as a spontaneous condition. Each participant answered truthfully in one condition and deceptively in the other, in both the prepared and spontaneous scenarios, counterbalanced across subjects. To increase motivation to deceive, participants were told that the most convincing participant – who was judged on whether the interviewer believed their answers – would have the opportunity to win €158 as a reward. This incentive is consistent with the idea that deception is only more difficult than telling the truth when there is a strong motivation to be believed (Vrij, Mann, et al., 2008).

Following the interview, participants completed a questionnaire in which they indicated which of their responses were true and which were deceptive. This allowed for accurate labelling of the data and a final cross-validation of the ground truth determination. Each participant then took part in a debriefing session which typically lasted between 5 and 30 minutes.

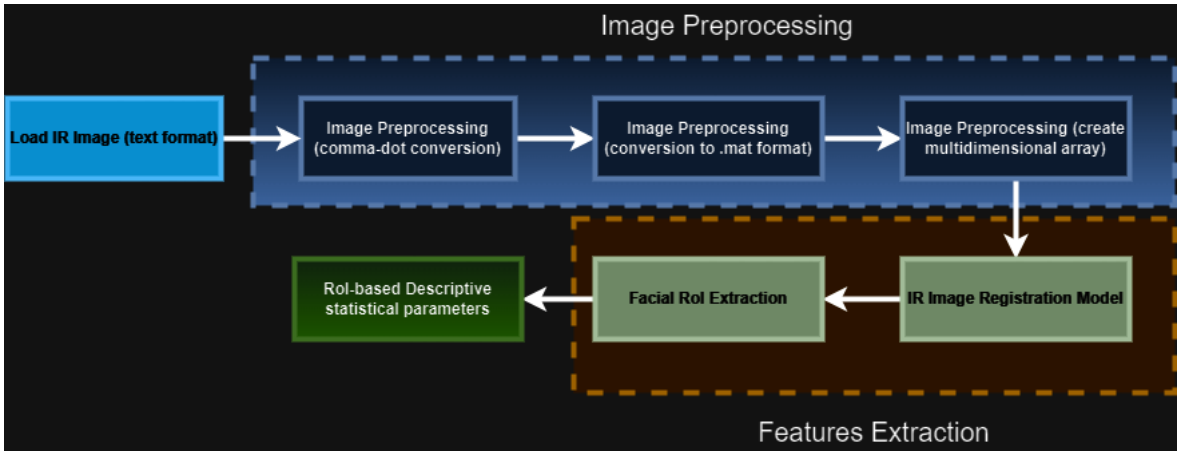
9.5.5. Data pre-processing

Thermographic data pre-processing

The framework for infrared data pre-processing, currently under review, was developed in collaboration with Ing. Jan Kubíček, Ph.D. from the Department of Cybernetics and Biomedical Engineering, VSB Technical University Ostrava. It leverages

fITI to detect physiological responses to psychological stimuli by analysing temperature changes across defined facial regions. The infrared video recordings are pre-processed in MATLAB and converted into a structured format that enables efficient statistical feature extraction. A schematic overview of the facial image processing workflow can be found in Fig. 18.

Figure 18: A schematic overview of the facial image processing workflow



A reference image from the baseline condition is used to align all frames using the Demons algorithm to ensure consistent registration and compensate for head movements. This method increases the reliability of temperature data extraction across the entire video sequence, as shown in Fig. 19.

Figure 19: Example of automatic alignment of all frames

Note. Before alignment (left); after alignment (right).

Manually selected ROIs[11] could be mapped onto all aligned images even if the participant is moving. From these ROIs, statistical features such as mean, median and standard deviation are calculated, allowing both time series analysis and condition-based comparison of thermal responses in truth and deception. In addition, the framework allows thermal data to be stored and exported in a proprietary raw format so that researchers can use their own preferred metrics and statistical analyses. A complete description of the framework and the source code is available on request from the author of this thesis.

FaceReader data pre-processing

To analyse raw heart rate, emotional valence and arousal of the participants, the video recordings of the experimental interviews were processed using FaceReader 9.0 software (Noldus Information Technology). Each video was uploaded to the FaceReader software, which automatically analyses heart rate and the facial expressions frame by frame. Once processed, the data was exported to Microsoft Excel format, where selected variables were extracted for further statistical analysis. These included:

- Heart rate, estimated by using rPPG and calculated over time to determine beats per minute (bpm).
- Valence, which represents the emotional expressions positivity or negativity on the participant's face and was calculated by the software as the difference between the intensity of positive and negative expressions.
- Arousal, which indicates the degree of emotional intensity, derived from a combination of facial muscle activity and expression dynamics.

The resulting Excel files contained time series data for each variable aligned to the video timeline.

Eye-tracking data pre-processing

Tobii Pro Lab software was used to analyse the participants' eye fixations on the interviewer's face. In contrast to pilot study 1, which used a static stimulus (a simulated photo of the interviewer's face), the current study used 55 eye-tracking video recordings[12]

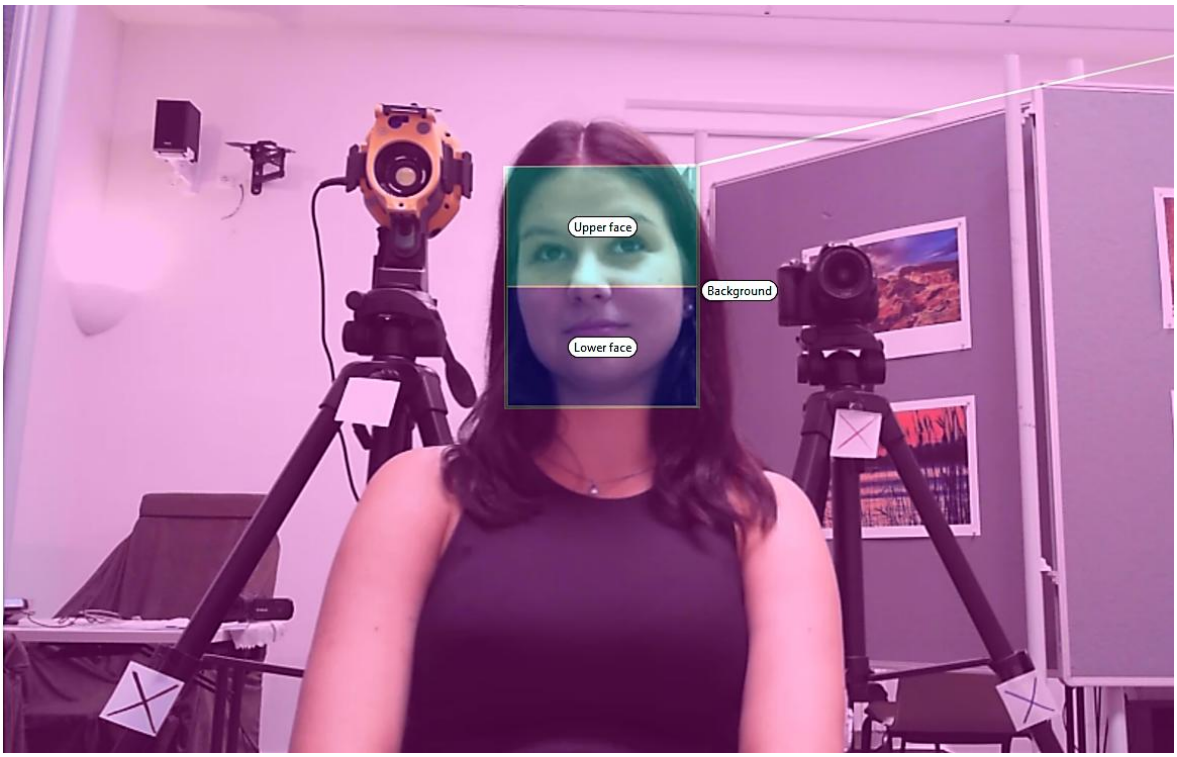
[11] **Note.** The framework allows researchers to select the ROIs they want to analyse according to their own needs and research objectives.
[12] **Note.** One eye-tracking video recording was available for each participant.

showing dynamic interactions with the real interviewer. These recordings captured where participants were looking throughout the interaction and required manual placement of ROIs frame by frame to account for the interviewer's head movements.

Three ROIs (see Fig. 20) were defined: upper face, lower face and background.

1. The ROI for the upper face included the area from the top of the eyebrows to the hairline, including the eyes and forehead.
2. The ROI for the lower face ranged from just below the nose to the chin.
3. The background ROI included all areas outside the face, such as the surroundings and visible devices.

Figure 20: Used ROIs for the eye-tracking analysis



Each ROI was manually adjusted for each video frame to maintain accuracy of size and position in relation to head movements. For future studies, we aim to automate this process of ROI detection, similar to the approach already implemented for thermal data pre-processing.

9.5.6. Statistical analyses

After all separate data pre-processing was completed, a single data matrix was created that included all collected behavioural, physiological and personality data. The final data set included a total of 51 variables:

- 15 eye-tracking data points: eye fixations across three ROIs (upper face, lower face, background) in five conditions (1 rehearsed truth; 1 rehearsed lie; 1 spontaneous truth; 1 spontaneous lie; 1 small talk),
- 20 fITI data points: temperature measurements across four facial ROIs (nose, forehead, right and left cheek) in five conditions (1 rehearsed truth; 1 rehearsed lie; 1 spontaneous truth; 1 spontaneous lie; 1 small talk),
- 15 FaceReader data points: valence, arousal and heart rate across 5 conditions (1 rehearsed truth; 1 rehearsed lie; 1 spontaneous truth; 1 spontaneous lie; 1 small talk),
- 1 personality value derived from the ECR questionnaire: attachment avoidance.

For further statistical analyses, the data set was split for each technology and also converted to long format, with each line representing a participant in one condition. The length of these conditions varied considerably between all experimental conditions. Therefore, within each condition, the progress of each time series in each condition was aggregated into a single number using the arithmetic mean.

All statistical analyses were performed using the R 4.4.1 environment. The following packages were used: *lme4* (Bates et al., 2015), *lmerTest* (Kuznetsova et al., 2017), *emmeans* (Lenth, 2017), *car* (Fox et al., 2001)*, performance* (Lüdecke et al., 2021), *effectsize* (Ben-Shachar et al., 2020), *cluster* (Maechler et al., 1999), *tidyverse* (Wickham et al., 2019), *dplyr* (Wickham et al., 2023), and *factoextra* (Kassambara & Mundt, 2016). Although most of our statistics included linear mixed-effects models, we will separate the statistical analyses according to the technology used for better clarity. All linear mixed-effects models met the required assumptions, including the absence of multicollinearity, normality of residuals, homoscedasticity, and model convergence. The assumptions were assessed using Q-Q plots of the residuals, VIF scores from the performance package and inspection

of homoscedasticity plots. In all models, participant's ID was included as a random intercept to account for within-subject variability. All categorical predictors were converted to factors, and rows with missing values were excluded to ensure model convergence and stability. Contrast coding was adjusted to contr.sum to allow valid Type III ANOVA tests to obtain F values from the linear mixed-effects models. Partial Eta-squared values (η_p^2) were calculated to quantify effect sizes, using the following equation (Bakeman, 2005; Lakens, 2013):

$$\eta_p^2 = \frac{F \times \mathrm{df}_{\mathrm{effect}}}{F \times \mathrm{df}_{\mathrm{effect}} + \mathrm{df}_{\mathrm{error}}}$$

- *F*: F-value for the effect
- df_{effect}: degrees of freedom for the effect
- df_{error}: degrees of freedom for the error

The Satterthwaite approximation was used to estimate the degrees of freedom. Post-hoc pairwise comparisons were performed using the *emmeans* package (Lenth, 2017) with Bonferroni correction for multiple testing.

Thermal imaging data

To investigate the temperature differences between the facial ROIs and the experimental conditions in line with the research questions operationalised for the fITI paradigm, a series of linear mixed-effects models were conducted, supported by exploratory and post-hoc analyses. These models included:

- effect of deception (i.e., veracity – truth vs. lie)

$$Facial\ temperature \sim Veracity * ROI + (1 \mid ID)$$

- effect of rehearsal (rehearsed vs. spontaneous)

$$Facial\ temperature \sim Rehearsal * ROI + (1 \mid ID)$$

- interaction effect of all conditions (small talk, rehearsed truth and lie, spontaneous truth and lie)

$$Facial\ temperature \sim All\ conditions * ROI + (1 \mid ID)$$

Based on the results of these models, a cluster analysis[13] was then performed for the nasal region, which showed the strongest conditional effects. Temperature changes from baseline were calculated for each participant, and participants were assigned to one of four clusters per condition based on predefined thermal thresholds drawn from previous thermal deception detection research (Gálvez-García et al., 2021). Participants were categorised into four clusters per condition based on the magnitude and direction of temperature deviation:

- **Cluster 1**: ΔTemp ≥ 0.300°C
- **Cluster 2**: 0 < ΔTemp < 0.299°C
- **Cluster 3**: –0.299°C < ΔTemp < 0
- **Cluster 4**: ΔTemp ≤ –0.300°C

These thresholds reflected the cut-off values for physiological changes frequently cited in the thermal lie detection literature. To further explore within-cluster variability, paired t-tests were conducted within each cluster to compare pairs of conditions (e.g., rehearsed truth vs. rehearsed lie; spontaneous truth vs. spontaneous lie), providing deeper insight into how temperature changes may vary according to individual thermal response patterns.

FaceReader

All variables were restructured into a long format. The data were then divided into three analytical subgroups based on three dependent variables: valence, arousal and heart rate. As the raw valence and arousal data had a non-normal distribution, an inverse hyperbolic sine transformation (asinh) was applied to both measures. This transformation improved the model fit and ensured approximate linearity without compromising interpretability. In contrast, the heart rate values were approximately normally distributed and therefore did not need to be transformed.

Given the repeated measures structure of the data, all models included random intercepts for participant ID. Nine models were implemented for each dependent value

[13] **Note.** Although these clusters were not derived using unsupervised clustering algorithms, they represent theoretically defined categories of thermal response magnitude.

and each effect (three FaceReader dependent variables × three effects) following this format:

- effect of deception (i.e., veracity – truth vs. lie)

$$FaceReader\ dependent\ variable \sim Veracity\ +\ (1\ |\ ID)$$

- effect of rehearsal (rehearsed vs. spontaneous)

$$FaceReader\ dependent\ variable \sim Rehearsal +\ (1\ |\ ID)$$

- effect of all conditions (small talk, rehearsed truth and lie, spontaneous truth and lie)

$$FaceReader\ dependent\ variable \sim All\ conditions +\ (1\ |\ ID)$$

Eye-tracker

Given the hierarchical structure of the data (i.e., repeated measures nested within individuals), linear mixed-effects models were chosen to account for both within- and between-subject variability.

Instead of applying a log transformation to fixation times, we calculated fixation proportions for each participant using the formula:

$$Proportional\ data = \frac{Fixation\ time\ on\ ROI}{Total\ interval\ duration}$$

This transformation was chosen because of the extremely low fixation values (especially in the upper facial area), which would have led to instability in a logarithmic transformation and would have required the addition of arbitrary constants (e.g., +1), which might have impaired interpretability. Proportional scaling standardised fixation times relative to each participant's condition duration and allowed models to converge with random intercepts.

Three linear mixed-effects model with the primary outcome variable *Fixation proportion* were fitted to examine the:

- effect of deception (i.e., veracity – truth vs. lie)

$$Fixation\ proportion \sim Veracity\ *\ ROI\ +\ (1\ |\ ID)$$

- effect of rehearsal (rehearsed vs. spontaneous)

$$Fixation\ proportion \sim Rehearsal\ *\ ROI\ +\ (1\ |\ ID)$$

- interaction effect of all conditions (small talk, rehearsed truth and lie, spontaneous truth and lie)

$$Fixation\ proportion \sim All\ conditions\ *\ ROI\ +\ (1\ |\ ID)$$

Attachment avoidance

In order to prepare the data for statistical modelling, the values for attachment avoidance derived from the ECR questionnaire were mean-centred (ECR_AVO_c). The centring was done to facilitate the interpretation of the linear mixed-effects models and to reduce possible multicollinearity between the main effects and the interaction terms that include this continuous predictor. Prior to these moderation analyses, Spearman rank-order correlations were calculated using the values for non-centred attachment avoidance in order to obtain an initial, exploratory overview of the relationships between avoidance and the dependent variables under different conditions.

In addition to all models described in chapters above, attachment avoidance was included as a moderator by specifying interaction terms between ECR_AVO_c and the main experimental conditions depending on the specific outcome measure (i.e., fixation proportions, valence, arousal, heart rate, and facial temperature of the nose, cheeks and forehead) and the tested effects (i.e., veracity, rehearsal and interaction), using following format for each technology:

- Attachment avoidance and fITI
  - $Temperature \sim All\ condition\ *\ ROI\ *\ ECR_AVO_c\ +\ (1|\ ID)$
- Attachment avoidance and FaceReader
  - $Heart\ rate \sim All\ conditions\ *\ ECR_AVO_c\ +\ (1|\ ID)$
  - $Valence \sim All\ conditions\ *\ ECR_AVO_c\ +\ (1|\ ID)$
  - $Arousal \sim All\ conditions\ *\ ECR_AVO_c\ +\ (1|\ ID)$
- Attachment avoidance and eye-tracking
  - $Eye\ fixations\ \sim All\ conditions * ROI\ *\ ECR_AVO_c\ +\ (1|\ ID)$

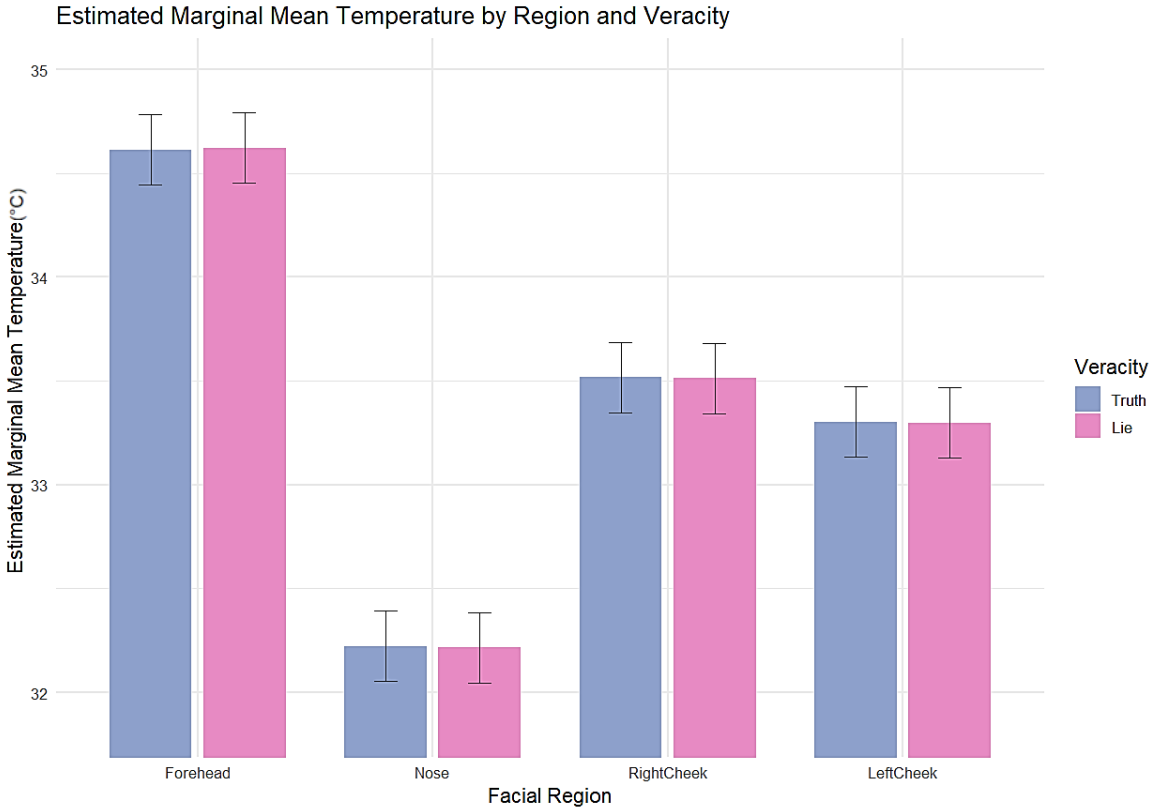
9.5.7. Physiological results

Thermal imaging

Aim 1: Effect of deception (i.e., veracity) on facial temperature (RQ1)

The analysis revealed a significant main effect of region, $F(3, 1320.0) = 655.30$, $p < .001$, $\eta_p^2 = .60$. However, there was no main effect of veracity, $F(1, 1320.0) = 0.002$, $p = .961$, $\eta_p^2 < .001$, and no significant veracity × region interaction, $F(3, 1320.0) = 0.008$, $p = .999$, $\eta_p^2 < .001$. Pairwise comparisons using Bonferroni-corrected estimated marginal means showed no significant temperature differences between truthful and deceptive conditions in any region, as shown in Fig. 21.

Figure 21: Estimated marginal mean temperature (°C) by region and veracity

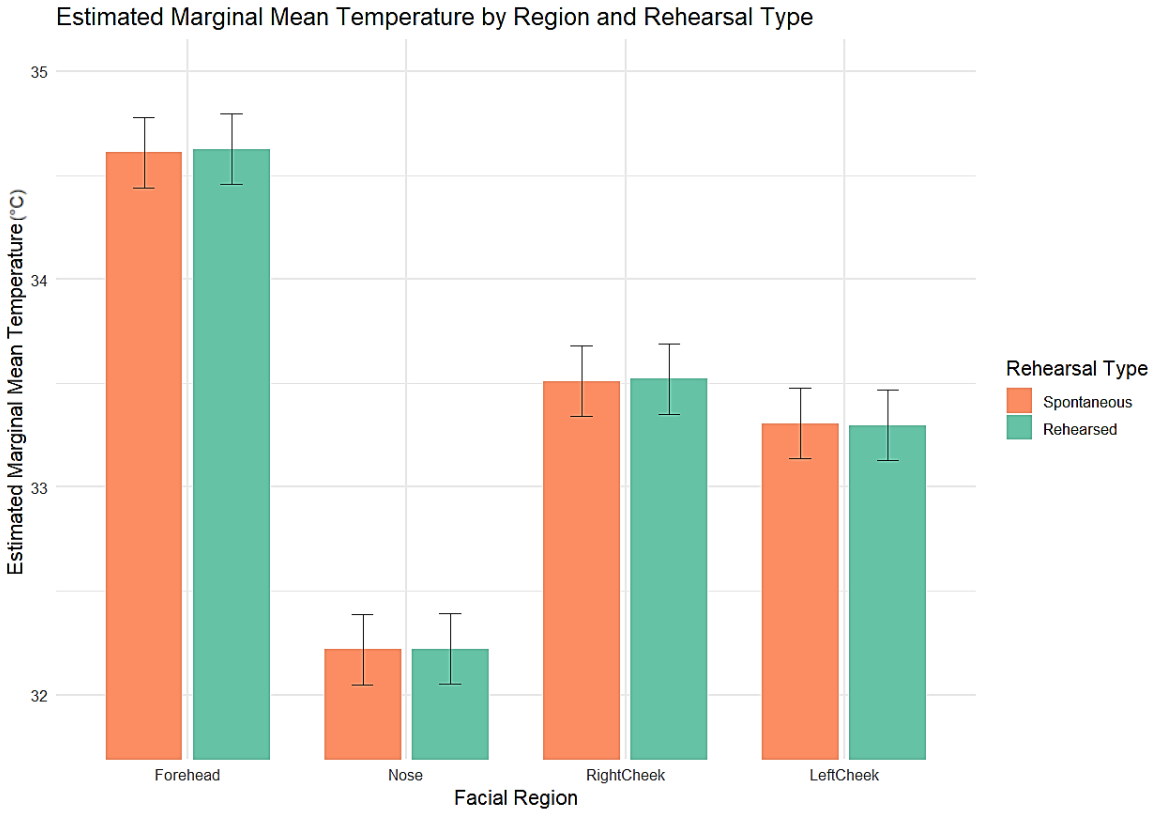


These results do not support hypotheses H1.1a – H1.1c, which predicted significant thermal changes during deception responses.

Aim 2: Effect of rehearsal on facial temperature (RQ2) and the interactions (RQ3)

The analysis revealed a significant effect of region, $F(3, 1320.0) = 655.33$, $p < .001$, $\eta_p^2 = .60$. However, there was no effect of rehearsal, $F(1, 1320.0) = 0.021$, $p = .883$, $\eta_p^2 < .001$ and no significant rehearsal × region interaction, $F(3, 1320.0) = 0.022$, $p = .999$, $\eta_p^2 < .001$. Pairwise comparisons using Bonferroni-corrected estimated marginal means showed no significant temperature differences between rehearsed and spontaneous conditions in any region, as shown in Fig. 22.

Figure 22: Estimated marginal mean temperature (°C) by region and rehearsal type



These results do not support hypothesis H2.1a, which predicted increased nasal temperature during rehearsed responses, nor the hypothesis H2.1b, which states that forehead temperature will be significantly higher during spontaneous conditions. Similarly, the results do not support H2.1c, as cheeks temperature was not lower during rehearsed responses.

To examine overall interactions, a linear mixed-effects model was conducted with all conditions and ROI as fixed effects and a random intercept for participant ID. The model

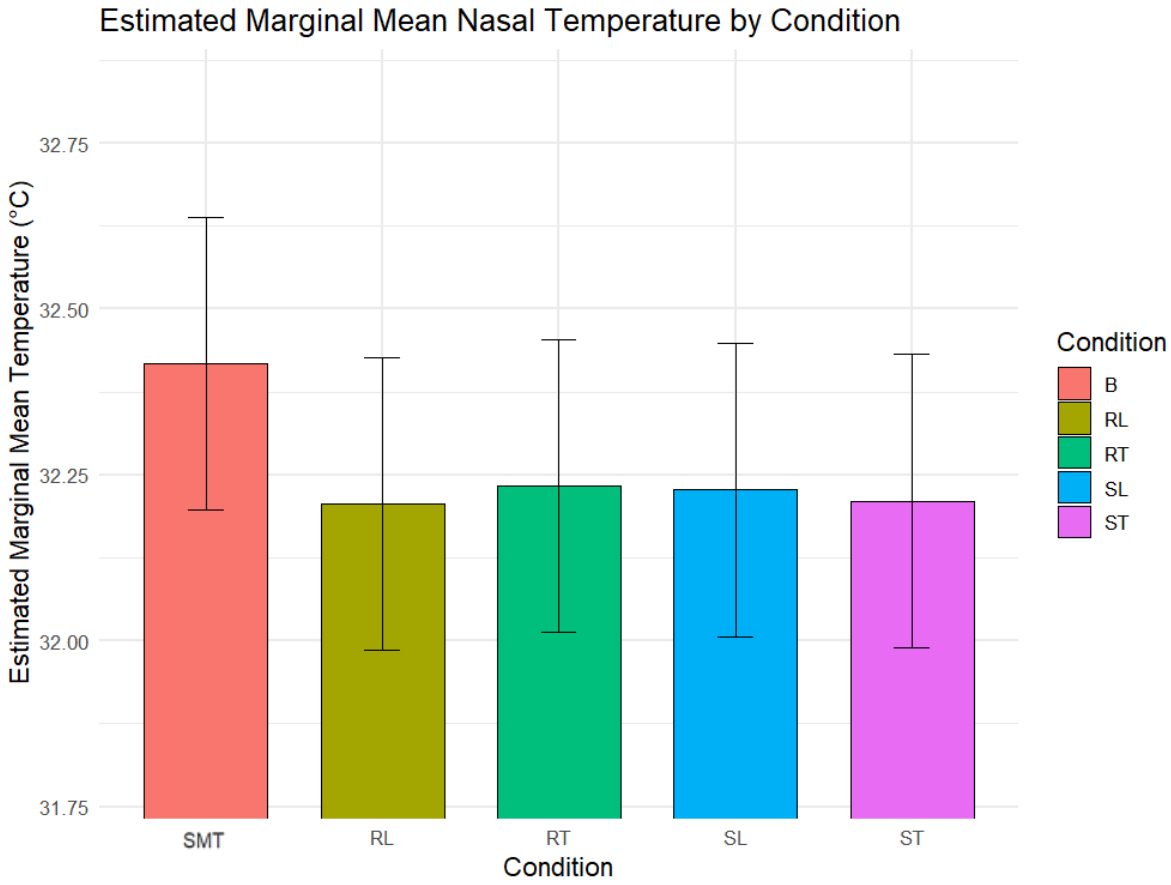
revealed a significant main effect of region, $F(3, 1672.0) = 791.87$, $p < .001$, $\eta_p^2 = .58$. In contrast, there was no effect of condition, $F(4, 1672.0) = 0.03$, $p = .999$, $\eta_p^2 < .001$, and no significant condition × region interaction, $F(12, 1672.0) = 0.56$, $p = .872$, $\eta_p^2 = .004$.

Post-hoc pairwise comparisons with Bonferroni correction revealed no significant differences between the experimental conditions within any facial region (all *p*s = 1.000). However, in the nasal region, the largest observed difference was between the small talk and rehearsed lie conditions (M_{diff} = 0.21°C, *SE* = 0.10), but this difference was not statistically significant (*p* = .419). For all other regions and conditions, temperature differences remained minimal (M_{diff} < 0.10°C) and non-significant.

Although the overall model showed no significant interaction between conditions and ROI, the estimated marginal means indicated a potential trend in temperature fluctuations in the nasal region. In particular, temperatures in the nasal region appeared to be consistently lower than small talk in all conditions. To investigate whether the nasal region alone showed sensitivity to condition differences, a linear mixed-effects model was conducted with conditions as a fixed effect and participant ID as a random intercept, using only the nasal temperature data.

The model revealed a significant main effect of condition, $F(4, 352) = 11.56$, $p < .001$, with a moderate effect size, $\eta_p^2 = .12$. Post-hoc pairwise comparisons using Bonferroni correction indicated that nasal temperature during small talk (*M* = 32.4°C, *SE* = 0.22) was significantly higher than all experimental conditions: rehearsed lie (M_{diff} = 0.21°C, *SE* = 0.04, *p* < .001), rehearsed truth (M_{diff} = 0.18°C, *SE* = 0.04, *p* < .001), spontaneous lie (M_{diff} = 0.19°C, *SE* = 0.04, *p* < .001), and spontaneous truth (M_{diff} = 0.21°C, *SE* = 0.04, *p* < .001). There were no significant differences between the deception and truth conditions themselves (all *p*s = 1.000), suggesting that the primary contrast was between the small talk and all task-related conditions, rather than between truthful and deceptive responses, as also shown in Fig. 23.

Figure 23: Estimated marginal mean nasal temperature (°C) by condition



Note. *SMT* – baseline (small-talk), *RL* – rehearsed lie, *RT* – rehearsed truth, *SL* – spontaneous lie, *ST* – spontaneous truth

To describe further individual differences to nasal temperature, participants were categorised into four clusters based on the direction and magnitude of their nasal temperature deviations from baseline. To examine whether temperature differed within these subgroups, separate paired-samples t-tests were conducted within each cluster comparing the deviations in nasal temperature during rehearsed truths vs. lies and spontaneous truths vs. lies. The results showed no significant differences between the paired conditions in all clusters (all *p*s > .23), with one exception: a marginal trend was observed in cluster 1 during the spontaneous response ($t(21) = -1.89$, $p = .072$), where the nasal temperature was lower during the spontaneous lies ($M_{diff} = -0.09$°C) compared to the spontaneous truths – however not significantly. This emerging pattern is consistent with hypothesis H3.1a, which proposes nasal cooling during spontaneous deception, and suggests that deception-related effects may only be detectable in subgroups characterised by greater physiological reactivity. However, given the exploratory nature of

this analysis and the limited sample size in some clusters (e.g., cluster 4), these results should be interpreted with caution and the H3.1a cannot be supported given the non-significance of our findings. We report them here primarily to take a detailed, exploratory look at this type of data, rather than to make a definitive interpretation. H3.1b and H3.1c were not supported as no significant increases in forehead or cheek temperatures were observed during the deception.

Aim 3: Attachment avoidance as a moderator (RQ4)

To examine whether attachment avoidance (ECR_AVO) moderates facial temperature across conditions and facial regions, a Spearman's rank order correlation was calculated and only temperature in the right cheek region showed significant positive associations with ECR avoidance, particularly during the rehearsed lie (ρ = .25, p < .05), rehearsed truth (ρ = .26, p < .05), and spontaneous lie (ρ = .25, p < .05) conditions. No other significant correlations were observed between any temperature variable and attachment avoidance.

The mixed-effects model revealed a significant main effect of region, $F(4, 1785.05) = 606.03$, $p < .001$, $\eta_p^2 = .58$. A marginal but not significant main effect of ECR_AVO_c was also observed, $F(1, 74.97) = 3.74$, $p = .057$, $\eta_p^2 = .05$. There were no significant interactions with conditions. Interestingly, a significant region × ECR_AVO_c interaction was found, $F(4, 1785.04) = 3.47$, $p < .05$, $\eta_p^2 = .008$, indicating that the relationship between attachment avoidance and facial temperature varies by facial region.

These patterns were supported by pairwise comparisons of estimated marginal means between low (–1 SD), medium and high (+1 SD) avoidance levels. Before Bonferroni correction for multiple comparisons, a significant difference in predicted temperature was found between low and high avoidance in the nose (M = –0.742, SE = 0.352, p < .05) and right cheek (M = –0.825, SE = 0.352, p < .05). A marginal effect was also observed in the left cheek (M = –0.677, SE = 0.352, p = .058). However, after applying a Bonferroni correction, none of the pairwise comparisons remained statistically significant: forehead: M = –0.523, SE = 0.352, p = .423, nose: M = –0.742, SE = 0.352, p = .113, right cheek: M = –0.825, SE = 0.352, p = .064, left cheek: M = –0.677, SE = 0.352, p = .173. The observed pattern – higher temperatures in the nose and right cheek in individuals with high

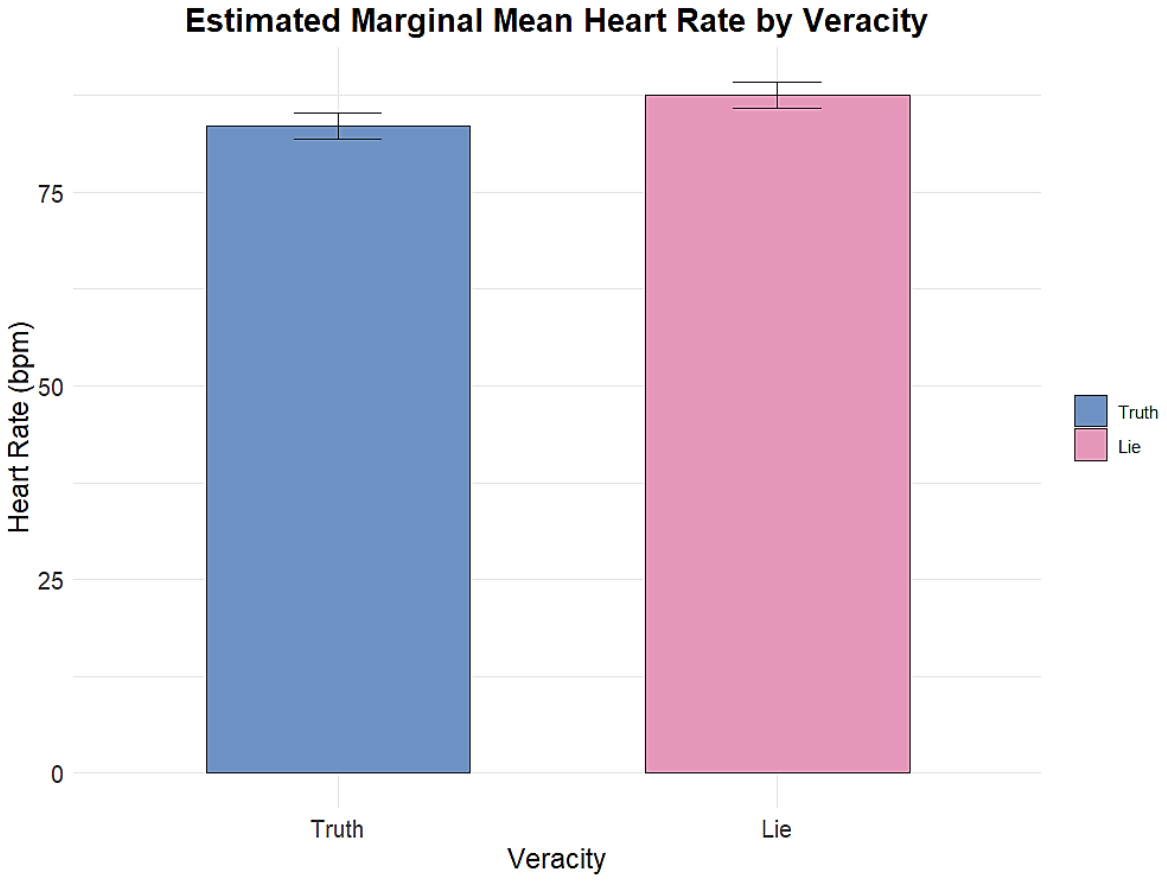
attachment avoidance – was consistent with our expectations. However, the pairwise comparisons did not reach significance after Bonferroni correction, so hypothesis H4.1a was not supported. Similarly, hypothesis H4.1b was not supported as no significant interaction between condition and attachment avoidance was found.

Heart Rate

Aim 1: Effect of deception (i.e., veracity) on heart rate (RQ1)

The model revealed a statistically significant effect of veracity on heart rate, $F(1, 290.15) = 10.67$, $p < .001$, $\eta_p^2 = .04$. The estimated marginal means indicated that participants had a significantly higher heart rate during lying ($M = 87.52$, $SE = 0.61$) than during truth telling ($M = 85.56$, $SE = 0.60$) as depicted in Fig. 24.

Figure 24: Estimated marginal mean heart rate by veracity

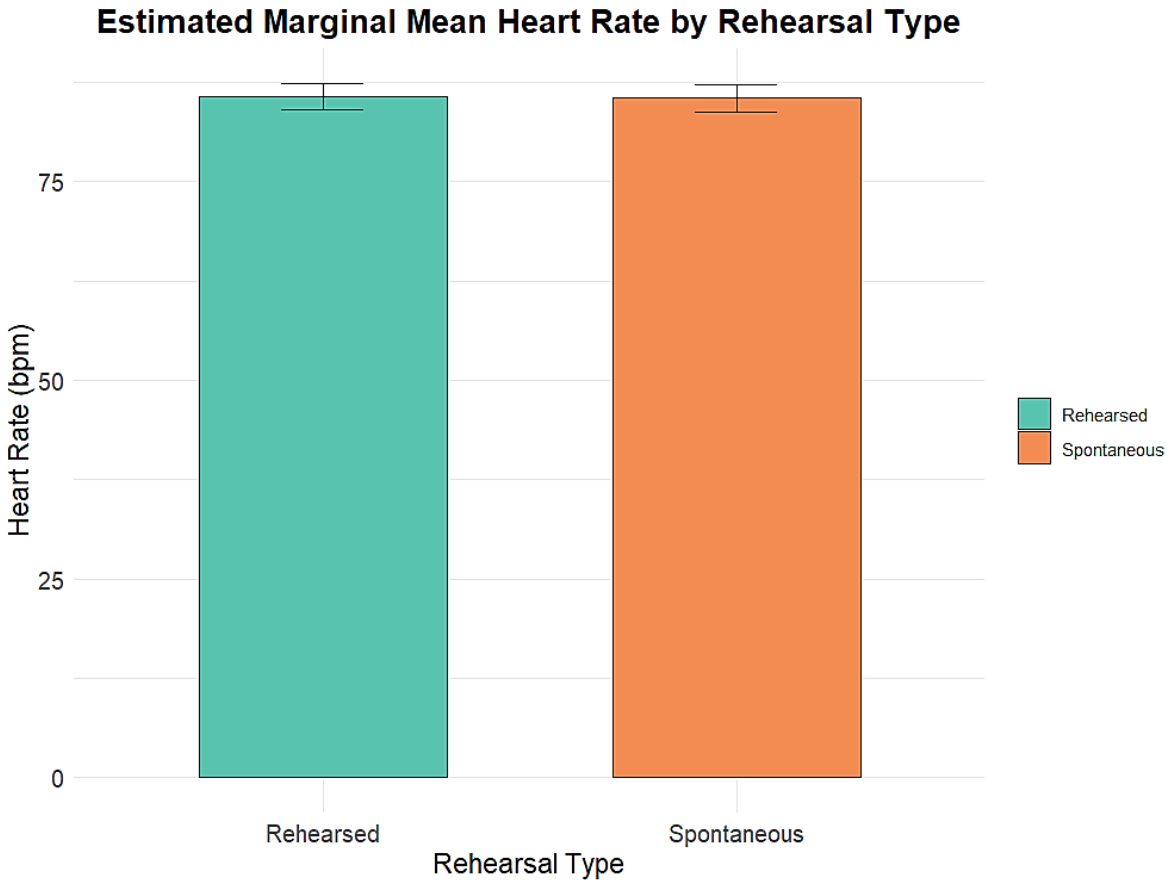


These results support the hypothesis H1.2a that deception is associated with increased heart rate.

Aim 2: Effect of rehearsal on heart rate (RQ2) and interaction effect (RQ3)

The analysis revealed no significant effect of rehearsal on heart rate, $F(1, 290.18) = 0.02$, $p = .90$, $\eta_p^2 < .001$. The estimated marginal means were nearly identical, with participants exhibiting an average heart rate of $M = 85.6$ bpm ($SE = 1.69$) during the rehearsed responses and $M = 85.5$ bpm ($SE = 1.69$) during the spontaneous responses. This pattern is illustrated in Figure 25.

Figure 25: Estimated marginal mean heart rate by rehearsal type

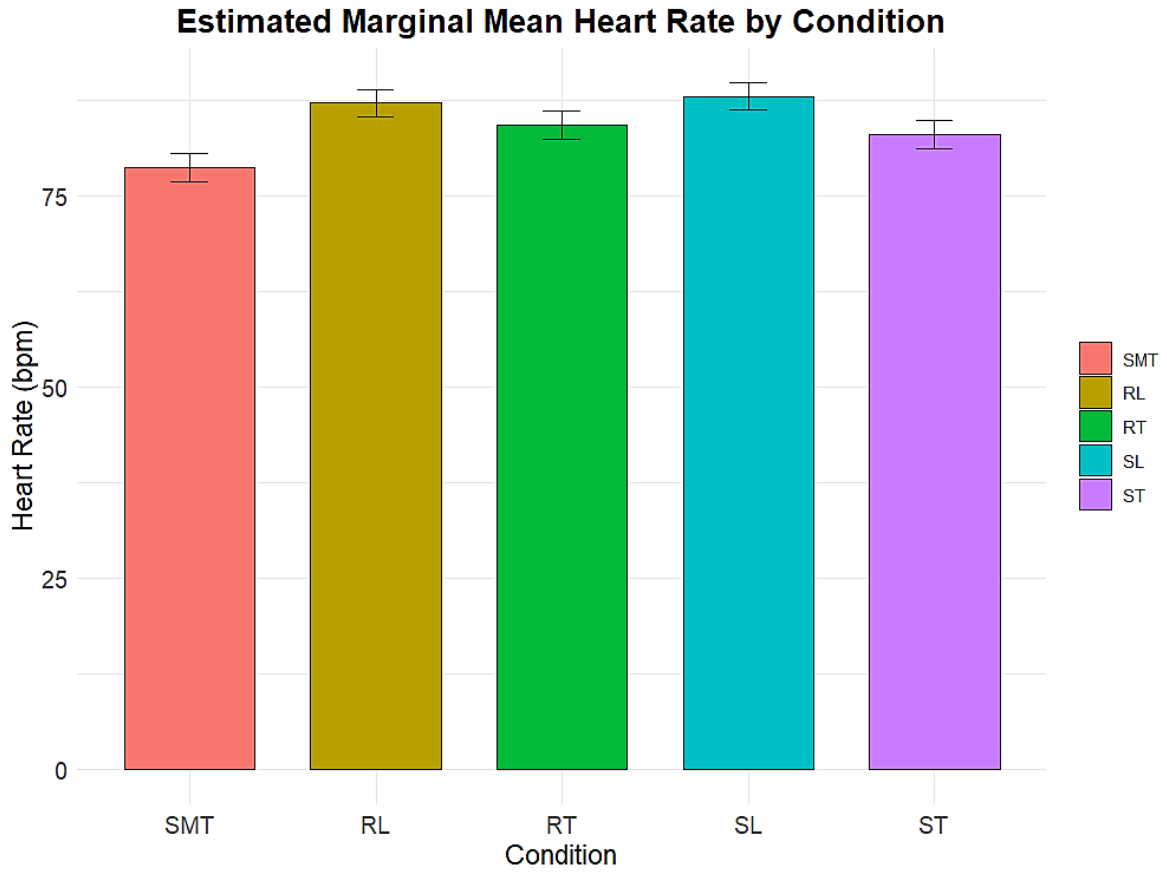


These results do not support hypothesis H2.2a, as there was no significant difference in heart rate between rehearsed and spontaneous responses, in contrast to the predicted decrease during rehearsed responses.

The model investigating all conditions and heart rate revealed a statistically significant effect of condition on heart rate, $F(4, 385.04) = 9.84$, $p < .001$, with a small to moderate effect size, $\eta_p^2 = .09$. The estimated marginal means (Bonferroni-adjusted) showed that participants had the lowest heart rate during the small talk condition

(*M* = 78.7 bpm, *SE* = 1.81). The highest heart rates were observed during the spontaneous lie condition (*M* = 88.0 bpm), followed by rehearsed lie (*M* = 87.1 bpm), rehearsed truth (*M* = 84.2 bpm) and spontaneous truth (*M* = 82.9 bpm). Post-hoc comparisons showed that heart rate was significantly lower in the small talk condition compared to rehearsed lie, rehearsed truth and spontaneous lie (all *p*s < .01). In addition, heart rate during spontaneous lie was significantly higher than during spontaneous truth (*p* < .05). No other differences reached significance. These results do not support Hypothesis H3.2a, as heart rate during spontaneous lies was not significantly higher than during rehearsed lies or rehearsed truths, as shown in Fig. 26.

Figure 26: Estimated marginal mean heart rate by condition



Note. *SMT* – baseline (small-talk), *RL* – rehearsed lie, *RT* – rehearsed truth, *SL* – spontaneous lie, *ST* – spontaneous truth

Aim 3: Attachment and heart rate (RQ4)

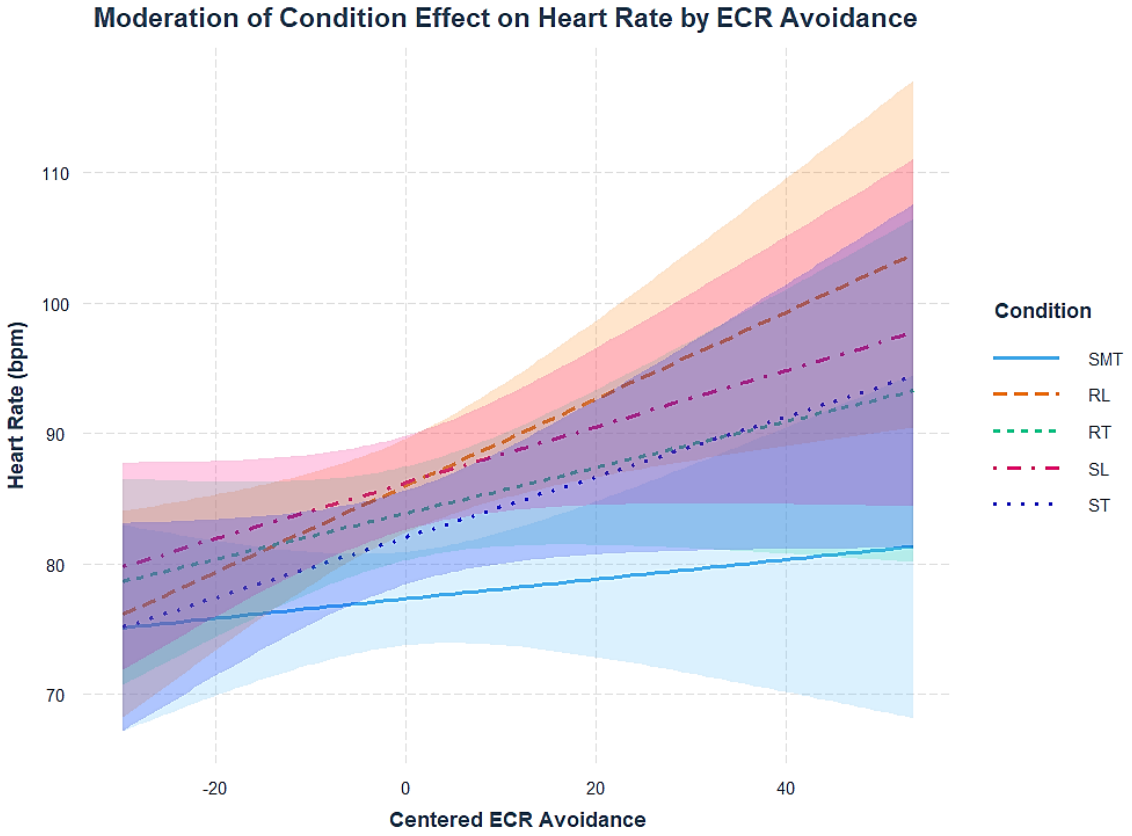
Spearman's rank order correlations showed a significant positive association between attachment avoidance (ECR_AVO) and heart rate during the rehearsed lie

condition (ρ = .22, p < 0.05), while no significant correlations were observed between ECR_AVO and heart rate in the other conditions.

To further investigate this relationship, a linear mixed-effects model was conducted to test whether attachment avoidance moderated the effect of all conditions on heart rate. There was a significant a significant main effect of ECR_AVO_c, $F(1, 82.12) = 4.42$, $p < .05$, $\eta_p^2 = .05$, suggesting that individuals who exhibited higher levels of avoidance generally had increased heart rates across conditions, supporting hypothesis H4.2a.

Although the interaction between condition and avoidance was not statistically significant overall, $F(4, 325.30) = 1.39$, $p = .238$, $\eta_p^2 = .02$, two marginal trends emerged. In the rehearsed lie condition, higher avoidance was associated with a greater increase in heart rate. Conversely, in the rehearsed truth condition, avoidance was associated with a lower heart rate, although again not significantly. These trends can be seen in the interaction plot depicted in Fig. 27.

Figure 27: Moderation of condition effect on heart rate by ECR avoidance



Note. *SMT* – baseline (small-talk), *RL* – rehearsed lie, *RT* – rehearsed truth, *SL* – spontaneous lie, *ST* – spontaneous truth

The interaction between conditions and attachment avoidance was not statistically significant and therefore does not provide support for hypothesis H4.2d, which states that individuals with high attachment avoidance have an increased heart rate, especially under deceptive conditions.

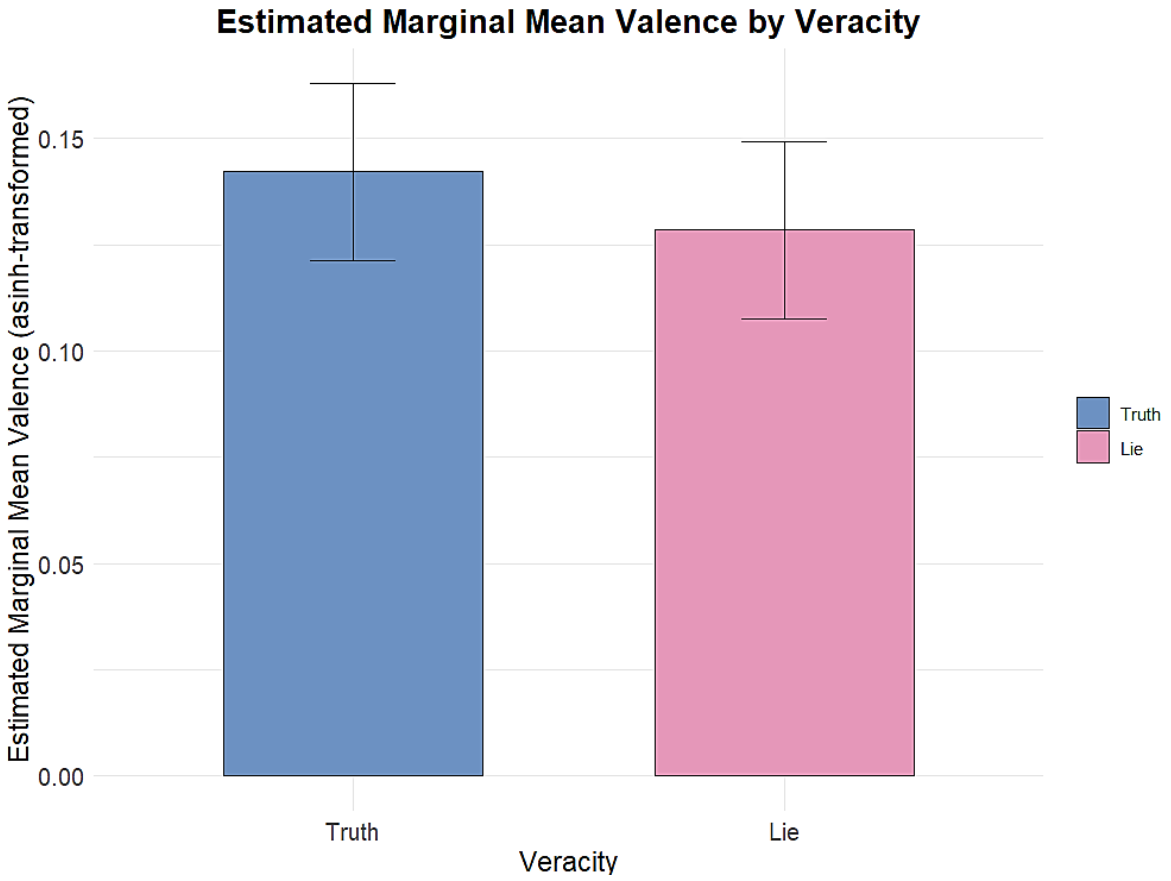
9.5.8. Behavioural results

Valence

Aim 1: Effect of deception (i.e., veracity) on emotional valence (RQ1)

The model revealed no significant main effect of veracity on valence, $F(1, 290.39) = 0.83$, $p = .362$, $\eta_p^2 = .003$. The estimated marginal means showed a slightly higher average valence during truth-telling ($M = 0.142$, $SE = 0.021$) than during lying ($M = 0.129$, $SE = 0.021$), but this difference was not statistically significant. A Bonferroni-corrected post hoc comparison further confirmed the non-significant difference between the conditions which is also apparent from the Fig. 28.

Figure 28: Estimated marginal mean valence by veracity

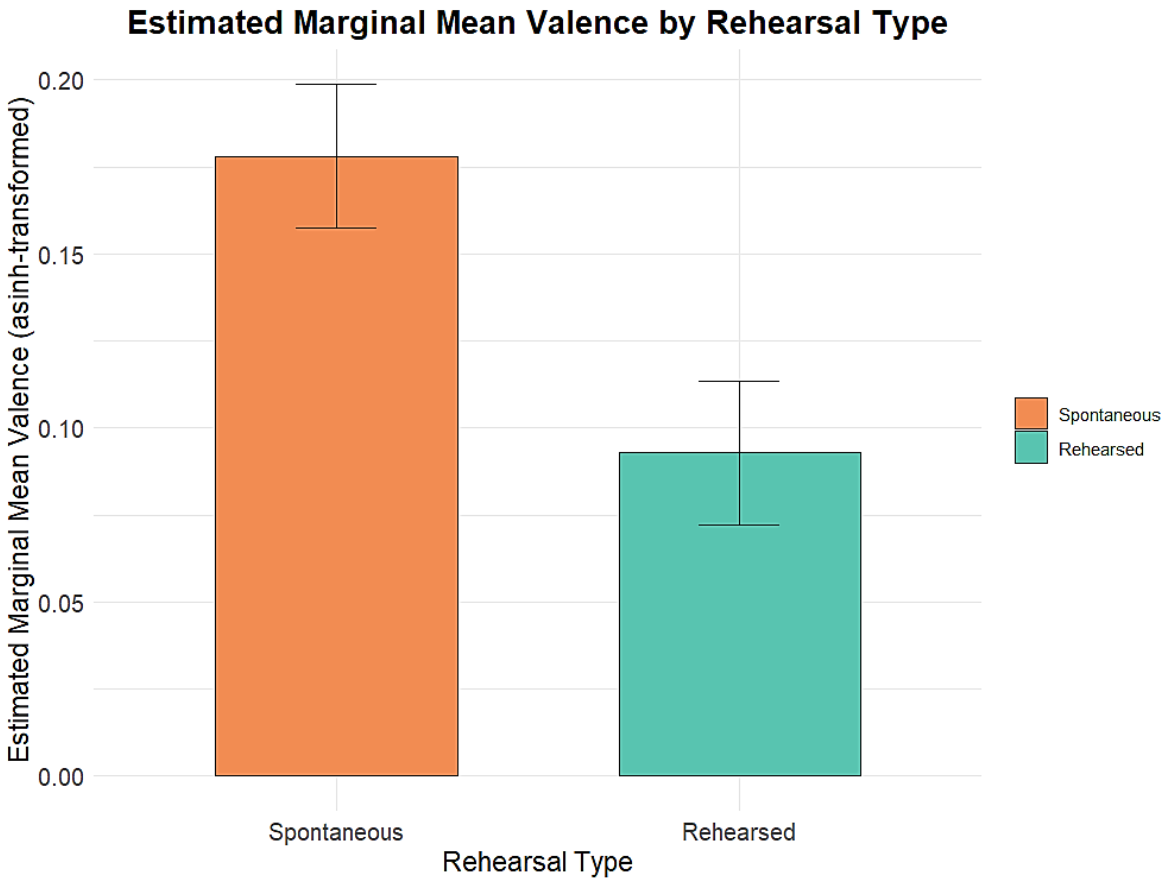


Therefore, hypothesis H1.2c was not supported; emotional valence did not differ significantly between deceptive and truthful responses.

Aim 2: Rehearsal effect on valence (RQ2) and the interaction effect (RQ3)

The analysis revealed a significant main effect of rehearsal, $F(1, 290.36) = 36.47$, $p < .001$, $\eta_p^2 = .11$, indicating that emotional valence was significantly lower for rehearsed responses than for spontaneous responses, contrary to the hypothesis H2.2c. The estimated marginal means with Bonferroni correction showed a higher valence during spontaneous responses ($M = 0.178$, $SE = 0.021$) than during rehearsed responses ($M = 0.093$, $SE = 0.021$), as shown in Fig. 29.

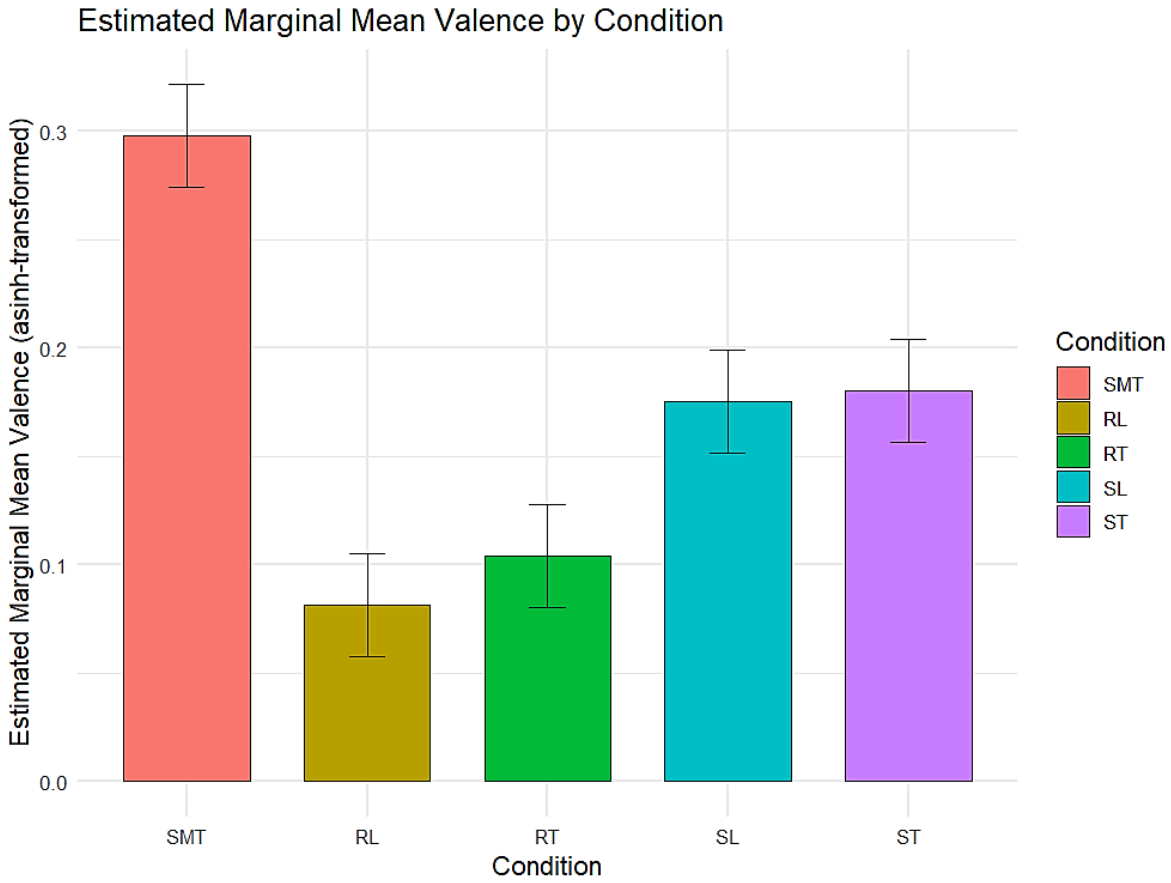
Figure 29: Estimated marginal mean valence by rehearsal type



To further explore whether emotional valence differed across all experimental conditions, a linear mixed-effects model was fitted with all conditions as a fixed effect and random intercepts for participant ID. The model revealed a significant main effect of condition on emotional valence, $F(4, 385.22) = 31.71$, $p < .001$, $\eta_p^2 = .25$. The estimated

marginal means with Bonferroni correction showed the most positive valence in the small talk condition (*M* = 0.298, *SE* = 0.024), followed by spontaneous lie (*M* = 0.175, *SE* = 0.024) and spontaneous truth (*M* = 0.180, *SE* = 0.024). The lowest valence values were observed in rehearsed lie (*M* = 0.081, *SE* = 0.024) and rehearsed truth (*M* = 0.104, *SE* = 0.024). Spontaneous lies and spontaneous truths did not differ significantly from each other (p = 1.00), but both had a significantly higher valence than rehearsed lies (spontaneous lie vs. rehearsed lie: $p < .001$; spontaneous truth vs. rehearsed lie: $p < .001$) and rehearsed truths (spontaneous lie vs. rehearsed truth: $p < .05$; spontaneous truth vs. rehearsed truth: $p < .05$). No significant difference was observed between rehearsed lie and rehearsed truth (p = 1.00), as shown in Figure 30.

Figure 30: Estimated marginal mean valence by condition



Note. *SMT* – baseline (small-talk), *RL* – rehearsed lie, *RT* – rehearsed truth, *SL* – spontaneous lie, *ST* – spontaneous truth

In contrast to hypothesis H3.2c, emotional valence was not more negative in spontaneous lies. Instead, valence was significantly more positive in the small talk

condition, which is consistent with the prediction that this initial interaction would be more likely to elicit more positive emotional expressions. However, spontaneous lies and truths were associated with more positive valence than rehearsed responses, contradicting the expectation that spontaneous deception would elicit negative valence. Therefore, the results do not support H3.2c.

Aim 3: Attachment avoidance and valence (RQ4)

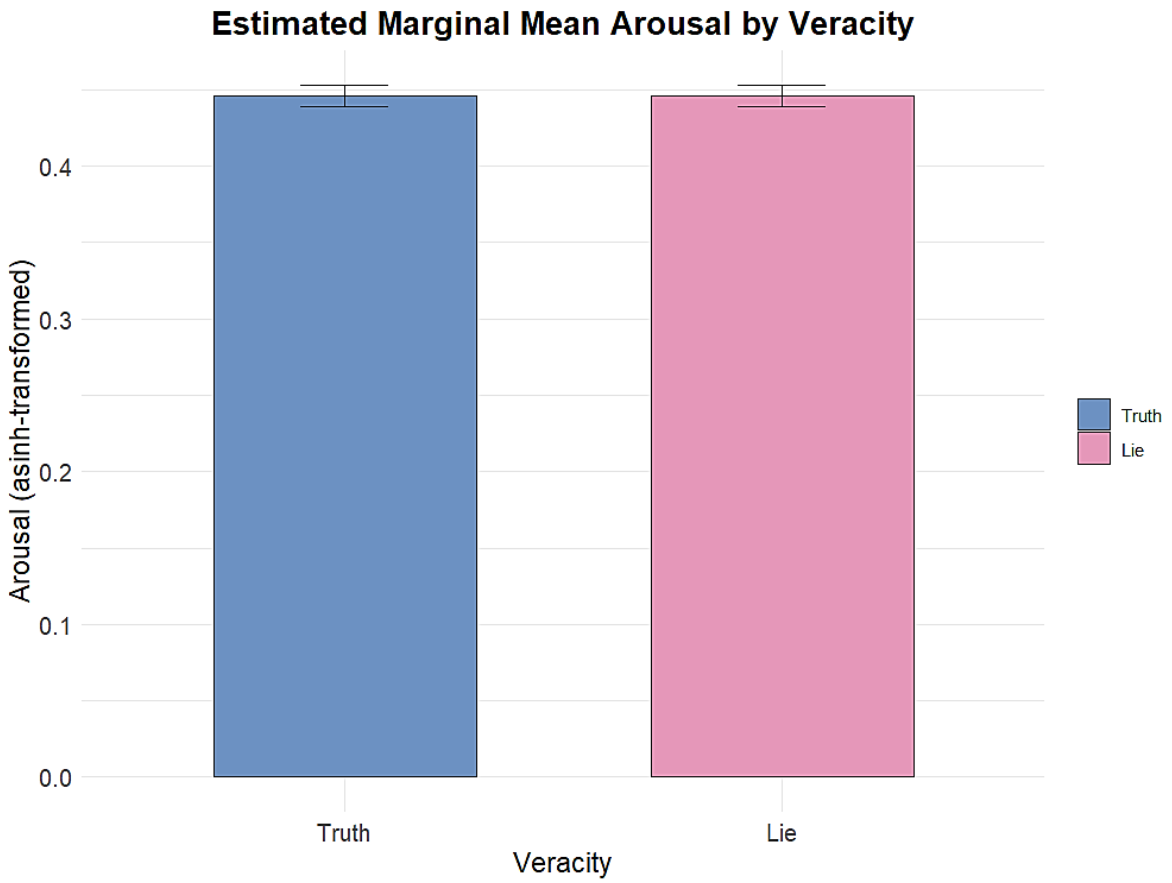
Although preliminary Spearman correlation analyses between emotional valence and attachment avoidance did not reveal any significant correlations, the moderation model was pursued further in line with the theoretical framework of the study. The model revealed a significant main effect of condition, $F(4, 325.17) = 24.25$, $p < .001$, $\eta_p^2 = .23$, indicating that valence levels differed between all conditions. However, neither the main effect of attachment avoidance, $F(1, 82.23) = 0.41$, $p = .526$, $\eta_p^2 = .005$, nor the interaction between condition and ECR_AVO_c, $F(4, 325.38) = 1.07$, $p = .374$, $\eta_p^2 = .01$ reached statistical significance. No consistent pattern emerged between attachment avoidance and emotional valence, contradicting hypothesis H4.2b, and neither the interaction with condition reached statistical significance, in contrast to hypothesis H4.2e.

Arousal

Aim 1: Effect of deception (i.e., veracity) on emotional arousal (RQ1)

The model revealed no significant main effect of veracity on arousal, $F(1, 290.43) = 0.003$, $p = .953$, $\eta_p^2 < .001$. Estimated marginal means indicated nearly identical arousal levels during truthful responses ($M = 0.446$, $SE = 0.0067$) and deceptive responses ($M = 0.447$, $SE = 0.0067$) as depicted in Fig. 31.

Figure 31: Estimated marginal mean arousal by veracity

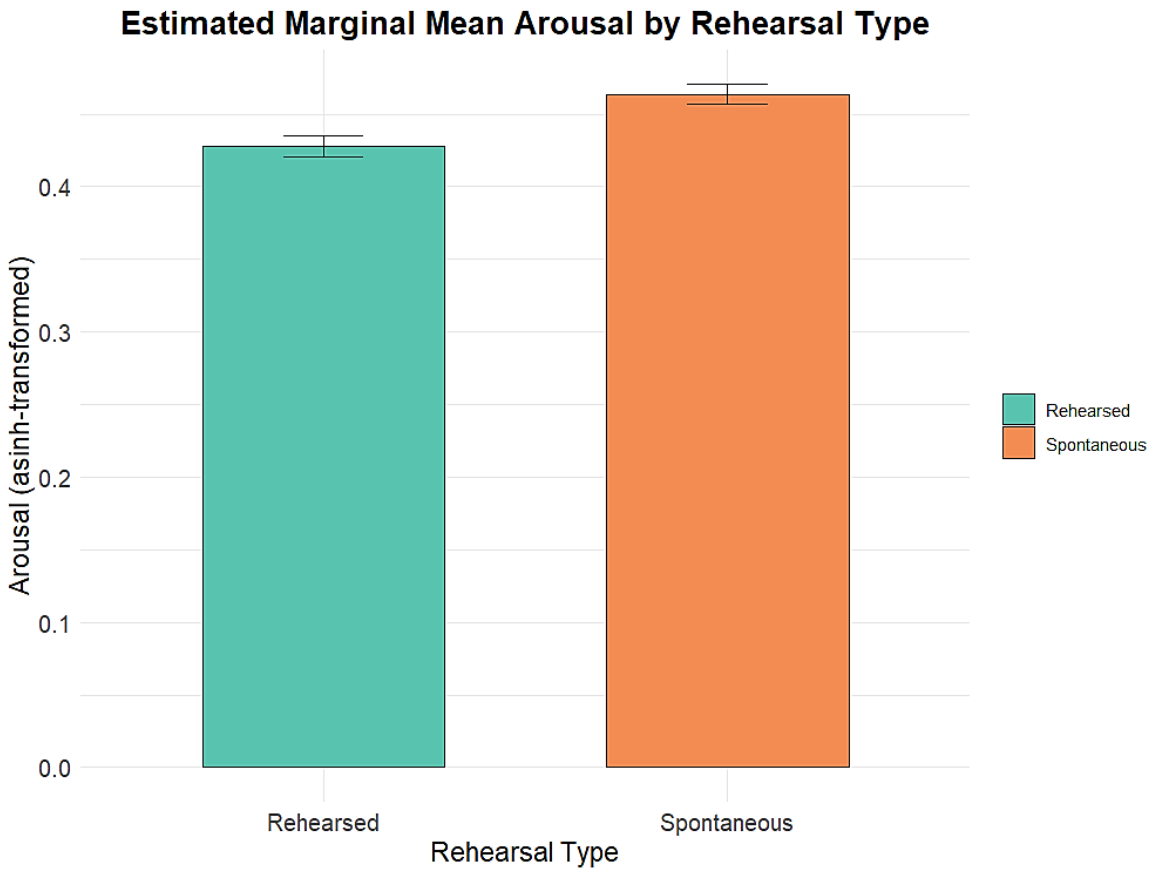


These findings suggest that arousal, as measured by FaceReader, did not differ between lying and truth-telling conditions. Consequently, the findings do not support hypothesis H1.2b, which predicted significantly higher arousal during deception due to the increased emotional and cognitive demands associated with lying.

Aim 2: Effect of rehearsal on emotional arousal (RQ2) and the interaction effect (RQ3)

The model revealed a significant main effect of rehearsal, $F(1, 290.35) = 73.92$, $p < .001$, with a large effect size, $\eta_p^2 = .20$. Estimated marginal means indicated significantly higher arousal during spontaneous responses ($M = 0.464$, $SE = 0.007$) compared to rehearsed responses ($M = 0.428$, $SE = 0.007$) as depicted on Fig. 32.

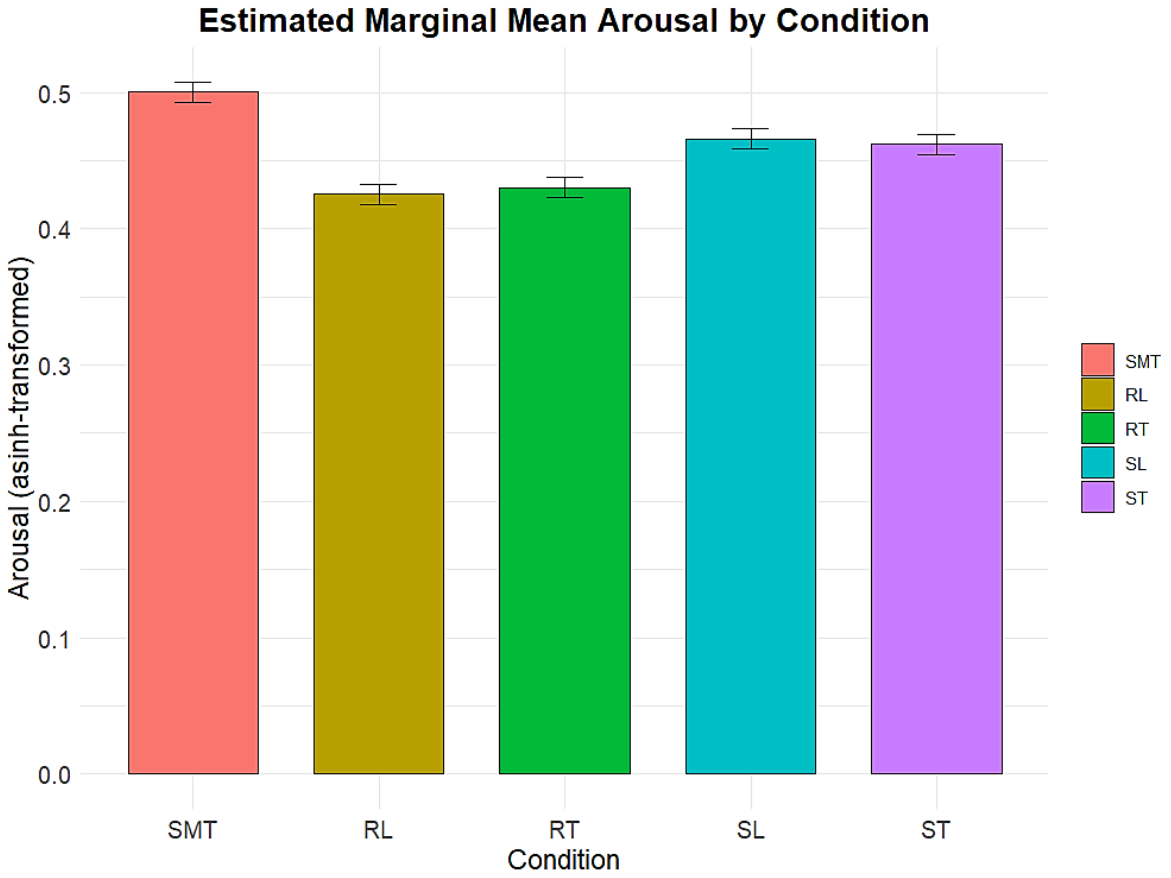
Figure 32: Estimated marginal mean arousal by rehearsal type



These results provide support for Hypothesis H2.2b, which predicted greater emotional arousal under spontaneous conditions.

The analysis of interaction effect revealed a significant main effect of condition, $F(4, 385.27) = 44.94$, $p < .001$, with a large effect size, $\eta_p^2 = .32$. The estimated marginal means showed that arousal was highest in the small talk condition ($M = 0.500$, $SE = 0.0075$), followed by spontaneous lie ($M = 0.466$, $SE = 0.0075$), spontaneous truth ($M = 0.462$, $SE = 0.0075$), rehearsed truth ($M = 0.430$, $SE = 0.0075$), and rehearsed lie ($M = 0.425$, $SE = 0.0075$). Bonferroni-adjusted pairwise comparisons showed that small talk condition was significantly different from all other conditions ($ps < .001$). Both spontaneous lie and spontaneous truth elicited significantly higher arousal than rehearsed lie and rehearsed truth ($ps < .001$), whereas spontaneous lie and spontaneous truth did not differ significantly from each other ($p = 1.00$), nor did rehearsed lie and rehearsed truth ($p = 1.00$) as shown in Fig. 33.

Figure 33: Estimated marginal mean arousal by condition



Note. *SMT* – baseline (small-talk), *RL* – rehearsed lie, *RT* – rehearsed truth, *SL* – spontaneous lie, *ST* – spontaneous truth

Although spontaneous responses were associated with greater arousal than rehearsed responses, the highest arousal was recorded during the small talk condition; therefore, hypothesis H3.2b was not supported.

Aim 3: Attachment and arousal (RQ4)

Although no significant Spearman correlations were found between ECR_AVO and arousal in any condition, the moderation model was tested. The model revealed a significant main effect of condition, $F(4, 325.26) = 32.61$, $p < .001$, $\eta_p^2 = .29$. However, there was no significant main effect of ECR_AVO_c, $F(1, 82.31) = 0.47$, $p = .497$, $\eta_p^2 < .01$, and no significant condition × ECR_AVO_c interaction, $F(4, 325.44) = 0.43$, $p = .785$, $\eta_p^2 < .01$, suggesting that attachment avoidance did not influence arousal responses directly, nor did it moderate arousal patterns for different social or cognitive demands. Therefore, the results do not support either hypothesis H4.2c, which predicted

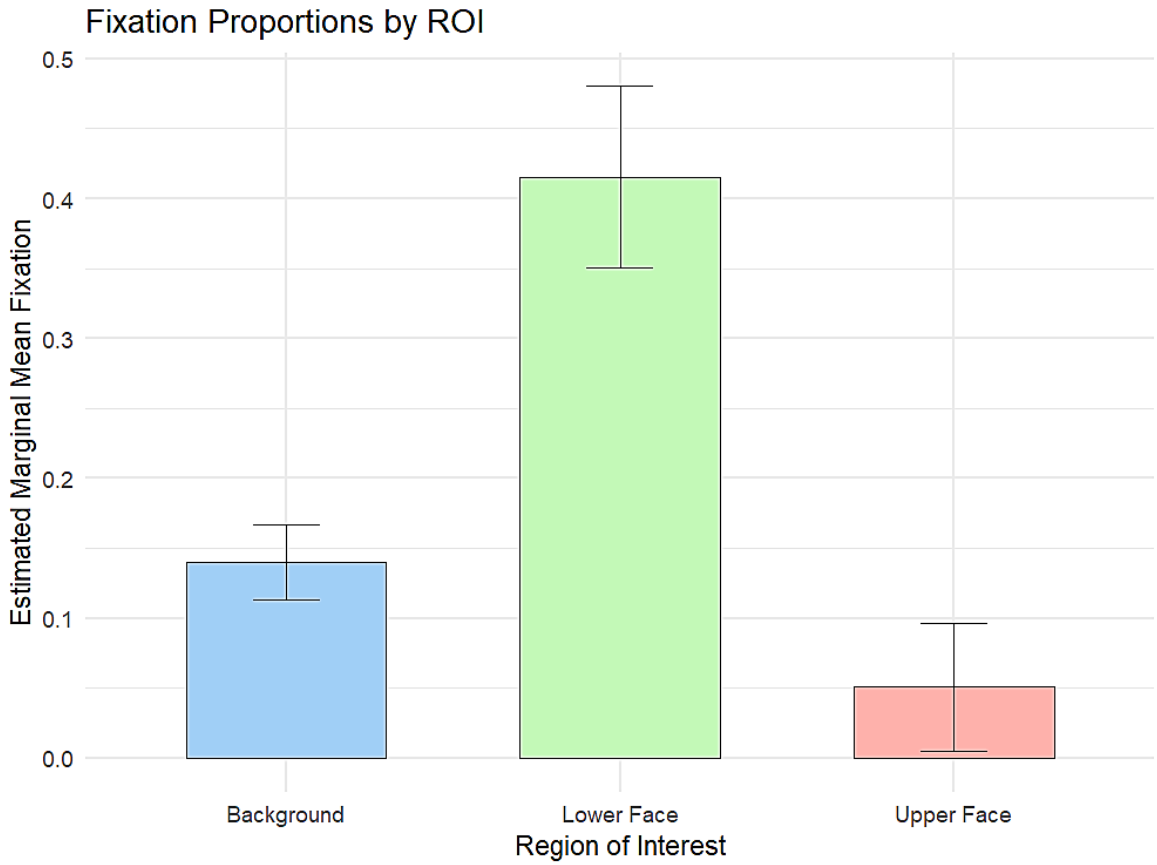
a general decrease in emotional arousal in individuals high in avoidance, or hypothesis H4.2f, which expected decreased arousal specifically under more emotionally demanding conditions.

Eye-tracking

Aim 1: Effect of deception (i.e., veracity) on eye fixations (RQ1)

The main effect of veracity was not significant, $F(1, 307.51) < 0.001$, $p = .993$, $\eta_p^2 < .001$. A significant main effect of ROI was observed, $F(2, 37.38) = 34.48$, $p < .001$, $\eta_p^2 = .65$. According to Bakeman (2005), the main effect of ROI showed a large effect size, $\eta_p^2 = .65$, suggesting that participants' eye fixation behaviour varied greatly between face regions regardless of condition. Estimated marginal means indicated that participants, on average, fixated most on the lower face ($M = 0.415$, $SE = 0.032$), followed by the background ($M = 0.140$, $SE = 0.013$) and upper face ($M = 0.051$, $SE = 0.022$) as depicted on Fig. 34.

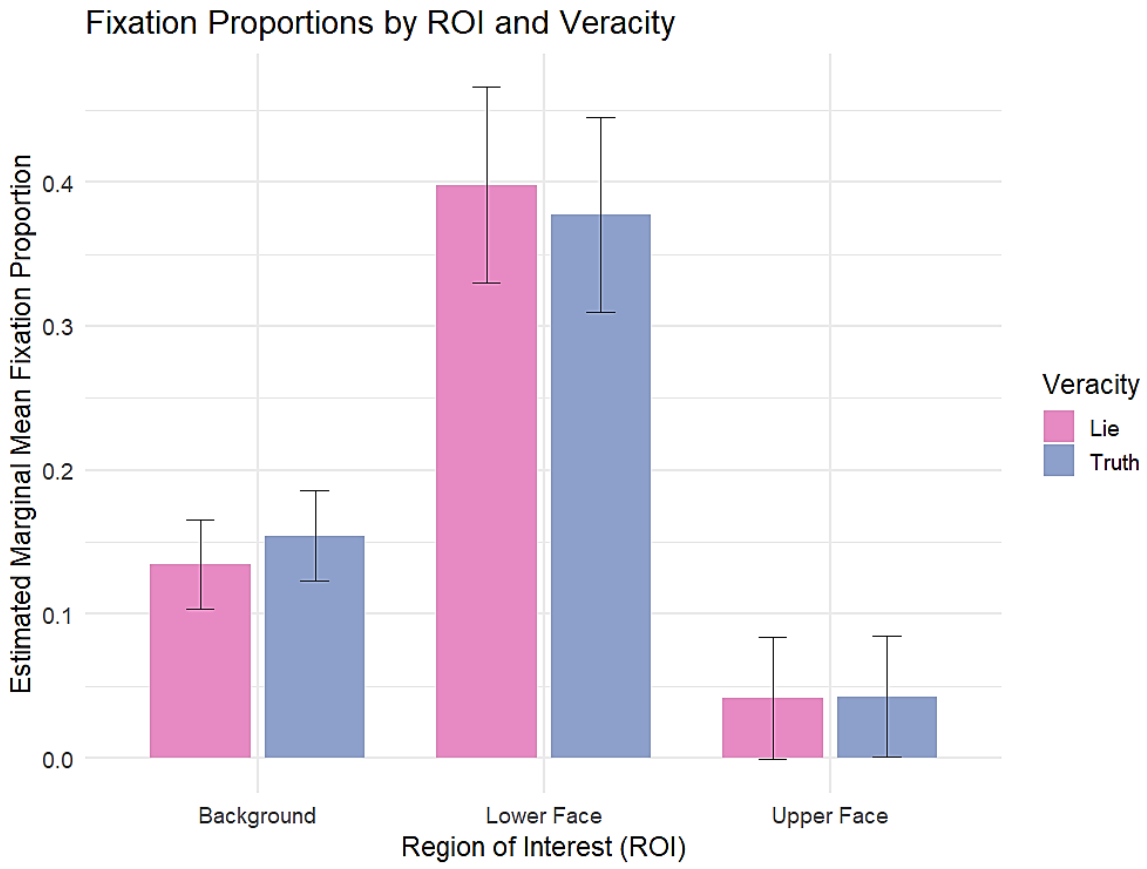
Figure 34: Fixation proportions by ROI



Bonferroni-corrected pairwise comparisons confirmed that all pairwise differences between ROIs were statistically significant: lower face temperatures were significantly higher than both the background ($t(40) = -7.57$, $p < .001$) and upper face ($t(39.1) = 8.44$, $p < .001$), and background temperature was significantly higher than upper face temperature ($t(36.1) = 3.13$, $p < .01$).

The interaction veracity × ROI was not significant, $F(2, 304.84) = 2.38$, $p = .094$, $\eta_p^2 = .02$. Estimated marginal means revealed that during lies, participants focused slightly more on the lower face ($M = 0.398$, $SE = 0.034$) and slightly less on the background ($M = 0.135$. $SE = 0.015$), compared to truthful responses (lower face $M = 0.378$, $SE = 0.034$, background $M = 0.155$, $SE = 0.015$). Gaze to the upper face was virtually identical ($M \approx 0.042$ for both). However, Bonferroni-adjusted pairwise comparisons revealed no significant ROI-specific differences between lies and truths, as shown in Fig. 35.

Figure 35: Fixation proportion by ROI and veracity



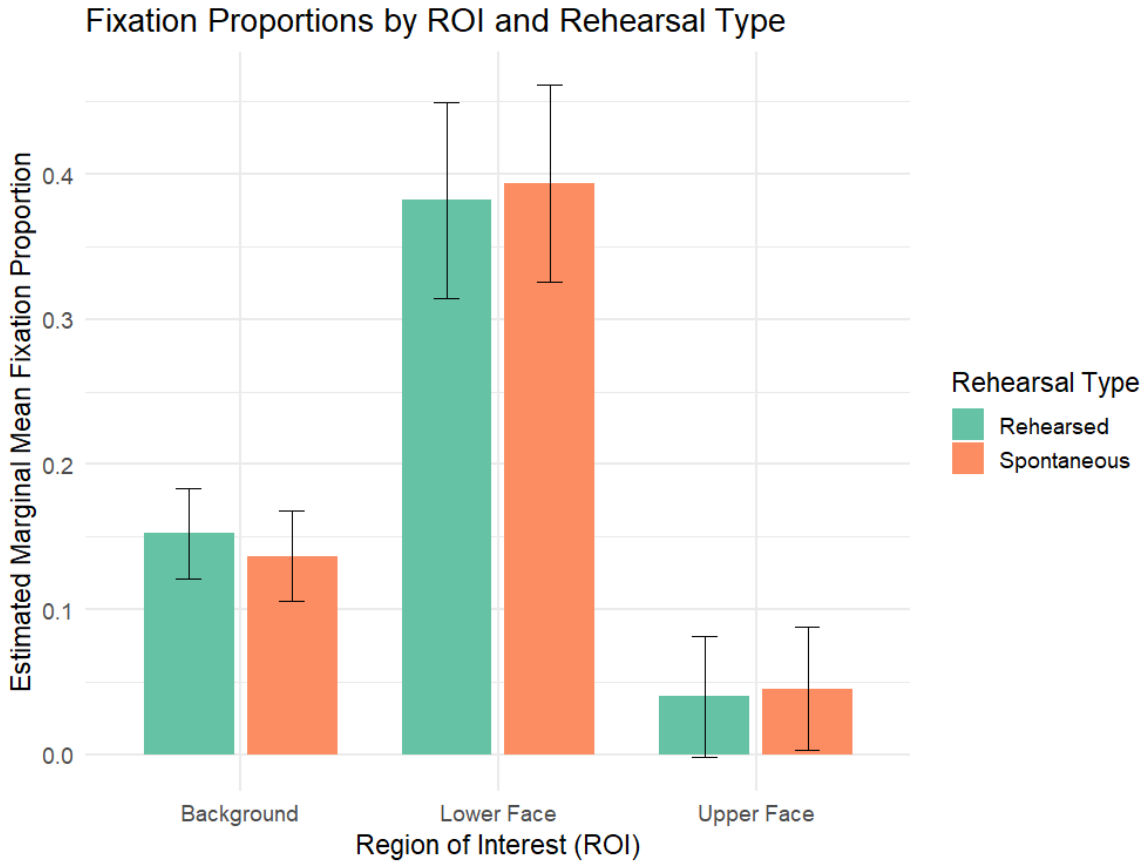
These findings do not support hypotheses H1.3a–H1.3c, which predicted that participants would look more at the upper face (H1.3a), less at the lower face (H1.3b) and less at the background (H1.3c) when lying compared to telling the truth.

Aim 2: Effect of rehearsal on eye fixations (RQ2) and the interaction effect (RQ3)

The model examining the effect of rehearsal on fixation proportion revealed no significant main effect of rehearsal, $F(1, 308.45) = 0.002$, $p = .968$, $\eta_p^2 < .001$, suggesting that the overall level of rehearsal did not significantly affect visual attention. A significant main effect of ROI, $F(2, 37.46) = 34.43$, $p < .001$, $\eta_p^2 = .65$, was found, suggesting strong differences in gaze allocation across facial regions. The interaction between rehearsal and ROI was not significant, $F(2, 305.31) = 1.13$, $p = .323$, $\eta_p^2 = .007$.

Estimated marginal means showed that participants fixated primarily on the lower face ($M = 0.393$, $SE = 0.034$ for spontaneous, $M = 0.382$, $SE = 0.034$ for rehearsed), followed by the background ($M = 0.137$, $SE = 0.016$ for spontaneous, $M = 0.152$, $SE = 0.015$ for rehearsed), and the upper face ($M = 0.045$, $SE = 0.021$ for spontaneous, $M = 0.040$, $SE = 0.021$ for rehearsed). However, Bonferroni-adjusted comparisons revealed no significant differences between rehearsed and spontaneous responses within any ROI (all ps > .23) as shown in Fig 36.

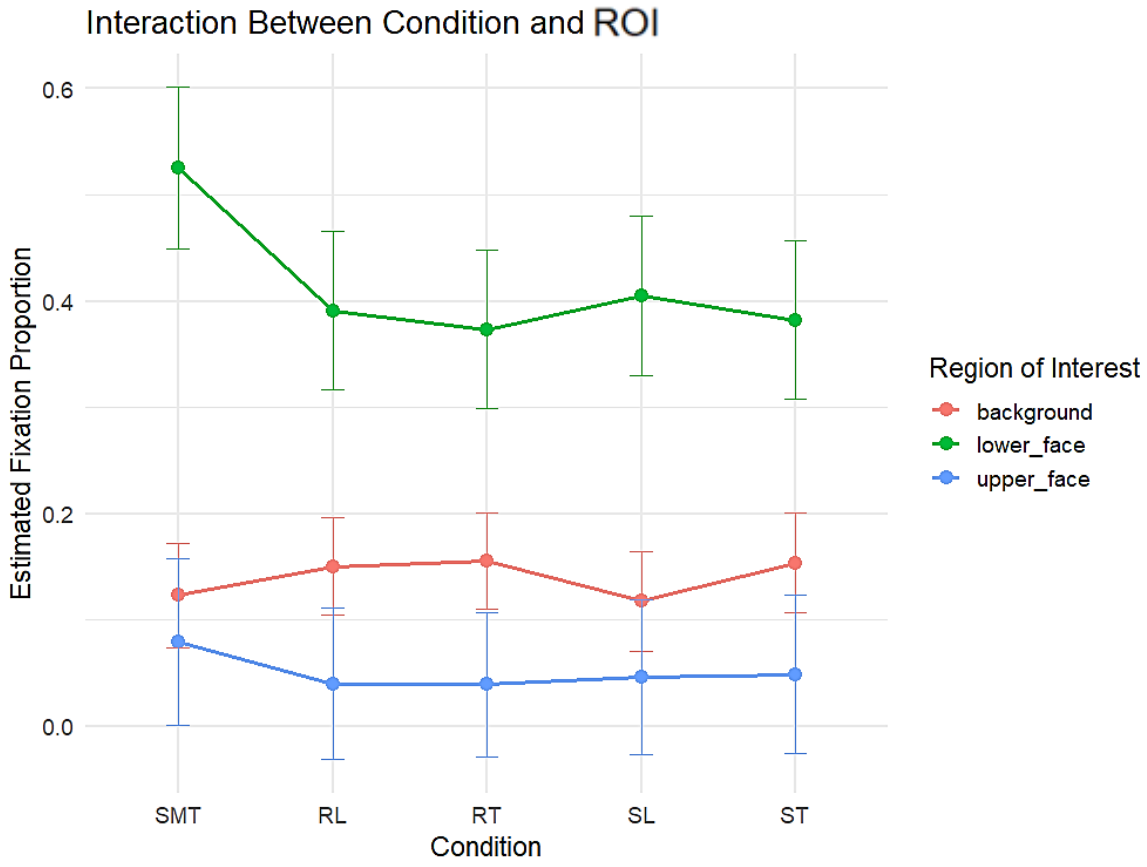
Figure 36: Fixation proportions by ROI and rehearsal type



These findings do not support hypotheses H2.3a–H2.3c, which predicted that gaze behaviour would vary according to the cognitive demands of the response type: more gaze to the upper (H2.3a) and less to the lower face (H2.3b) and background (H2.3c) during rehearsed responses compared to spontaneous responses.

The analysis of interaction effect revealed that the effect of condition was not significant, $F(4, 391.70) = 2.08$, $p = .082$, $\eta_p^2 = .02$. However, both the main effect of ROI, $F(2, 39.79) = 37.45$, $p < .001$, $\eta_p^2 = .65$, and the interaction effect between conditions and ROI, $F(8, 389.24) = 2.86$, $p < .05$, $\eta_p^2 = .06$ was significant. Pairwise post-hoc comparisons within each condition and each ROI were analysed and depicted in Fig. 37.

Figure 37: Interaction between all conditions and ROI



Note. *SMT* – baseline (small-talk), *RL* – rehearsed lie, *RT* – rehearsed truth, *SL* – spontaneous lie, *ST* – spontaneous truth

The small talk condition resulted in significantly higher fixation proportions in the lower face compared to all other conditions: rehearsed lie ($t(365) = 4.31$, $p < .001$), rehearsed truth ($t(365) = 4.88$, $p < .001$), spontaneous lie ($t(365) = 3.84$, $p < .05$), and spontaneous truth ($t(365) = 4.60$, $p < .001$). There were no condition-related differences in fixations on the upper face or the background (all $p > .05$). These findings do not support hypotheses H3.3a–H3.3c, which predicted that gaze would change in response to cognitive and emotional demands associated with deception and spontaneity.

Aim 3: Attachment and eye fixations (RQ4)

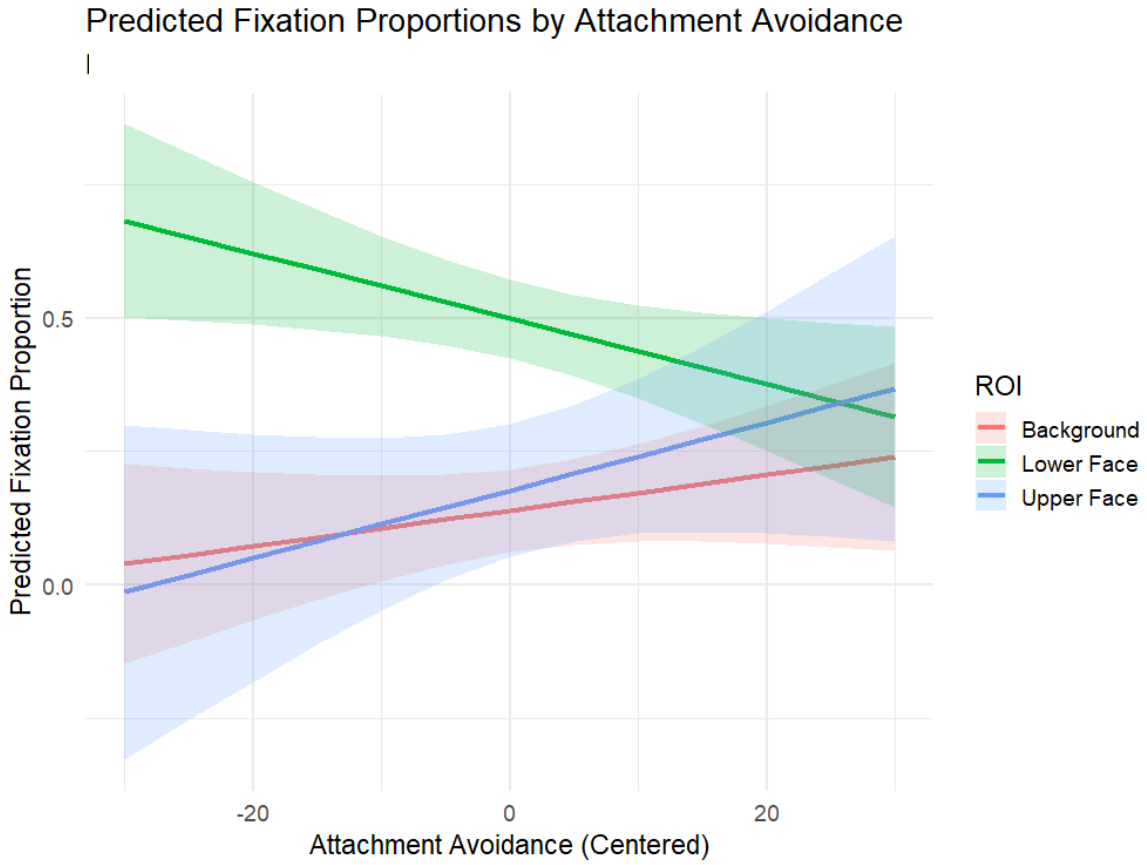
According to Spearman correlation matrix, attachment avoidance was negatively correlated with fixation on the lower face during the rehearsed lying condition ($\rho = -.38$, $p < .05$), suggesting that individuals with higher avoidance spent less time fixating on the mouth/jaw area when lying in a rehearsed context. In contrast, positive correlations were

observed between attachment avoidance and fixations on the background during several conditions: rehearsed lie (ρ = .35, p < .05), rehearsed truth (ρ = .41, p < .05), spontaneous lie (ρ = .46, p < .05), and small talk (ρ = .42, p < .05).

A linear mixed-effects model then revealed a significant main effect of ROI, $F(2, 320.91) = 98.18$, $p < .001$, $\eta_p^2 = .38$ as well as a significant ROI × ECR-AVO_c interaction, $F(2, 321.82) = 8.53$, $p < .001$, $\eta_p^2 = .05$. However, the main effect of ECR-AVO_c was not significant, $F(1, 33.03) = 0.01$, $p = .923$, $\eta_p^2 < .01$ and the interactions with condition were also not statistically significant. These results indicate that attachment avoidance significantly influenced gaze distribution across facial regions, regardless of condition. Specifically, individuals with higher avoidance showed less fixation on the lower face (mouth/jaw) and increased fixation on the upper face and background — consistent with a socially avoidant visual strategy. This supports hypothesis H4.3a, which predicted greater gaze avoidance and less socially connective eye contact in avoidant individuals in all conditions.

Estimated marginal means revealed that for the lower face, higher attachment avoidance was associated with decreased fixation proportion ($M_{diff} = -0.0023$, $SE = 0.001$, $p < .05$) and for the upper face, higher avoidance was associated with a higher fixation proportion ($M_{diff} = 0.0040$, $SE = 0.001$, $p < .001$). No significant moderation by avoidance was observed for the background region ($M_{diff} \approx 0$, $p = .923$), as shown in Fig. 38.

Figure 38: Predicted fixation proportions by attachment avoidance



Thus, hypothesis H4.3b was not supported: the avoidant gaze pattern did not vary significantly between task conditions. Instead, the findings suggest that gaze avoidance in individuals with high attachment avoidance reflects a stable, trait-like pattern rather than a context-dependent modulation driven by the emotional or social demands of specific interaction types.

9.5.9. Hypotheses summary

Hypothesis	Statement	Result	Note
	Infrared thermal imaging hypotheses		
H1.1a	Nasal temperature will significantly decrease during deceptive responses compared to truthful conditions.	Not supported	
H1.1b	Forehead temperature will significantly increase during deceptive responses compared to truthful conditions.	Not supported	
H1.1c	Cheek's temperature will significantly increase during deceptive responses compared to truthful conditions.	Not supported	
H2.1a	Nasal temperature will be significantly higher during rehearsed responses compared to spontaneous responses.	Not supported	
H2.1b	Forehead temperature will be significantly higher during spontaneous responses compared to rehearsed responses.	Not supported	
H2.1c	Cheek temperatures will be lower during rehearsed responses compared to spontaneous responses.	Not supported	
H3.1a	Nasal temperature will significantly decrease during spontaneous lies, with a smaller decrease observed during rehearsed lies. Small talk and both rehearsed and spontaneous truths will elicit higher nasal temperature.	Not supported	Separate model with nose temperature data only showed significant differences between small talk and all conditions. However, no difference between truth/lies.
H3.1b	Forehead temperature will significantly increase during spontaneous lies, but will remain stable during rehearsed lies and other conditions.	Not supported	
H3.1c	Cheek temperature will increase during both rehearsed and spontaneous lies, with a more pronounced rise observed during spontaneous deception.	Not supported	
H4.1a	Higher levels of attachment avoidance will be associated with increased facial temperature in all ROIs, regardless of condition.	Not supported	The trend has emerged across all ROIs, however after Bonferroni correction, the pairwise comparison were no longer significant.

H4.1b	Attachment avoidance would interact with condition, such that individuals high in avoidance would show a greater increase in temperature under certain conditions – particularly those requiring more spontaneous or deceptive responses – reflecting higher physiological arousal when emotional or social demands are heightened.	Not supported	
	FaceReader hypotheses		
H1.2a	Heart rate will significantly increase during deceptive responses compared to truthful conditions.	Supported	
H1.2b	Emotional arousal will be significantly higher during deceptive responses compared to truthful conditions.	Not supported	
H1.2c	Emotional valence will be significantly lower (i.e., more negative) during deceptive responses compared to truthful conditions.	Not supported	
H2.2a	Heart rate will be significantly lower during rehearsed responses compared to spontaneous responses.	Not supported	
H2.2b	Emotional arousal will be significantly lower during rehearsed responses compared to spontaneous responses.	Supported	
H2.2c	Emotional valence will be significantly higher (i.e., more positive) during rehearsed responses compared to spontaneous responses.	Not supported	Opposite effect emerged: valence was significantly lower during rehearsed responses than during spontaneous responses.
H3.2a	Heart rate will be significantly higher during spontaneous lies than during rehearsed lies, truth-telling, and small talk.	Not supported	Spontaneous lies triggered the highest heart rate overall and were significantly higher than spontaneous truths and small talk. However, the difference between spontaneous and rehearsed lie and truth was not significant.
H3.2b	Emotional arousal will be significantly higher during spontaneous lies than during rehearsed lies, truthful responses, and small talk.	Not supported	Spontaneous responses were associated with increased arousal compared to rehearsed responses, although the highest arousal was observed during small talk.

H3.2c	Emotional valence will be significantly more negative during spontaneous lies, while small talk, rehearsed lies and truthful responses will show more neutral or positive valence.	Not supported	Opposite effect emerged: Spontaneous lies and spontaneous truths had higher valence (i.e., more positive) than rehearsed lies and rehearsed truths. However, the most positive valence was found during small talk.
H4.2a	A higher level of attachment avoidance will be associated with an increased heart rate under all conditions.	Supported	
H4.2b	A higher level of attachment avoidance will be associated with lower emotional valence across all conditions.	Not supported	
H4.2c	A higher level of attachment avoidance will be associated with lower emotional arousal across all conditions.	Not supported	
H4.2d	Attachment avoidance would interact with condition, such that individuals high in avoidance would show a greater increase in heart rate under certain conditions – particularly those requiring more spontaneous or deceptive responses – reflecting higher physiological arousal when emotional or social demands are heightened.	Not supported	Individuals with higher attachment avoidance consistently showed increased heart rate, confirming the main hypothesis. Although moderation was not statistically significant, the trend supported greater physiological reactivity in avoidant individuals during deception.
H4.2e	Attachment avoidance would interact with conditions, such that individuals high in avoidance would show lower emotional valence under certain conditions – particularly those requiring more spontaneous or deceptive responses – indicating increased deactivation strategies when emotional or social demands are heightened.	Not supported	
H4.2f	Attachment avoidance would interact with conditions, such that individuals high in avoidance would show lower emotional arousal under certain conditions – particularly those requiring more spontaneous or deceptive responses – indicating increased deactivation strategies when emotional or social demands are heightened.	Not supported	

	Eye-tracking hypotheses	
H1.3a	Participants will fixate the interviewer's upper face (e.g., eye region) significantly more during deceptive responses compared to truthful conditions.	Not supported
H1.3b	Participants will fixate the interviewer's lower face (e.g., mouth and jaw region) significantly less during deceptive responses compared to truthful conditions.	Not supported
H1.3c	Participants will fixate the background (i.e., avoidant gaze behaviour) significantly less during deceptive responses compared to truthful conditions.	Not supported
H2.3a	Participants will fixate more on the interviewer's upper face (e.g., eye region) during rehearsed responses compared to spontaneous responses.	Not supported
H2.3b	Participants will fixate less on the interviewer's lower face (e.g., mouth and jaw region) during rehearsed responses compared to spontaneous responses.	Not supported
H2.3c	Participants will fixate the background (i.e., display avoidant gaze behaviour) significantly less during rehearsed responses compared to spontaneous responses.	Not supported
H3.3a	Fixation on the interviewer's upper face (e.g., eyes) will be significantly higher during small talk and rehearsed lies than during spontaneous lies, and rehearsed truth will also elicit more upper-face fixation than spontaneous truth.	Not supported
H3.3b	Fixation on the interviewer's lower face (e.g., mouth and jaw) will decrease significantly more during spontaneous lies than during small talk, rehearsed lies, rehearsed truths, or spontaneous truths.	Not supported
H3.3c	Background fixation (i.e., gaze aversion) will increase significantly during spontaneous lies compared to all other conditions, while small talk, rehearsed lies and both truth conditions will show more stable, face-directed gaze behaviour.	Not supported

H4.3a	A higher level of attachment avoidance is associated with increased background (i.e., gaze avoidance) and upper face (i.e., scanning not connecting) fixations and decreased lower face fixation in all conditions.	Supported	
H4.3b	Attachment avoidance will moderate the relationship between the type of condition and gaze behaviour across ROIs, such that the avoidant gaze pattern (i.e., increased fixation on the background and upper face and decreased fixation on the lower face) is more pronounced in small talk and spontaneous deceptive conditions and is attenuated in rehearsed deceptive and truthful conditions.	Not supported	Avoidant individuals showed consistent gaze avoidance (↑ background and upper face, ↓ lower face), but these patterns were not moderated by condition, suggesting a stable trait-like gaze strategy rather than context-specific adaptation.

10 GENERAL DISCUSSION

The main objectives of this thesis were: (1) to assess the individual predictive value of four non-invasive modalities (fITI, rPPG, facial expression analysis and eye-tracking) in distinguishing between truthful and deceptive responses; and (2) to investigate how different levels of cognitive load (rehearsed truth, rehearsed lie, spontaneous truth and spontaneous lie) affect deception detection accuracy for each modality. In addition, to these primary aims, a secondary aim was to develop and test a customised software tool for thermal data pre-processing and to explore its potential for future applications in deception detection. Finally, the study investigated whether individual differences in attachment avoidance moderate the relationship between behavioural and physiological responses and deception detection accuracy, with moderation effects analysed separately for each modality.

10.1. Discussion of physiological results

10.1.1. Facial temperature

Despite a comprehensive theoretical review and the conduction of a case study and two pilot studies to determine the best approach for the use of fITI in the context of deception detection, suggesting clear expectations regarding variations in facial temperature, most hypotheses were not supported.

The effect of deception

Contrary to previous findings (Abouelenien et al., 2019; Gálvez-García et al., 2021; Moliné et al., 2017, 2018; Panasiti et al., 2016; Pavlidis et al., 2002; Pollina et al., 2015; Pollina & Ryan, 2004; Rajoub & Zwiggelaar, 2014; Satpathi et al., 2024; Zhu et al., 2007), we found no significant effect of deception on facial temperature in all ROIs. The absence of deception-specific thermal effects could also be attributed to the structured low-stakes experimental scenarios. In contrast to mock crimes or highly emotional tasks used in other studies (e.g., Moliné et al., 2017; Panasiti et al., 2016), our design was cognitively engaging

but arguably not affective enough to elicit strong thermal responses associated with deception.

Another possible explanation lies in the fact that both liars and truth tellers experience a variety of emotions and feelings that lead to different physiological responses that may not differentiate between deception and truth telling (Synnott et al., 2015). This premise is consistent with our statistical approach to analyse truth and deception data – simply any information that participants labelled as a deception (whether spontaneous or rehearsed) was scored as a deception, and the same for truth telling. Therefore, we did not consider other factors such as cognitive load or psychological load when analysing the deception effect, which is in line with common practise in this field. Nevertheless, our non-significant results contrast with those reported in previous studies (Gálvez-García et al., 2021; Moliné et al., 2017, 2018), suggesting possible methodological differences. A key factor that could account for this discrepancy is the choice of statistical analysis. Specifically, many of these studies relied on a repeated-measures ANOVA in which thermal responses were treated as a dependent variable, with truth/deception conditions and facial ROIs included as fixed effects. While this technique is widely accepted for repeated measures designs (Kristensen & Hansen, 2004; Zloteanu & Vuorre, 2024), it may overestimate the importance of physiological outcomes if individual-level variability is not accounted for. Repeated measures ANOVA is based on the assumption of homogeneity of variance and covariance between participants, which may not be true for complex physiological data (Kristensen & Hansen, 2004). Therefore, we opted for linear mixed-effects models (LMMs) instead of the traditional repeated-measures ANOVA. This choice was motivated by several important considerations: (a) the inclusion of both fixed and random effects, which is crucial when modelling physiological responses (Kenny & Judd, 1986); (b) greater flexibility to capture complex interactions while adjusting for individual-level differences; and (c) reducing of the likelihood of statistical error (Gelman & Hill, 2006). We argue that the lack of significant effects in our results may therefore be due to our rigorous analytical approach, which includes controlling for participant variability and applying Bonferroni corrections to reduce the likelihood of Type I errors. Nevertheless, it is important to recognise that additional factors may have influenced the observed results, as described in the section on study limitations.

The effect of rehearsal and the interaction effect

Surprisingly, and in contrast to our previous findings from the second pilot study (Hypšová et al., in review), we found no significant effect of rehearsal on any ROI.

We argue that the lack of observable effects of rehearsal may be due to the methodology used – similar to that described for the effect of deception. In contrast to paradigms involving high emotional stakes or risk (e.g., mock crime scenarios; Pavlidis et al., 2002; Moliné et al., 2017), our semi-structured interview was intentionally designed to simulate a natural, low-stakes conversational context and to include both rehearsed and spontaneous responses. This was a central aim of the experiment: to evaluate the functionality of non-contact instruments under conditions that resemble everyday interpersonal communication. While this format was cognitively demanding, it likely did not elicit the differential arousal or stress necessary to trigger measurable autonomic responses. In this vein, it is important to remember that participants are safe in a laboratory, therefore they experience so-called cooled, attenuated or cognitive emotions, but not real emotions (Moliné et al., 2018), which probably rules out differences between these conditions.

Interestingly, although there was no significant interaction in the overall analysis of ROI × all conditions, an exploratory focus on the nasal region revealed a consistent decrease in its temperature under all conditions compared to baseline. This is consistent with previous findings on nasal sensitivity linking nasal cooling with increased emotional arousal (Diaz-Piedra et al., 2019; Kosonogov et al., 2017; Or & Duffy, 2007; Pavlidis et al., 2012) and high cognitive or emotional load (Bonyad et al., 2024; Or & Duffy, 2007; Pavlidis et al., 2012). However, this response appeared uniform across both rehearsed and spontaneous conditions, suggesting that the task was inherently demanding but had no condition-specific effects. Further evidence is that only a subset of participants with strong physiological reactivity showed a marginal trend towards lower nasal temperature during spontaneous lying. This demonstrates the importance of accounting for individual differences in thermal reactivity (Ebisch et al., 2012).

10.1.2. Heart rate

The current study also investigated the role of raw heart rate as a physiological indicator of deception using rPPG through the FaceReader software. We used raw heart rate as a secondary physiological variable and for descriptive purposes.

The effect of deception

We observed significantly higher heart rates under deceptive conditions compared to honest conditions, which is consistent with existing research on the physiological basis of deception. From a cognitive-affective perspective, deception simultaneously activates several processes, such as the inhibition of truthful responses, the construction of alternative narratives, and IM (Vrij, Fisher, et al., 2008). It is known that each of these processes increases autonomic arousal and thus increases cardiovascular responses.

In addition, heart rate and its fluctuations are closely linked to the interplay of sympathetic and parasympathetic nervous system activity (Appelhans & Luecken, 2006; Berntson et al., 2017; Lane et al., 2009; Luque-Casado et al., 2016; Somsen et al., 2004; Thayer et al., 2012; Wu et al., 2019). Since deception alters autonomic reactions, the observed increases in heart rate are likely due to increased sympathetic nervous system activation, decreased parasympathetic nervous system activity, or both. This physiological pattern underscores the body's heightened state of arousal during the deceptive behaviour.

The effect of rehearsal and the interaction effect

Contrary to our second hypothesis, the analysis revealed no significant difference in heart rate between rehearsed and spontaneous responses. This finding stands in contrast to previous literature suggesting that spontaneous responses are associated with greater physiological activity (DePaulo et al., 1983; Ganis & Keenan, 2009). As with the fITI results, we attribute this to the low-stakes nature of the laboratory setting, which may have attenuated the physiological differences observed in more emotionally charged or high-stakes contexts.

Beyond the low-stakes scenarios, there is another explanation for the non-existent differences between rehearsed and spontaneous responses. Planning is only effective

when liars accurately anticipate the questions they will be asked (Paige et al., 2022). In the present study, participants only knew a few of the questions they would be asked, the rest were spontaneous, which may have led to varying degrees of discomfort depending on how well each individual is able to handle unpredictable questions. Therefore, some participants may have been mentally preoccupied with maintaining their deceptive role in the rehearsed response, leading to further cognitive load (Vrij et al., 2011) and eliminating the differences between rehearsed and spontaneous scenarios.

Interestingly, heart rate was elevated for both the rehearsed lies and the rehearsed truths compared to small talk, suggesting that the act of performing any narrative – regardless of its truthfulness – can cause activation of the sympathetic nervous system. A plausible explanation for the general increase in heart rate is that it reflects not only the arousal specifically associated with the deception, but also a more general physiological response to the complexity of the task and the attentional demands (Andreassi, 2010). Under all experimental conditions – whether truthful or deceptive responses were involved – participants had to recall and articulate detailed narratives, self-monitor and maintain coherence, while being observed. It is known that the laboratory environment itself may have contributed to increased sympathetic activation. As suggested by the social evaluation threat model (Dickerson & Kemeny, 2004), observation and evaluation – even without explicit consequences – can trigger a stress response due to perceived social evaluation. We argue that this is the reason why the heart rate was higher in all experimental tasks than in small talk, which involved familiar, neutral and, above all, non-evaluated interactions. Thus, the physiological increase observed in all conditions may have reflected a combination of deception-induced arousal, cognitive demands, and the general social stress of participating in an evaluative experimental context.

10.1.3. Attachment avoidance as a moderator of physiological responses to deception

To further explore individual differences that might influence physiological responses during deception, we examined the moderating role of attachment avoidance on facial temperature and heart rate.

A consistent trend emerged suggesting that higher attachment avoidance was associated with increased facial temperature, particularly in the nose and cheeks. Although the interaction between attachment avoidance and condition was not statistically significant in the thermal data, we found a significant main effect of avoidance on heart rate in all conditions. This pattern is consistent with previous research indicating that individuals with avoidant attachment styles often show increased physiological arousal under stress despite their outward emotional restraint (Diamond et al., 2006; Dias et al., 2011; Mikulincer, 1998). While our behavioural data showed no clear evidence of emotional suppression, the increased autonomic activity may reflect the internal costs of secondary regulation strategies typically employed by avoidant individuals, such as suppressing or downregulating emotional experiences to maintain distance and self-control (Frías et al., 2014; Holmberg et al., 2011; Mikulincer & Shaver, 2019; Pascuzzo et al., 2013; Shallcross et al., 2014). While these strategies can limit overt behavioural cues, they often represent a cognitive and physiological burden, particularly in socially demanding situations (Diamond et al., 2006; Dias et al., 2011; Vrtička et al., 2012). The increased autonomic activity observed in our study may have therefore reflected the internal costs of maintaining these regulatory efforts.

Even though the pairwise comparisons of facial temperature and heart rate between high and low levels of avoidance did not remain statistically significant after Bonferroni corrections, the observed patterns may suggest that avoidant individuals experience arousal as a general, trait-like response – regardless of whether their truth or lie is rehearsed or spontaneous.

10.2. Discussion of behavioural results

10.2.1. Emotional valence and emotional arousal

In this modality, we aimed to investigate whether emotional arousal and emotional valence can serve as significant cues to deception and whether their intensity is moderated by attachment avoidance. The decision to use these dimensions was based on the assumption that they provide a more flexible and nuanced representation of emotion than macro-expressions (Posner et al., 2005). In contrast to several theoretical predictions based on classical deception models such as leakage theory (Ekman & Friesen, 1969), four-factor

theory (Zuckerman et al., 1981), strategic models (Hilgendorf & Irving, 1981; Vrij et al., 2019) or self-presentation theories (DePaulo, 1992), the analysis provided only limited evidence for an emotional differentiation between lies and truths, but showed robust effects of rehearsal across the dimensions of valence and arousal.

Valence and effect of deception

Contrary to our expectations, no significant differences were found between deceptive and truthful responses. Based on leakage theory, we hypothesised that deception would be accompanied by subtle emotional cues – such as fear or guilt (Ekman, 2009) which are generally associated with lower (i.e., more negative) valence. Although FaceReader data included subtle negative valence values, these were not significantly linked to deception, suggesting that emotional leakage was either too weak or effectively regulated by participants. This finding aligns with critiques of leakage theory and supports interactional perspectives such as self-presentation theory (DePaulo, 1992), which assumes that everyone – regardless of whether they are deceptive – uses self-presentation strategies to appear in a better light. Furthermore, since both liars and truth-tellers share the common goal of appearing truthful (Vrij et al., 2019), both groups may have consciously managed and controlled their emotional expressions, thus further reducing observable differences between deceptive and truthful behaviours.

Valence, the rehearsal effect and the interaction effect

Interestingly, our results showed that – contrary to the initial hypothesis – during spontaneous responses, the valence was significantly higher (i.e., more positive) than during the rehearsed responses, regardless of deception.

From a cognitive load theory perspective (Vrij, Fisher, et al., 2008, 2017), rehearsed responses are expected to be less cognitively demanding than spontaneous responses, which is consistent with the assumption that people typically prepare for the anticipated interview (Schudlik et al., 2021), which may lead to a reduction in cognitive load (Hartwig et al., 2007; Vrij et al., 2009; Vrij, Fisher, et al., 2017). However, this cognitive advantage may paradoxically cost the emotional engagement in the interaction. In particular, when participants aimed to maintain consistency, avoid overacting, and suppress emotional signals that might appear suspicious – regardless of whether they

were truthful or deceptive – these strategic efforts may have muted affective expression. We argue that such regulation likely resulted in reduced affect intensity during rehearsed responses compared to spontaneous ones.

Moreover, our results are consistent with a broader perspective on the production of facial expressions. Spontaneously expressed emotional expressions are usually involuntary and closely related to a person's genuine affective state, whereas deliberately posed expressions reflect the sender's communicative intention rather than their inner emotion (Zloteanu et al., 2021). These posed expressions are often shaped by social norms or goals of self-presentation, such as compliance, IM or deception, and are usually less emotionally authentic or intense (Ekman & Rosenberg, 2005). Zloteanu et al. (2021) provide further empirical evidence for this distinction by showing that intentionally generated expressions – whether through internal simulation (memory of affect) or external mimicry (imitation of facial configurations) – can achieve superficial plausibility without reflecting the underlying affect. Their research shows that even trained participants who attempted to mimic a genuine-looking facial expression had difficulty conveying emotional authenticity, especially when relying on their internal memory. Therefore, we argue that the overall reduction in affective intensity observed in our study during rehearsed responses is likely due to participants' reliance on controlled, deliberately constructed expressions rather than spontaneously felt emotions.

Arousal and effect of deception

Contrary to our initial expectations, no significant differences in emotional arousal across deceptive and truthful conditions were observed. One possible explanation lies in the strategic suppression of emotional expression. As our valence data suggest, participants actively suppressed or attenuated their facial expressions during the task, then this suppression may also have attenuated the expressive components associated with arousal. This interpretation is consistent with the concept of self-presentation (DePaulo, 1992), which assumes that people – regardless of their veracity – strategically regulate their expressive behaviour in socially evaluative contexts in order to appear calm, composed and credible. Such IM efforts can lead to the deliberate dampening of both overtly displayed emotions and facially expressed arousal.

Based on four-factor theory (Zuckerman et al., 1981), emotional arousal is typically expected when individuals experience inner conflict, fear of detection, or guilt when deceiving. However, arousal does not only occur when lying. People who tell the truth can also experience heightened arousal when they are scrutinised, especially if they fear that they will not be believed or that they will be falsely accused. This reflects the well-known false-positive dilemma in polygraph research – the non-specificity of arousal responses to deception (Ben-Shakhar & Elaad, 2003).

Furthermore, the non-significant differences between deception and truth-telling in emotional arousal may have been caused by the methodological design of our study. The semi-structured, low-stakes experimental context likely contributed to participants' sense of control and emotional distance from the consequences of their responses. The intensity of fear, anxiety or guilt, which are thought to be associated with deception (Ekman, 2009), was therefore either not present or not strong enough to manifest in observable emotional arousal.

Arousal, the effect of rehearsal and the interaction effect

Similar to valence, the level of arousal was significantly higher in spontaneous responses than in rehearsed responses. As already mentioned, the increased cognitive effort in cognitively demanding tasks (such as spontaneous responses) leads to increased activation, which is reflected in an increased level of arousal. Rehearsed responses, on the other hand, enabled participants to plan and pre-structure their content, thereby reducing the immediate cognitive demands (Vrij et al., 2009; Vrij, Mann, et al., 2008). The current results confirm that this cognitive simplification during rehearsal correlates with a reduction in emotional arousal.

Crucially, the consistent reduction of arousal in rehearsed responses supports the notion that rehearsal functions not only as a cognitive tool, but also as a form of emotional regulation. Similar to expressive suppression (Gross & John, 2003), rehearsal may help individuals to mute both the external display and physiological intensity of their emotional responses, resulting in a more composed but less emotional performance. This is particularly important in social evaluation contexts where people expect to be

judged and therefore strategically downregulate their arousal in order to appear calm and credible (DePaulo, 1992; Ekman & Rosenberg, 2005).

Interestingly, the highest arousal levels were measured during the small talk condition, which preceded the main interview and served as a baseline. This result could be due to anticipatory arousal, as the participants did not know what would happen next and were aroused by the laboratory situation per se. This is consistent with the findings of interpersonal deception theory (Buller & Burgoon, 1996), which posits that the dynamics of deception unfold within a larger social and interactive system in which anticipation, self-presentation and uncertainty can influence physiological and behavioural responses. It also highlights the importance of using appropriate baselines in psychophysiological and behavioural studies of deception (Ioannou, Morris, et al., 2014) – because neutral social engagement is not always affectively neutral.

Taken together, these results emphasise that arousal and valence are better understood as a function of task spontaneity, cognitive effort and emotional self-regulation than as a direct index of deception. The observed differences between rehearsed and spontaneous conditions emphasise the importance of considering the temporal and cognitive structure of responses rather than focusing solely on their content. From a methodological perspective, this emphasises the value of including rehearsal as a factor in research designs on deception and supports a move away from simplistic lie–truth dichotomies towards a more nuanced experimental design that reflects different conditions.

Attachment avoidance as a moderator of valence and arousal

Contrary to theoretical expectations, our results showed neither a significant interaction between attachment avoidance and emotional arousal and valence, nor a main effect of avoidance in all experimental conditions. One possible explanation for this is that the low-stakes laboratory setting combined with the structured and predictable nature of the interview limited participants' emotional engagement in general, thus reducing the variability required to detect such effects. In this context, it is important to consider that participants were aware that they were in a safe and controlled environment, which likely led them to experience what Moliné et al. (2018) describe as 'cooled',” attenuated,

or cognitively processed emotions rather than genuine affective reactions. This emotional dampening may have further masked potential differences in facial expressions between conditions and attachment avoidance.

Avoidantly attached individuals rely on deactivating strategies resulting in emotion suppression (Frías et al., 2014; Holmberg et al., 2011; Mikulincer & Shaver, 2019; Pascuzzo et al., 2013; Shallcross et al., 2014). With this in mind, we argue that our findings may not reflect the absence of emotional engagement per se, rather, they likely reflect the effectiveness of these individuals' suppression or masking strategies in relation to facially expressed affective responses.

Although no explicit associations between attachment avoidance and overt facial expressions of valence or arousal were found in the current study, such null findings can still be reasonably interpreted within the framework of attachment theory. Rather than indicating a genuine lack of emotional or physiological activation, these findings are likely indicative of the ability of individuals with avoidance behaviours to control and suppress external emotional expressions – a proposition supported by the aforementioned findings in relation to more subtle physiological indices such as changes in facial temperature and heart rate variability.

10.2.2. Eye fixations

The aim of the eye-tracking part of this study was to investigate whether gaze behaviour changes can serve as significant cues to deception and whether their duration is moderated by attachment avoidance.

The effects of deception, rehearsal and interaction

Regarding the detection deception by gaze behaviour, no significant differences were found in fixations on the upper face (eye region) or background between the deception, truth and small talk conditions. The most stable finding across all conditions was the significant main effect of the ROI. Participants spent significantly more time fixating the lower face (mouth and jaw area) than the upper face (eyes/forehead) or background. This pattern is consistent with existing research suggesting that the mouth plays a key role in social interaction and speech perception. For example, fixation on the mouth may help

listeners to anticipate verbal content, as it is the main source of visual speech information (Buchan et al., 2008; Paré et al., 2003; Rosenblum et al., 2007). In addition, the lower half of the face often provides emotionally neutral information, such as lip movement or articulation, which is less emotionally charged than eye contact, making it a favoured focus point in socially controlled or formal interactions (Itier & Batty, 2009).

While there was a significant main effect of ROI showing that participants fixated more on the lower face overall than on the upper face or background, this pattern did not differ significantly between the deception and non-deception conditions. These findings do not support previous assumptions that liars increase eye contact to appear credible (Griffin & Oppenheimer, 2006; Hypšová et al., 2024) or to observe the interlocutor's reactions (Schweitzer et al., 2002) nor the stereotypical assumptions that liars avoid eye contact with the interlocutor (Vrij, Akehurst, et al., 2006). A possible explanation for the lack of gaze-related deception cues could be individual variability in gaze behaviour. Social behaviour, including eye contact, varies greatly from person to person due to factors such as personality (Vehlen et al., 2024), cultural norms (McCarthy et al., 2006), and social anxiety (Chen et al., 2020). This variability could obscure the effects associated with deception, especially in a socially dynamic context. Furthermore, the use of a real, dynamic interviewer in this study, while improving ecological validity, may have constrained participants' gaze behaviour through implicit social norms such as politeness or maintaining appropriate eye contact (Hessels et al., 2018; Holleman et al., 2020).

In addition, the interviewer's affective demeanour may have also played a role in shaping participants' gaze patterns. Emotional expressions influence the allocation of attention: the mouth often receives more attention when positive expressions such as joy are perceived, while the eyes may be more prominent in the context of negative emotions such as sadness or anger (Beaudry et al., 2014; Calvo et al., 2018; Green et al., 2003; Hunnius et al., 2011). Because the interviewer in the present study appeared generally neutral or positive, participants may have naturally focussed more on the mouth region. Conversely, less expressive affect may have reduced this effect, contributing to the lack of differentiation between conditions. These findings highlight the complexity of affective and interpersonal dynamics in modulating gaze behaviour during interaction (Vehlen et al., 2024).

Attachment avoidance as a moderator of eye fixations

The current results partially support our hypothesis regarding the moderating role of attachment-related avoidance on gaze behaviour. While the main effect of avoidance was not significant, we found a robust ROI × ECR-AVO interaction, suggesting that individuals with higher levels of attachment avoidance systematically adjusted their gaze depending on the region of the face. Specifically, higher avoidance was associated with significantly decreased fixation on the lower face (mouth/jaw region) and increased fixation on the background regardless of condition. This pattern supports the idea that avoidantly attached individuals selectively disengage from emotionally rich or interpersonally meaningful cues (Clear et al., 2020; Mikulincer & Shaver, 2007; Uccula et al., 2022).

Interestingly, the fixations on the upper face also increased the higher the avoidance, which is probably not a sign of deeper social connection or emotional attunement. Rather, we interpret this as a strategic scanning pattern aimed at observing the interlocutor's facial reactions while maintaining emotional distance. This behaviour is consistent with the vigilance-avoidance hypothesis, which states that avoidant individuals initially show increased attention to potential social threats (e.g., facial expressions) but then withdraw to regulate their emotional arousal (Gu et al., 2023).

In addition, further research shows that avoidant individuals have difficulty processing emotional facial expressions and often focus on less emotionally salient areas of the face (Clear et al., 2020; Mikulincer & Shaver, 2007; Uccula et al., 2022). This behaviour supports the assumption that the increased fixation on the upper half of the face is a strategy to monitor reactions without engaging in emotional processing (Török-Suri et al., 2025).

Although the background fixation moderation was not statistically significant, we still observed positive correlations between background fixation and avoidance in several specific conditions (rehearsed truth, spontaneous lie, small talk). These patterns suggest a complementary interpretation: background fixation may serve as a form of visual distraction or "perceptual escape" for avoidant individuals. As the background is emotionally neutral and socially irrelevant, averting gaze from the face may allow avoidant

individuals to regulate internal arousal and reduce exposure to emotionally distressing cues – consistent with previous findings on gaze avoidance during cognitive and emotional distress (Servais et al., 2023).

Importantly, however, we found that this effect was not modulated by condition – suggesting a trait-like consistency of gaze aversion that exists regardless of whether the individual is lying, telling the truth, or engaging in small talk. According to our findings, the gaze patterns of avoidant individuals – characterised by reduced attention to emotionally expressive areas such as the mouth – may have reflected an underlying motivation to suppress engagement with emotionally revealing cues. This is particularly notable in the context of deception, where emotional expression and interpersonal IM are of central importance. It appears that attachment-related avoidance not only determines the direction of visual attention, but also does so in a way that is relatively stable across interpersonal situations. This supports theoretical perspectives that view attachment as a deactivating emotion regulation strategy, with avoidant individuals showing deactivating patterns even when strategic interpersonal monitoring would be beneficial (Mikulincer & Shaver, 2019).

10.3. Contributions of this study

This study makes a significant contribution to the field of non-contact deception detection. As far as we know, it is one of the first experiments to use eye tracking, fITI, FaceReader software and rPPG in a within-subject experimental design focussing on deception during socially interactive conversations in a controlled laboratory environment. It is noteworthy that all technologies used are non-invasive. They represent a complementary alternative to traditional contact-based techniques such as polygraphy, which are known to increase participants' anxiety and reduce the naturalness of social interaction (Derakhshan et al., 2020).

A key strength of this study lies in its withdrawal from highly controlled, emotionally charged paradigms of deception, such as mock crimes, frequently used in previous research (e.g., Abouelenien et al., 2019; Derakhshan et al., 2020; Pavlidis & Levine, 2002; Pollina et al., 2006; Proudfoot et al., 2016; Satpathi et al., 2024; Speth et al., 2021; Tsiamyrtzis et al., 2007). Instead, a low-stakes, conversational situation in a laboratory

setting was intentionally chosen to reflect everyday interpersonal interactions. Although this design did not provide significant physiological or behavioural indicators that distinguish deception from truth-telling, this null result itself is an important contribution. It emphasises that deception under naturalistic, low-stakes conditions, which better correspond to everyday social exchanges, may not elicit particular signs. This calls into question the generalisability of previous results obtained under artificially induced emotional stress. By focusing on conversational realism, a transparent methodology, and a within-subjects design, this study provides a more ecologically valid basis for future studies aimed at identifying cues that are both replicable and relevant outside the laboratory. The absence of deception markers under these conditions is not a limitation, but emphasises the need not to overestimate the effectiveness of current detection technologies under realistic conditions.

Another contribution of this study is the use of a real, dynamic interviewer who introduced natural interpersonal variability into the interaction. While this variability may have influenced participants' behaviour and physiological responses, it also reflected the complex social dynamics in which deceptions typically occurs. In contrast to screen-based or scripted paradigms, live interviews allow for the study of deception in an environment where emotional synchrony, rapport, and mutual responsiveness may have played an important role. Recent research by Solbu et al. (2024) suggests that the context of the situation, such as the synchrony of emotional expressions between interviewer and interviewee, can influence the reactions associated with deception and enhance deception detection itself. In deception, negative emotions (fear, contempt, disgust, anger, sadness) tend to be more pronounced when they do not match the verbal content, especially under conditions of high synchrony between interviewer and interviewee. This suggests that the interpersonal dynamics of the interaction – rather than deception alone – may have played an important role in emotional expression (Solbu et al., 2024). Given the growing evidence that synchronised emotional expressions can facilitate rapport and alter the interviewee's emotional state (Dianiska et al., 2021; Dunbar et al., 2020, 2023; Novotny et al., 2021; Sharma et al., 2021; Solbu et al., 2024), future studies should investigate whether synchrony also influences behavioural and physiological markers of deception. This would not only advance research on deception detection,

but also contribute to the growing body of work investigating the influence of interviewer behaviour on participant responses (Dianiska et al., 2021; Dunbar et al., 2020, 2023; Solbu et al., 2024).

The within-person design allowed for control of interindividual variability and provided large primary data sets across multiple conditions: rehearsed truth, rehearsed lie, spontaneous truth, spontaneous lie, and small talk. By including spontaneous and rehearsed scenarios in the truth and deception conditions, the study also provided an explanation for the influence of cognitive load and mental effort. In addition, the inclusion of attachment avoidance as a moderator variable provided insights into the trait-like regulatory patterns that might influence gaze, physiology and emotional expression.

The study also included practical contribution such as the development of a semi-automatic framework for pre-processing of infrared thermal data, which opens a space for further evaluation and use in future experiments not only in deception detection but in thermal human research in general. Although our framework does not currently enable real-time classification of truth or deception, we have identified this as an important future direction. Automating ROI extraction through machine learning – such as adapting for example Viola-Jones algorithms (Viola & Jones, 2004) for fITI – could improve reproducibility and support real-world applications.

In addition to its empirical contributions, this thesis provides a comprehensive and structured theoretical basis. The theoretical part draws on more than 580 academic sources and provides an in-depth exploration of deception detection from different disciplinary perspectives. It systematically maps the landscape of current research and highlights emerging trends and key concepts in non-invasive physiological and behavioural approaches to deception detection. The synthesis of historical, philosophical, psychological and methodological perspectives not only contextualises the empirical studies, but also deepens the broader understanding of how deception is conceptualised, studied and ethically addressed in social science.

Last but not least, this work makes a scientific contribution by opening up new ways for interdisciplinary research on deception detection. By combining methods from

psychology, psychophysiology and computer science, the research demonstrates the value of integrating technological innovation with psychological theory. It also challenges the traditional focus on isolated deception cues by promoting a more holistic, context-sensitive understanding of deception and truth telling. The non-invasive framework presented here lays the foundation for future studies investigating not only deception but also related phenomena such as emotion regulation, IM, or stress in social evaluation. Furthermore, the inclusion of individual difference variables – such as attachment avoidance – encourages a step towards personalised models of deception that could be further evaluated and described.

10.4. Limitations and future research

Despite significant contributions, several methodological, technological and contextual limitations must be recognised, as well as clear directions for future research that emerge both from this thesis and from our previous publications.

Spontaneous condition design

Before the experimental task, the participants were asked to fulfil a mission: They were to walk through a predetermined location in the city of Olomouc with the help of a paper map (they could also use their phones). This task served two main purposes. Firstly, it was to ensure that the participants could recall a specific, personal experience during the interview to ensure the veracity of their statements. By embedding participants in a current, self-directed activity, we minimised the risk of contrived or vague truthful responses – a potential problem in experimental designs where participants may forget or invent details due to lack of personal involvement. However, this design may have introduced an additional source of increased cognitive load, especially in truth-telling condition – particularly for participants who do not live in Olomouc and are therefore completely unfamiliar with the city. Research shows that the retrieval of autobiographical memory is a cognitively demanding task, especially when it comes to the detailed reconstruction of temporally and spatially rich experiences (Cabeza & St Jacques, 2007). When the remembered environment is unfamiliar, such retrieval may draw on additional executive resources for orientation and place recognition (Burgess et al., 2002; Epstein et al., 2007), which could lead to increased mental effort when individuals are asked

to report their activities in a coherent narrative under observation. Furthermore, we argue that this would not only increase cognitive load under honest, spontaneous conditions, but also the fear of not being believed and of being falsely accused of deception (Hypšová et al., in review). This is in line with research findings on polygraphs, which show that innocent people can show stronger physiological responses under cognitive pressure or fear of being falsely accused of deception (Ben-Shakhar, 2008). Thus, the spontaneous truth condition may have induced a cognitive profile similar to that of deception and impaired our ability to discriminate between truth and deception based on physiological or behavioural cues.

To address this problem, future studies should integrate techniques that have been shown to support narrative coherence and reduce cognitive load. For example, the work of Deeb et al. (2021, 2022, 2024) on sketching during narration has shown that asking participants to draw their experiences as they speak can improve recall and provide additional cues for detecting deception. Incorporating these techniques could help to increase the asymmetry in cognitive load between truth-telling and lying, especially under challenging conditions. In addition, future studies could systematically manipulate the familiarity of the environment – e.g., by comparing narratives from familiar and unfamiliar environments – to better isolate the effect of contextual knowledge on physiological and behavioural cues to deception.

Emotional valence and arousal metrics

While the use of emotional valence and arousal data helped us to overcome the limitations of using only macro-expressions (Posner et al., 2005), it still posed a methodological challenge. While emotional valence and arousal measures are useful for tracking overall affective state, they may lack the temporal and structural detail required to detect momentary micro-leakages or emotionally inconsistent expressions that may be associated with deception. A possible solution could lie in analysing specific combinations of facial AUs. Rather than mapping AUs solely to basic emotions – a common approach in deception detection studies (Avola et al., 2019; Carissimi et al., 2018; Jaiswal et al., 2016; Mathur & Matarić, 2020; Monaro et al., 2022), researchers should consider identifying individual AU configurations that are uniquely characteristic of deceptive behaviour.

Empirical findings suggest that certain AUs (e.g., AU5, AU6, AU7, AU10, AU12, AU14, AU23, AU28) are particularly relevant in this context, especially when considering activation patterns, asymmetry and duration (for more details and an overview, see Chapter 4.2.2. of this thesis). Such AU-level analysis could significantly improve the sensitivity of deception detection systems, particularly when combined with the temporal tracking of micro-expressions and their matching with cognitive load or emotional arousal. However, these benefits depend on well-designed training datasets. As Delmas et al. (2024) note, many existing classifiers are trained on limited or secondary datasets that vary in their quality and labelling accuracy – particularly when deception is operationalised by court judgements or polygraph classifications. This poses a challenge to the generalisability and reliability of AU-based deception classifiers.

Moreover, the majority of existing research employing AUs has been conducted in the field of computer science and engineering, often without considering further psychological theories (see Delmas et al., 2024 for a detailed systematic review). To address this problem, greater interdisciplinary collaboration between psychology, psychophysiology and computer science is needed. Psychologists can provide the theoretical framework and experimental paradigms necessary to put machine learning models on a solid behavioural science foundation, while computer scientists can contribute the computational tools to extract and model complex facial dynamics. Bridging these areas is critical not only to improve the accuracy of algorithms, but also to ensure that automated deception detection tools are valid, explainable and applicable across different contexts and populations. By presenting original datasets containing different types of lies and truths, we aim to contribute to addressing this gap in future research. Our aim is to promote closer integration between psychological theory, computer science and biomedical engineering to improve both the scientific validity and practical applicability of automated deception detection systems.

Heart rate metrics and its acquisition

Our heart rate analysis was based solely on raw heart rate, which, while useful as a general indicator of autonomic activity, lacks the sensitivity of HRV (Berntson et al., 2017; Shaffer & Ginsberg, 2017). HRV reflects the variability of time intervals between heartbeats

and allows researchers to distinguish between sympathetic and parasympathetic activations – something that is not possible with heart rate alone. As described in the literature, specific HRV metrics (e.g. RMSSD, HF-HRV) are more sensitive to affective and cognitive changes and are particularly valuable in tasks involving deception, stress or emotional regulation (Appelhans & Luecken, 2006; Gillie et al., 2014; Paige et al., 2022). Accordingly, we interpret the current heart rate results as descriptive and complementary to other physiological and behavioural indicators in the context of our non-invasive approach towards deception detection.

In terms of data acquisition, heart rate was measured using rPPG – a technique currently gaining momentum in deception detection research (Li et al., 2024; Speth et al., 2021; Vance et al., 2022). While rPPG offers important advantages in terms of comfort and non-contact (Xiao et al., 2024), it is also more susceptible to measurement noise, including motion artefacts, lighting variations and resolution limitations (Benedetto et al., 2019). Although we carefully controlled for these factors – ensuring consistent lighting, minimising participant movement and using validated equipment – rPPG still has several sensitivity limitations compared to traditional contact-based methods. Therefore, we strongly recommend combining other physiological measures – such as ECG or high-resolution PPG – for comparison with the calculation of HRV in follow-up studies to more accurately identify cardiovascular patterns associated with deception.

Previous studies using concealed information paradigms have described a characteristic biphasic heart rate pattern during deception: an initial acceleration phase due to increased vigilance and cognitive load, followed by a deceleration phase associated with attentional activity and evaluative processing (Gamer, 2010; Gamer et al., 2006, 2008; Verschuere, Crombez, De Clercq, et al., 2004; Verschuere, Crombez, & Koster, 2004; Verschuere et al., 2009). While this established pattern underlines the relevance of detailed temporal analyses of cardiovascular data, such an approach was not explicitly pursued in the current study. In particular, the heart rate curves were not subjected to detailed temporal or curve-based analyses. This limitation restricted our ability to draw definitive conclusions about the precise physiological dynamics involved in the deceptive responses observed in our participants. In subsequent studies, we plan to use advanced analytical techniques such as curve fitting or time series analyses to further investigate the nuanced

cardiovascular responses associated with deception and thus expand our understanding of the underlying cognitive and emotional processes.

Eye-fixations metrics

The eye-tracking findings opened up several important directions for future research. First, since gaze behaviour appears to be modulated by stable interpersonal and situational characteristics rather than by the veracity or spontaneity of responses, future studies should consider the inclusion of individual differences as a central rather than a peripheral element in experimental design. For example, grouping participants by attachment style could reveal interaction effects that remain hidden in aggregated analyses.

In addition to traditional grouping based on questionnaire cut-offs, data-driven techniques such as cluster analysis, latent profile analysis or person-centred modelling approaches could help to uncover hidden subgroups with different gaze behaviour patterns. For example, these approaches could identify participants who combine high levels of avoidance with high levels of cognitive control, or those who show a dissociation between emotional arousal and visual engagement – providing a more detailed understanding of how different regulatory styles manifest themselves during interpersonal communication and deception.

The consistent gaze behaviour under different conditions suggests that deception-related cues may not be detectable in static gaze metrics alone. Instead, researchers should consider analysing gaze dynamics over time, such as gaze transitions between ROIs, saccade patterns, or sequential shifts in attention. These time-sensitive features could be for example investigated using deep learning architectures (e.g., LSTM networks), which are able to capture the temporal evolution of gaze behaviour and potentially reveal subtle changes related to deception that are overlooked in average fixations.

Future research should also investigate other metrics in the eye of the participant. Given the growing evidence linking pupil dynamics to cognitive and emotional states, future research should also investigate pupillometry as a promising way for deception detection. Pupil diameter has been shown to reliably reflect stress (Alshanskaia et al., 2024;

Alshanskaia & Martynova, 2023; Sabatino DiCriscio et al., 2018; Simonovic et al., 2018), arousal (Bradley et al., 2008; Kinner et al., 2017; Partala & Surakka, 2003; Sabatino DiCriscio et al., 2018; Unsworth & Robison, 2015), cognitive load and mental effort (Ahmad et al., 2023; Franzen et al., 2022; He et al., 2012; Krejtz et al., 2018; Menekse Dalveren & Cagiltay, 2018; Prabhakar et al., 2020; Ruiz Puentes et al., 2023; Wu et al., 2022; Yoo et al., 2021) – all of which are associated with deception. Indeed, several studies using polygraph-like paradigms have found that pupil dilation increases in guilty individuals when exposed to crime-relevant stimuli or while attempting to conceal information (Hochman et al., 2016; Proudfoot et al., 2015, 2016; Trifiletti et al., 2020). In addition, the use of machine learning to analyse eye-tracking and pupil data has shown high classification accuracy (Gallardo-Antolín & Montero, 2021), suggesting that the integration of pupillometry within non-invasive deception detection frameworks could significantly improve predictive performance.

Data extraction

The manual extraction of areas of interest for eye-tracking analysis in Tobii Pro Lab may have introduced additional bias into the data obtained. In contrast to frame-locked ROIs in static image paradigms, this method introduced observer variability as each ROI is manually placed within thousands of frames per eye-tracking video. To address this limitation, future research should aim to implement machine learning or deep learning approaches for automatic ROI recognition that would enable more consistent, frame-by-frame mapping of facial regions in dynamic interview situations. This would not only reduce human error, but also increase the reproducibility and scalability of gaze-based deception research. A similar advance has already been implemented in our fITI framework, where facial features were automatically recognised and tracked. Extending this automated approach to eye-tracking analysis would significantly improve both the accuracy and efficiency of processing data collected during natural, socially complex interactions.

An alternative, particularly for contexts where access to advanced computing tools or programming skills is limited, would be to engage at least two independent coders to manually identify and track ROIs within the existing eye-tracking software. Inter-rater

reliability could then be calculated to assess the consistency of coding. Whilst this method would not improve the quality of data extraction per se, it could strengthen the reliability and validity of the analysis, thereby increasing the overall robustness of the results.

Statistical analyses

Last but not least, given the non-significant results in most of used modalities during honest and deceptive responding and the discrepancy between our statistical analysis approach in comparison with existing studies we propose the following directions for future research. Firstly, we would like to compare different statistical techniques – including repeated measures ANOVA, linear mixed-effects models, and both linear and non-linear mixed models – to examine how methodological choices affect both the results and their interpretation within deception research.

Moreover, the application of signal detection theory (SDT) within the framework of a generalised linear mixed model would be a further step towards improving the statistical approach to deception detection, as it could highlight the statistical ability to distinguish response bias from true discriminability (Zloteanu & Vuorre, 2024). Based on the guidance of Zloteanu and Vuorre (2024), the SDT GLMM framework simplifies the analysis of deception detection by avoiding fragmented procedures and data transformations required by traditional methods. It models both participant and item variability in a single step, resulting in more accurate and realistic effect estimates. Especially in complex experimental designs, this approach reduces bias, preserves information and improves the reliability of conclusions – addressing the main limitations of traditional analyses in deception research (Zloteanu & Vuorre, 2024).

10.5. Practical implications

The results presented in this thesis have practical implications for various fields, including forensics, personnel selection, security screenings and occupational safety. Although the technologies tested have not been shown to be reliable stand-alone tools for detecting deception, the research offers important insights into how these technologies could be used to support wider assessment processes.

In forensic contexts, for example, the possibility to measure physiological and behavioural responses unobtrusively during an interrogation could complement current investigative procedures without creating additional psychological pressure, such as by attaching electrodes or other devices directly to the person's skin. While these methods should not be used to directly detect deception, they could help identify moments of heightened cognitive load, emotional regulation or behavioural control – information that could help guide further questioning.

In human resources, the non-invasive approach could serve as an additional tool in high-stakes interviews where truthfulness and consistency of answers are crucial. Although ethical constraints still need to be carefully considered, the possibility to detect signs of cognitive stress or information distortion, could provide additional insight into an applicant's behavioural profile, especially when evaluated alongside standard psychological assessments. Similarly, this approach could help interviewers working on insurance investigations, particularly in cases involving workplace incidents, such as when an employee reports an injury or files a claim under unclear circumstances. The possibility to assess behavioural and physiological indicators in such interviews could help identify inconsistencies or signs of exaggerated or fabricated accounts, providing insurers with additional information when determining the validity of a claim.

In addition, the non-invasive nature of this framework could open up new possibilities for border controls and security checks. In particular, the integration of behavioural analysis – such as gaze patterns – into existing security systems could help to identify incongruent or atypical behaviour that requires further attention. While further development and validation is needed, especially for real-time applications, this approach could increase efficiency by reducing the need for invasive procedures or staff labour.

From a technological point of view, the customised software frameworks developed as part of this work represent an important contribution to this area. These frameworks improve the quality and reproducibility of thermal data and thus close an important gap in thermal psychophysiology. By offering a reproducible, customisable solution, we promote open scientific practises and provide a valuable resource for interdisciplinary research that goes beyond the field of deception.

In summary, this thesis contributes to both theory and practise by demonstrating that deception is a complex, multidimensional phenomenon that cannot be captured by single physiological or behavioural cues. Instead, it must be understood in the broader context of individual differences, cognitive demands and social dynamics.

11 CONCLUSION

Deception is a multifaceted phenomenon, shaped not only by individual intentions and characteristics, but also by contextual and cognitive demands that generally encompass human communication with lower or higher needs for its detection. Therefore, detection deception remains a methodological and conceptual challenge in both psychological research and practise. The present thesis addresses several of these challenges by proposing a non-invasive approach to deception detection using fITI, facial expression analysis, rPPG, and eye-tracking, while also considering the role of cognitive load and individual differences in attachment avoidance. Thorough conduction of one case study, two pilot studies and a final main study, this thesis systematically investigated deception detection in various spontaneous and rehearsed scenarios with the aim of contributing both empirically and methodologically to the field.

The theoretical background of this thesis provides readers with a detailed overview of various approaches to deception detection. First, the meaning of dishonesty in human interaction is discussed from a philosophical and moral perspective, and several definitions of deception and related constructs are offered. In following chapters, four general approaches to deception detection – physiological, behavioural, verbal and neuropsychological – are presented with the aim of outlining current methods and research trends in the field. Building on this foundation, three main chapters are devoted to approaches directly applied in the empirical part: physiological responses assessed by fITI and rPPG, and behavioural indicators investigated by emotional expression analysis and eye-tracking. In each of these chapters, we provide a systematic overview of the existing evidence, combining theoretical discussions with comprehensive summary tables. As individual differences were also a focus, a separate chapter presents the current state of knowledge on the role of attachment avoidance in deception and conversations in general. The theoretical section concludes with a reflection on the ethical aspects of deception detection research, a topic that continues to pose complex challenges for researchers.

The initial case study, already published in Hypšová and Seitl (2022), served as a technical and conceptual proof of concept. The results showed that spontaneous lying was associated with a lower nasal temperature and a slight increase in cheek temperature, heart rate and expression of fear/surprise. However, the most important finding was procedural: manual processing of the thermal images was excessively time-consuming and led to data loss and low reproducibility. This was the basis for the later development of a PC algorithm for the automatic pre-processing of thermal data.

Building on this foundation, a standardised paradigm was introduced in the first pilot study published in Hypšová et al. (2024), which included both rehearsed and spontaneous responses. In addition to fITI, an eye tracker was also used. This study confirmed the importance of distinguishing between the deception itself and the cognitive demands associated with its production. While no significant differences were observed in physiological markers between truth and lies, spontaneous responses – regardless of veracity – were consistently associated with increased facial temperature, particularly in the cheeks and forehead. These results suggested those physiological changes are associated with cognitive effort rather than intent to deceive. In contrast, gaze behaviour proved to be a more robust indicator of deception: participants fixated less on the interviewer's eyes during spontaneous lies than during spontaneous truths. However, no such effect was observed under rehearsed conditions. Here, participants fixated the interviewer's eyes significantly more during rehearsed deceptions than during rehearsed truths. This finding supports the notion that the behavioural strategies used during deception are modulated by cognitive load, with liars showing lower visual engagement when attentional resources are limited. Furthermore, the interaction between veracity and preparation highlighted the dynamic nature of deceptive behaviour and the need for context-sensitive analysis. This study also introduced a preliminary PC algorithm for pre-processing infrared thermal data, which includes automatic image alignment and standardised ROI tracking that takes into account participants' head movements. While this solution significantly improved the efficiency and consistency of data processing, its technical complexity highlighted the ongoing need for more accessible tools. As the algorithm was developed using ArcGIS Pro, a licenced and domain-

specific software not commonly used in psychological research, the second pilot study focussed on developing a more flexible and generally applicable solution.

The second pilot study, which is currently under review (Hypšová et al., in review), extended the line of thermal research proposed in previous experiments by introducing a real-life interaction with a real interviewer to increase ecological validity. This study also marked a methodological advance by developing and evaluating a MATLAB-based thermal data processing framework that allowed continuous tracking of facial regions across the thermal recordings. Contrary to expectations based on previous literature, no consistent deception-specific thermal signatures were observed. Instead, the most pronounced differences emerged between spontaneous and rehearsed responses, with nose temperature showing the highest sensitivity to cognitive demands rather than the deception itself. Interestingly, even spontaneous truthful responses elicited significant thermal changes, possibly reflecting anticipatory arousal or concern about being perceived as deceptive – a well-documented phenomenon in the psychophysiological literature. These results support the argument that physiological markers are not per se indicative of deception and must be interpreted in the broader context of cognitive and emotional processes.

Finally, in the main experimental study, the methodological refinements and theoretical insights from the detailed theoretical review and the pilot and case studies were brought together and tested in a fully integrated multimodal design. Participants engaged in semi-structured interviews under conditions that differed in terms of cognitive load and veracity, while physiological (i.e., facial temperature on forehead, nose, and cheeks; raw heart rate) and behavioural data (i.e., emotional arousal, emotional valence, and gaze fixations of the interviewer's face) were measured. Contrary to initial expectations, the results did not show consistent deception-specific effects in facial temperature: while nasal temperature decreased significantly from baseline in all experimental conditions, this effect was the same for truths and lies, indicating increased task-related arousal rather than deception per se. Heart rate, on the other hand, was significantly higher for deceptive responses than for truthful responses and highest for spontaneous lies – indicating increased autonomic arousal under cognitively demanding deceptive conditions. Emotional valence and arousal measured with the FaceReader did

not differ between deception and truth-telling, but were significantly lower in rehearsed responses than in spontaneous responses, suggesting that cognitive preparation may act as an emotion-regulating mechanism. Eye-tracking data showed a consistent gaze pattern across conditions, with participants fixating primarily on the lower face with no significant changes attributable to deception or rehearsal. However, individuals with higher attachment avoidance showed reduced fixation on emotionally salient areas (e.g., the mouth) and increased background fixation, indicating stable, trait-like avoidance of emotional cues. Similarly, attachment avoidance was associated with increased heart rate and facial temperature, although these effects did not interact with condition. Taken together, these results suggest that deception itself may not elicit unique physiological or behavioural reactions, but rather that individual traits and task demands – particularly spontaneity – influence how cognitive and emotional distress is expressed across modalities.

This thesis introduces a novel experimental framework for non-invasive deception detection and proposes clear direction for future research. The future focus is on improving data processing automation – especially for thermal and eye-tracking measurements – using machine learning and on increasing ecological validity through emotionally engaging scenarios where the stakes are high. The importance of accounting for individual differences, such as attachment-related characteristics, through person-centred approaches to analysis is needed. Findings across studies consistently suggest that deception is not characterised by distinct physiological or behavioural signatures; instead, responses are shaped by cognitive load, emotional regulation and individual characteristics. While some markers, such as heart rate, showed signs of deception, others, including facial temperature, emotional arousal, emotional valence and eye fixations, reflected broader task and interpersonal dynamics rather than deception itself. These findings challenge the idea of a universal deception profile and argue for a more nuanced, context-sensitive model that combines stable personality traits with situational demands, and emphasise the need for flexible, theory-driven, and interdisciplinary approaches to deception research.

12 ANNOTATION

Human communication is fundamentally based on the assumption of honesty, where deception is the anomaly (Kalbfleisch & Docan-Morgan, 2019). Philosophical traditions offer different perspectives on when, if ever, deception can be justified. The Aristotelian view condemns all lies as damaging to individual character and social trust (Zembaty, 1993), while Kantian view truth as a categorical imperative that makes all deception morally unacceptable (Ikuenobe, 2002). In contrast, Plato allows the “noble lie” if it serves the greater good, emphasising the importance of context and intention (Baima & Paytas, 2020). This complexity informs modern ethical and psychological taxonomies. Deception is broadly defined as the intent to mislead (DePaulo et al., 2003) extending beyond lies to include omission, manipulation, and exaggeration (Englehardt & Pritchard, 2019; Levine, 2014). Understanding its forms and detection is important both individually and socially (Granhag et al., 2015).

Despite interest, people are poor at recognising lies performing near chance level (Bond & DePaulo, 2006). Deceptive cues are masked by individual differences and cognitive strategies (Vrij & Ganis, 2014). The methods for detecting deception are therefore divided into physiological, behavioural, verbal and neural. In this thesis we have focused on physiological and behavioural approaches. *Physiological approaches* monitor autonomic responses such as heart rate and facial temperature using instruments such as polygraphs or non-contact methods such as fITI and rPPG (Meijer & Verschuere, 2014; Benedetto et al., 2019). Deception often leads to decreased nasal temperature or fluctuations in heart rate associated with stress and cognitive effort (Panasiti et al., 2016; Gamer et al., 2006). *Behavioural approaches* focus in particular on micro-expressions, which provide another way to identify hidden emotions such as fear or guilt using systems such as FACS (Ekman, 2009; Avola et al., 2019). In addition, the dimensions of emotional valence and arousal capture the underlying physiological and affective states associated with deception and provide a more comprehensive view (Posner et al., 2005). Last but not least, eye-tracking studies shows that liars under cognitive stress often avoid eye contact (Hypšová et al., 2024), although when cognitive resources are available, they can exaggerate it to appear

credible (Mann et al., 2013). Attachment theory also contributes to understand deceptive behaviour. Individuals with avoidant attachment styles typically use deactivating strategies that suppress emotional expression under stress (Frías et al., 2014; Mikulincer & Shaver, 2019). Although they often appear calm and composed on the outside, their internal physiological responses, such as increased heart rate or skin conductance, indicate increased arousal and internal tension (Diamond et al., 2006; Ehrenthal et al., 2011).

The study of deception, particularly through the use of advanced tools such as fITI, rPPG and eye-tracking, also raises complex ethical issues. These techniques can record unconscious or involuntary responses, potentially violating participants' privacy (Fischer, 2020). Consequently, such technologies must be treated as supporting indicators rather than definitive measures of dishonesty. According to APA ethical standards, such research requires clear communication about their purpose, informed consent, and institutional ethical approval. Full transparency regarding procedures, potential risks, and participants' rights is essential to preserve the autonomy, confidentiality, and integrity of the research.

Taken together, deception remains one of the most complex and consequential behaviours in human communication, with far-reaching implications for criminal justice, security screenings, organisational contexts and interpersonal relationships. Despite a long history of empirical research, efforts to reliably and validly detect deception have been repeatedly challenged by methodological, ethical and conceptual issues. Traditional instruments such as the polygraph are often criticised for their invasiveness, limited ecological validity and vulnerability to countermeasures. In this context, there is growing interest in non-invasive methods that can be used to assess behavioural and physiological indicators of deception in a more naturalistic way. In this vein, this dissertation investigates a non-invasive approach to deception detection that combines fITI facial expression analysis, rPPG, and eye-tracking.

The primary research objectives were twofold: (1) to assess the individual predictive value of four non-invasive modalities (fITI, rPPG, facial expression analysis and eye-tracking) in distinguishing between truthful and deceptive responses; and (2) to investigate how different levels of cognitive load (rehearsed truth, rehearsed lie, spontaneous truth and spontaneous lie) affect deception detection accuracy for each modality. In addition,

to these primary aims, a secondary aim was to develop and test a customised software tool for thermal data pre-processing and to explore its potential for future applications in deception detection. Finally, the study investigated whether individual differences in attachment avoidance moderate the relationship between behavioural and physiological responses and deception detection accuracy, with moderation effects analysed separately for each modality. Although all measurements were conducted in controlled laboratory environment, the setting was designed to resemble everyday interpersonal communication, reflecting the thesis's focus on the applicability of non-contact methods in realistic social contexts.

To address the objectives, a multi-stage process was followed in this thesis, comprising a case study, two pilot studies and a main study. Across these phases, the thesis incrementally built on the results to refine both the methodological and the experimental design of the main study.

The case study, already published in Hypšová and Seitl (2022) served primarily as a methodological pilot to test the feasibility of integrating thermographic, behavioural, and cardiovascular measurements in a controlled deception task. A female participant underwent a within-subject experimental design that included both spontaneous and rehearsed truthful and deceptive responses while interacting with a simulated interviewer to standardise the procedure and control for confounding factors such as tone of voice and non-verbal behaviour. Data were collected using Fluke TI450 Pro thermal camera, and a 4k camera and analysed by FaceReader and Fluke SmartView software. Although the findings were descriptive, they revealed promising trends – particularly the sensitivity of nasal temperature and heart rate to task conditions. The time-consuming and inaccurate manual analysis of infrared thermal data highlighted the limitations of existing tools and motivated the development of automated pre-processing frameworks that would ultimately improve the accuracy and replicability of future studies. In addition, the case study raised critical conceptual questions about the ecological validity of simulated interviewers, which led to a re-evaluation of the experimental design in later phases of the research.

In the first pilot study (N = 15), published in Hypšová et al. (2024), we aimed to evaluate the feasibility of combining functional fITI and eye-tracking for deception detection. The study investigated the differences in physiological (facial temperature) and behavioural (eye fixations) responses to rehearsed and spontaneous truths and lies told to the simulated interviewer for standardisation. The data were collected using the Fluke TI450 Pro thermal imaging camera and the Tobii Pro Spectrum 300 eye tracker and analysed using linear and Poisson mixed effects models, which allowed for more flexible modelling of individual variability in repeated measurements. The results showed no significant differences in facial temperature between truthful and deceptive responses. However, spontaneous responses were associated with higher forehead and cheek temperature, probably due to increased cognitive load. In rehearsed lies, participants maintained more eye contact, indicating conscious IM, whereas in spontaneous lies, gaze on the interviewer was reduced, reflecting the effects of increased cognitive load. These results showed that behavioural indicators of deception are highly context-dependent and influenced by cognitive availability. In this study, we also presented our first PC algorithm developed in collaboration with RNDr. Stanislav Popelka, Ph.D. from the Department of Geoinformatics, Palacký University for automatic ROIs selection. It was developed using ArcGIS Pro and Python and enabled standardised temperature analysis despite head movements. Since the algorithm, despite its functionality, was developed in a licenced and domain-specific software not commonly used in psychological research, the second pilot study focused on developing a more flexible and generally applicable solution.

The second pilot study (N = 27), which is currently under peer review (Hypšová et al., in review), increased ecological validity by simulating a job interview with a real interviewer. In this study, facial temperature was the only physiological measure analysed. The data was collected with the Fluke TI450 Pro thermal imaging camera. Participants answered questions under four conditions: spontaneous truth, spontaneous lie, rehearsed truth and rehearsed lie. A financial reward provided an incentive for realistic deception and was used as a simulation for a hiring decision. The data were analysed using linear mixed-effects models to account for individual variability in repeated measurements. Contrary to our expectations, the findings did not reveal consistent thermal patterns

associated with deception. Instead, the most notable differences emerged between spontaneous and rehearsed responses, with nose temperature reflecting cognitive load rather than the deception itself. In particular, spontaneous truths elicited significantly stronger thermal changes than spontaneous lies, probably due to anticipatory stress or fear of not being believed. These results reinforced our view that physiological signals should be understood in the wider context of cognitive and emotional dynamics rather than as direct indicators of deception. A significant practical contribution of this pilot study also lies in a new software developed in collaboration with Ing. Jan Kubíček, Ph.D. from the Department of Cybernetics and Biomedical Engineering at the Technical University of Ostrava in the MATLAB environment, which enables the continuous extraction of thermal features across the entire video sequence and automates the selection and tracking of ROIs despite head movements. Based on the pilot testing of this framework, we implemented it in the main study. It can be re-evaluated or used in other thermal infrared studies upon request to the author of this thesis.

The main study (N ~ 100) used a full design combining fITI, behavioural analysis, rPPG, and eye tracking. The study employed a within-subject experimental design with real interviewers, where participants took part in semi-structured interviews. Each participant completed four conditions: spontaneous truth, spontaneous lie, rehearsed truth and rehearsed lie, which were presented in a counterbalanced order to control for sequence effects. In addition, each participant underwent a short small talk at the beginning of the experiment, which served as a baseline. Both physiological data (facial temperatures of forehead, nose and cheeks; and raw heart rate) and behavioural data (emotional arousal, emotional valence and gaze fixations on the interviewer) were recorded. For gaze fixations the ROIs included the upper face, the lower face and background, and fixation duration were calculated for each ROI and condition. A number of statistical methods was used to analyse the complex relationships between behavioural, physiological and personality variables under different conditions. The primary method for testing condition effects and individual differences was linear mixed-effects models, which allowed for the inclusion of both fixed and random effects and took into account repeated measures within subjects. This approach was particularly suitable for modelling data collected under different conditions (e.g., spontaneous

vs. rehearsed, truthful vs. deceptive). In addition, a moderation analysis was used to investigate the role of attachment avoidance in shaping physiological and behavioural responses to deception. To further explore individual variability in thermal reactivity, a theory driven cluster analysis of nasal temperature data was conducted. Across all conditions, our findings showed no consistent deception-specific effects in facial temperature. However, nasal temperature emerged as the most sensitive thermal marker – but not to deception. Instead, it decreased continuously under all experimental conditions compared to the baseline. This indicated the influence of increased task-related arousal on nasal temperature and not deception per se. Furthermore, a cluster analysis of the nasal temperature data indicated that deception-related thermal effects might be detectable in physiologically reactive subgroups. Interestingly, when heart rate was analysed – although only raw heart rate and not HRV was used – a significant effect of deception was found, with heart rate being higher for deceptive responses than truthful responses and highest for spontaneous lies – indicating increased autonomic arousal under cognitively demanding deceptive conditions. The emotional valence and arousal analysed with FaceReader did not differ significantly between truthful and deceptive responses, but were significantly lower in rehearsed responses, suggesting that preparation may contribute to the regulation of emotional responses. Eye-tracking results revealed a consistent focus on the lower half of the face, with no major differences in deception or rehearsal. However, participants with higher levels of attachment avoidance tended to fixate less on emotionally relevant areas such as the mouth and more on the background, indicating a stable tendency to avoid emotional cues. Interestingly, higher avoidance was connected with increased fixation on the upper face, which we interpret as a strategic scanning pattern aimed at observing the interlocutor's facial reactions while maintaining emotional distance. In addition, attachment avoidance was associated with increased heart rate and facial temperature, although these responses did not vary between conditions. Overall, the findings suggest that deception may not trigger distinct physiological or behavioural markers. Instead, individual characteristics and contextual factors – particularly spontaneity – play a key role in the expression of behavioural and physiological responses.

This thesis presents a novel experimental framework for non-invasive deception detection, but also outlines a number of concrete directions for future research. Key future improvements would include further automation of data processing, especially for thermal and eye-tracking data, through machine learning techniques that enable dynamic ROI detection. Expanding the role of individual differences – especially attachment-related traits – requires person-centred analysis strategies, such as latent profile analysis or clustering techniques, to uncover different deception-related regulatory patterns. The inclusion of gaze dynamics and pupillometry metrics is recommended to improve sensitivity in deception detection. In addition, the use of real interviewers introduced important interpersonal variability, such as emotional synchrony, which should be systematically investigated in relation to deception cues. From a physiological perspective, future work should go beyond raw heart rate to include measures of heart rate variability that could provide more comprehensive insights into autonomic function under cognitive and emotional stress. Finally, advancing statistical analysis through generalised linear mixed models and signal detection theory is recommended for improving the sensitivity and interpretability of deception detection findings.

Across all studies, the findings consistently show that deception is not reliably associated with modality-specific physiological or behavioural cues. Rather, responses appear to be more strongly influenced by cognitive load, and individual differences, particularly when deception is produced under spontaneous conditions. While an increased heart rate during lying indicates some autonomic reactivity, other markers such as facial temperature, emotional valence, emotional arousal and gaze behaviour were found to reflect task-related demands and interpersonal characteristics rather than deception itself. These findings challenge the notion of a universal physiological and behavioural cues to deception and instead point to a more dynamic, context-sensitive model of deceptive behaviour.

Nevertheless, the research has important practical implications. By rigorously testing a non-contact framework under ecologically valid conditions, this work provides a critical assessment for applications in areas such as forensics, security screenings and personnel assessment. The results do not provide ready-to-use tools for lie detection, but highlight the limitations of current technologies and suggest that caution should

be exercised when using them in practise. However, the development of an automated framework for pre-processing thermal data represents a valuable methodological contribution that can improve data quality and reproducibility in psychophysiological thermal research in general. Furthermore, this research encourages future applications of non-invasive technologies, not for detecting deception per se, but for understanding cognitive and emotional states in interpersonal contexts where the stakes are high. In summary, this thesis contributes to a more nuanced understanding of the relationship between physiological responses, cognitive load, individual characteristics (such as attachment avoidance) and deceptive behaviour, and highlights that any use of these technologies needs to consider the broader psychological and situational context.

13 CZECH SUMMARY / ČESKÝ SOUHRN

Lidská komunikace je primárně založena na předpokladu upřímnosti, přičemž klamání představuje odchylku od této normy (Kalbfleisch & Docan-Morgan, 2019). Filozofické tradice se různí v názorech na to, zda a kdy lze klamání ospravedlnit. Aristoteles považuje každou lež za škodlivou jak pro individuální charakter, tak pro společenskou důvěru (Zembaty, 1993), zatímco Kantova etika vnímá pravdu jako kategorický imperativ, který činí jakékoli klamání morálně nepřijatelným (Ikuenobe, 2002). Naproti tomu Platón připouští tzv. „ušlechtilou lež“, pokud je vyřčena s úmyslem sloužit vyššímu dobru, a akcentuje význam kontextu a záměru (Baima & Paytas, 2020). Tato filozofická rozmanitost se promítá do současných etických a psychologických přístupů ke klamání. To je dnes obecně chápáno jako záměrné uvedení druhého v omyl, přičemž zahrnuje nejen přímé lži, ale i úmyslné zatajování, manipulaci či přehánění (DePaulo et al., 2003; Englehardt & Pritchard, 2019; Levine, 2014). Porozumění formám klamu a mechanismům jeho odhalování je významné jak z hlediska jednotlivce, tak z hlediska společenského fungování (Granhag et al., 2015).

Navzdory rozsáhlému výzkumu lidé běžně nerozeznávají lži lépe než náhodou (Bond & DePaulo, 2006), což je způsobeno absencí univerzálních ukazatelů klamání a přítomností individuálních rozdílů a kognitivních strategií (Vrij & Ganis, 2014). V této návaznosti tedy existují čtyři základní metody detekce lži: fyziologické, behaviorální, verbální a neurální. V této práci jsme se však zaměřili pouze na fyziologický a behaviorální přístup. *Fyziologická měření* sledují zejména autonomní reakce jako je srdeční tep či změny teploty v obličeji, a to buď pomocí tradičních zařízení jako je polygraf, nebo moderních bezkontaktních technologií (např. fITI či rPPG) (Meijer & Verschuere, 2014; Benedetto et al., 2019). Studie ukazují, že během klamání dochází např. ke snížení teploty nosu či ke změnám srdeční frekvence v souvislosti se stresem a kognitivní náročností (Panasiti et al., 2016; Gamer et al., 2006). V případě *behaviorálních přístupů* je využívána zejména analýza emočních mikro-expresí, které například pomocí systému FACS umožňují odhalit skryté emoce, jako jsou strach nebo vina (Ekman, 2009; Avola et al., 2019). Emoční valence a emoční arousal obohacují analýzu emočních expresí o dimenzionální ukazatele,

jež mohou komplexněji přispět k odhalování zkreslených informací (Posner et al., 2005). Eye-trackingové studie dále ukazují, že lháři se při zvýšené kognitivní zátěži často vyhýbají pohledu do očí, zatímco při připraveném klamání mohou oční kontakt naopak posilovat (Hypšová et al., 2024; Mann et al., 2013). Teorie vztahové vazby nabízí další potenciální proměnnou, jež může usnadnit odhalování úmyslného zkreslování informací, neboť jedinci s vyhýbavým stylem potlačují emoční projevy navenek, ale zároveň vykazují zvýšenou vnitřní fyziologickou aktivitu (Diamond et al., 2006; Mikulincer & Shaver, 2019).

I přes potenciál výše uvedených přístupů je však důležité zmínit, že aplikace bezkontaktních metod pro detekci lži vyvolává závažné etické otázky, jelikož mnohé z nich měří nevědomé nebo nedobrovolné reakce (Fischer, 2020). Tyto technologie by proto měly být chápány jako podpůrné indikátory, nikoliv jako absolutní nástroje pro odhalování lži. Podle standardů APA (2017) je nezbytné zajistit informovaný souhlas, transparentnost výzkumných postupů a etické schválení, aby byla ochráněna autonomie a soukromí účastníků.

Souhrnně řečeno, klamání zůstává jedním z nejsložitějších a nejkomplexnějších způsobů chování v lidské komunikaci, které má dalekosáhlé důsledky pro justiční systém, bezpečnostní prověrky, organizační prostředí a mezilidské vztahy. Navzdory dlouhé historii empirického výzkumu byly snahy o spolehlivé a validní odhalení klamání opakovaně zpochybňovány metodologickými, etickými a koncepčními problémy. Tradiční nástroje, jako je polygraf, jsou často kritizovány zejména pro svou kontaktní povahu a omezenou ekologickou validitu. V této souvislosti roste zájem o neinvazivní multimodální metody, které lze použít k hodnocení behaviorálních a fyziologických ukazatelů klamání přirozenějším způsobem. V tomto duchu se tato disertační práce zabývá neinvazivním multimodálním přístupem k detekci klamání, který kombinuje fITI, analýzu emoční exprese, rPPG a eye-tracking.

Byly operacionalizovány dva primární cíle: (1) posoudit individuální prediktivní hodnotu čtyř neinvazivních modalit (fITI, rPPG, analýza emoční exprese a eye-tracking) při rozlišování mezi pravdivými a klamavými odpověďmi; (2) zjistit, jak různé úrovně kognitivní zátěže (připravená pravda, připravená lež, spontánní pravda a spontánní lež) ovlivňují přesnost detekce klamání u každé modality. Kromě těchto primárních cílů bylo sekundárním cílem vyvinout a otestovat vlastní softwarový nástroj pro předzpracování

termovizních dat a prozkoumat jeho potenciál pro budoucí využití v oblasti detekce klamání. V neposlední řadě se studie zabývala otázkou, zda individuální rozdíly v míře vztahové vyhýbavosti moderují vztah mezi behaviorálními a fyziologickými reakcemi a přesností detekce klamání. Tyto moderační efekty byly analyzovány zvlášť pro každou modalitu. Přestože všechna měření probíhala v kontrolovaném laboratorním prostředí, byly experimentální designy navrženy tak, aby co nejvíce připomínaly běžnou mezilidskou komunikaci.

K naplnění stanovených výzkumných cílů byl zvolen vícestupňový výzkumný design, který zahrnoval případovou studii, dvě pilotní studie a hlavní experiment. Případová studie poskytla metodologický základ pro první pilotní studii, která následně vedla k optimalizaci návrhu druhé pilotní studie. Obě pilotní fáze pak společně vytvořily pevný základ pro konstrukci a realizaci hlavní studie.

Případová studie, publikovaná Hypšovou a Seitlem (2022), sloužila především jako metodologický pilot k ověření možnosti integrace termografických, behaviorálních a kardiovaskulárních měření ve vnitro-subjektovém experimentálním designu detekce úmyslného zkreslování informací. Participantka byla instruována, aby v rámci interakce se simulovaným tazatelem poskytovala spontánní i připravené odpovědi (jak pravdivé, tak klamavé). Důvodem pro využití simulované osoby tazatele bylo zajištění standardizovaného výzkumného postupu a eliminace matoucích faktorů, zejména v oblasti paralingvistiky a neverbálního chování. Data byla sbírána pomocí termokamery Fluke TI450 Pro a 4k kamery a analyzována pomocí softwaru FaceReader a Fluke SmartView. Přestože zjištění byla pouze popisná, odhalila slibné trendy, zejména citlivost nosní teploty a srdeční frekvence na podmínky úkolu. Časově náročné a nepřesné manuální zpracování oblastí zájmu (tedy částí obličeje určených k analýze – například nos, čelo, tváře) v rámci fITI poukázalo na potřebu vývoje automatizovaných nástrojů pro předzpracování dat, které by umožnily efektivnější a přesnější analýzu s výraznou časovou úsporou. Kromě toho případová studie otevřela metodologické otázky týkající se omezení ekologické validity vlivem využití simulované osoby tazatele, což vedlo k přehodnocení experimentálního designu v pozdějších fázích výzkumu.

V první pilotní studii (N = 15), publikované Hypšovou et al. (2024), jsme se zaměřili na vyhodnocení proveditelnosti kombinace fITI a eye-trackingu pro detekci klamání. Studie

zkoumala rozdíly ve fyziologických (teplota obličeje) a behaviorálních (fixace očí) reakcích na připravené a spontánní pravdy a lži, které byly řečeny simulovanému tazateli za účelem standardizace. Data byla sbírána pomocí termokamery Fluke TI450 Pro a eye-trackeru Tobii Pro Spectrum 300 a analyzována pomocí lineárních a Poissonových modelů se smíšenými efekty, které umožnily flexibilnější modelování individuální variability při opakovaných měřeních. Výsledky neprokázaly žádné významné rozdíly v teplotě obličeje mezi pravdivými a klamavými odpověďmi. Spontánní odpovědi však byly spojeny s vyšší teplotou čela a tváří, pravděpodobně v důsledku zvýšené kognitivní zátěže. Při nacvičených lžích účastníci udržovali větší oční kontakt, což svědčí o vědomé snaze o vytvoření dobrého dojmu. Naopak při spontánních lžích se pohled na tazatele snížil, což odráží účinky zvýšené kognitivní zátěže. Tyto výsledky ukázaly, že behaviorální ukazatele klamání jsou vysoce závislé na kontextu a ovlivněné aktuální kognitivní kapacitou. V této studii jsme také představili náš první počítačový algoritmus vyvinutý ve spolupráci s RNDr. Stanislavem Popelkou, Ph.D. z Katedry geoinformatiky Univerzity Palackého pro automatický výběr oblastí zájmu. Tento algoritmus byl vyvinut v rámci licencovaného software ArcGIS Pro a programového prostředí Python a umožnil standardizovanou analýzu teploty v různých částech obličeje navzdory pohybům hlavy participanta. Vzhledem k tomu, že algoritmus byl navzdory své funkčnosti vyvinut v licencovaném a doménově specifickém softwaru, který se v psychologickém výzkumu běžně nepoužívá, zaměřila se druhá pilotní studie na vývoj flexibilnějšího a obecně použitelného řešení, které by umožnilo jeho širší využití v navazujících výzkumech.

Druhá pilotní studie (N = 27), která je v současné době v recenzním řízení (Hypšová et al., v recenzním řízení), byla zaměřena na analýzu obličejové teploty v rámci simulovaného pracovního pohovoru se skutečným tazatelem. Účastníci odpovídali na čtyři otázky v rámci následujících podmínek: spontánní pravda, spontánní lež, připravená pravda a připravená lež. Možnost výhry finanční odměny představovala pobídku k realistickému klamání a byla použita jako simulace rozhodnutí o přijetí do zaměstnání. Data byla sbírána pomocí termokamery Fluke TI450 Pro a analyzována pomocí lineárních modelů se smíšenými efekty, které zohledňovaly individuální variabilitu při opakovaných měřeních. Oproti našemu očekávání výsledky neodhalily konzistentní teplotní vzorce spojené s klamáním. Místo toho se objevily nejvýraznější rozdíly mezi spontánními a připravenými

odpověďmi, přičemž teplota nosu odrážela spíše kognitivní zátěž než samotné klamání. Zejména spontánní pravdy vyvolávaly výrazně silnější teplotní změny než spontánní lži, pravděpodobně v důsledku anticipačního stresu nebo strachu z toho, participanti budou falešně obviněni ze lži. Tyto výsledky posilují náš názor, že fyziologické signály je třeba chápat spíše v širším kontextu kognitivní a emoční dynamiky než jako přímé ukazatele klamání. Významný praktický přínos této pilotní studie spočíval mimo jiné také v novém softwaru vyvinutém ve spolupráci s Ing. Janem Kubíčkem, Ph.D. z Katedry kybernetiky a biomedicínského inženýrství Technické univerzity Ostrava v prostředí MATLAB, který umožňuje kontinuální extrakci teplotních oblastí zájmu v celé videosekvenci a automatizuje výběr oblastí zájmů navzdory pohybům hlavy participanta. Na základě pilotního testování tohoto algoritmu jsme jej implementovali do hlavní studie. Na vyžádání autora této práce jej lze evaluovat nebo použít v jiných studiích zaměřených na aplikaci fITI v různých kontextech.

V hlavní studii (N ~ 100) byl použit kompletní design kombinující fITI, behaviorální analýzu, rPPG a eye-tracking. Studie využívala vnitro-subjektový experimentální design se skutečnými tazateli, v němž se participanti účastnili polostrukturovaných rozhovorů. Každý participant absolvoval čtyři podmínky: spontánní pravdu, spontánní lež, připravenou pravdu a připravenou lež, které byly prezentovány ve vyváženém pořadí, aby se kontroloval efekt pořadí. Kromě toho proběhl s každým participantem na začátku experimentu krátký neutrální rozhovor, který sloužil jako baseline. Byly měřeny jak fyziologické údaje (teplota čela, nosu a tváří a srdeční frekvence), tak behaviorální údaje (emoční arousal, emoční valence a délka trvání oční fixace tazatele - horní část obličeje, dolní část obličeje a pozadí za tazatelem). Vedle fyziologických a behaviorálních proměnných bylo zahrnuto posouzení vztahové vyhýbavosti participantů prostřednictvím sebe-posuzujícího dotazníku ECR. K analýze komplexních vztahů mezi behaviorálními, fyziologickými a osobnostními proměnnými za různých podmínek byla použita řada statistických metod. Primární metodou byly lineární modely se smíšenými efekty, které umožňovaly zahrnout fixní i náhodné efekty a zohledňovaly opakovaná měření v rámci subjektů. Tento přístup byl zvláště vhodný pro modelování multimodálních údajů získaných za různých podmínek (např. spontánní vs. připravené, pravdivé vs. klamavé). Kromě toho byla použita moderační analýza ke zkoumání vlivu vztahové vyhýbavosti při utváření fyziologických a behaviorálních

reakcí na klamání. K dalšímu zkoumání individuální variability tepelné reaktivity byla provedena clusterová analýza teploty nosu. Ačkoli tyto shluky nevznikly na základě algoritmů neřízeného shlukování, představují teoreticky vymezené kategorie intenzity tepelné odezvy. Ve všech podmínkách naše zjištění neprokázala žádné konzistentní reakce specifické pro klamání v oblasti obličejové teploty. Jako nejcitlivější tepelný marker se však ukázala nosní teplota, která se v experimentálních podmínkách ve srovnání s baseline kontinuálně snižovala. To poukazuje na vliv zvýšeného vzrušení souvisejícího s úkolem na nosní teplotu, nikoliv na důsledek klamání jako takového. Kromě toho clusterová analýza teploty nosu naznačila, že tepelné účinky související s klamáním mohou být zjistitelné ve fyziologicky reaktivních podskupinách. Zajímavé je, že při analýze srdeční frekvence – ačkoli byla použita pouze hrubá srdeční frekvence, nikoli její variabilita – byl zjištěn významný vliv klamání, přičemž srdeční frekvence byla vyšší u klamavých odpovědí než u pravdivých odpovědí a nejvyšší u spontánních lží – což naznačuje zvýšené autonomní vzrušení za kognitivně náročných klamavých podmínek. Emoční valence a arousal analyzované pomocí FaceReaderu se mezi pravdivými a klamavými odpověďmi významně nelišily, ale byly významně nižší u připravených odpovědí, což naznačuje, že příprava může přispívat k regulaci emočních reakcí. Výsledky očních fixací odhalily konzistentní zaměření participantů na dolní polovinu obličeje tazatele, bez výraznějších rozdílů v klamání a připravenosti. Účastníci se zvýšenou vyhýbavostí však měli tendenci méně fixovat emočně relevantní oblasti, jako jsou ústa, a více se zaměřovat na pozadí za tazatelem, což naznačuje stabilní tendenci vyhýbat se emočním signálům. Zajímavé je, že vyšší vztahová vyhýbavost zvýšila fixaci na horní část obličeje, což interpretujeme jako strategický vzorec skenování zaměřený na pozorování reakcí tazatele při zachování emočního odstupu. Kromě toho byla vztahová vyhýbavost spojena se zvýšenou srdeční frekvencí a teplotou obličeje, ačkoli se tyto reakce v jednotlivých podmínkách nelišily. Celkově tato zjištění naznačují, že klamání nemusí vyvolávat odlišné fyziologické nebo behaviorální reakce. Namísto toho hrají klíčovou roli individuální charakteristiky a kognitivní zátěž, nikoliv klamání jako takové.

Na základě výsledků této disertační práce rovněž nastiňujeme řadu doporučení pro budoucí výzkum. Jednou z hlavních priorit budoucího výzkumu zůstává pokračující automatizace datového zpracování, především v oblasti identifikace oblastí zájmu u fITI a eye-trackingu, s využitím metod strojového učení pro jejich flexibilní a přesnou detekci

v reálném čase. Zapojení reálných tazatelů zároveň vnáší do interakce důležitou mezilidskou variabilitu, jako je emoční synchronizace, jež by měla být systematicky zkoumána v souvislosti s projevy klamání. Z fyziologického hlediska je vhodné překročit rámec jednoduchého měření srdeční frekvence a zahrnout také analýzu variability srdeční frekvence (HRV), která poskytuje komplexnější vhled do fungování autonomního nervového systému při kognitivním a emočním stresu. V neposlední řadě je pro zvýšení citlivosti a lepší interpretaci výsledků žádoucí aplikovat pokročilejší statistické metody, například zobecněné lineární smíšené modely (GLMM) a principy teorie detekce signálů (SDT).

Výsledky všech studií konzistentně ukázaly, že klamání není spolehlivě spojeno se specifickými fyziologickými ani behaviorálními ukazateli. Naopak se zdá, že naměřené reakce jsou výrazněji ovlivněny kognitivní zátěží a individuálními rozdíly, zejména v situacích, kdy ke klamání dochází spontánně. Zatímco zvýšená srdeční frekvence během lhaní může naznačovat určitý stupeň autonomní reaktivity, jiné indikátory – jako teplota obličeje či směr a trvání pohledu – spíše odrážejí nároky úkolu a interpersonální charakteristiky než samotný akt klamání. Tato zjištění zpochybňují představu o univerzálních fyziologických či behaviorálních znacích lži a podporují dynamičtější, na kontext citlivý model klamavého chování.

Navzdory těmto výsledkům má výzkum významné praktické dopady. Systematické testování bezkontaktního rámce poskytuje kritické zhodnocení možností jeho využití v oblastech, jako jsou forenzní šetření, bezpečnostní prověrky či výběr zaměstnanců. Ačkoli výsledky nenabízejí okamžitě využitelné nástroje pro detekci lži, upozorňují na limity současných technologií a vyzdvihují nutnost opatrnosti při jejich zavádění do praxe. Vývoj automatizovaného systému pro předzpracování termálních dat přitom představuje cenný metodologický přínos, který může přispět ke zvýšení kvality a reprodukovatelnosti dat v psychofyziologickém výzkumu nejen v oblasti klamání. Zároveň tato práce podporuje budoucí využití neinvazivních technologií nikoli k přímé detekci lži, ale spíše k porozumění kognitivním a emočním stavům v náročných mezilidských situacích. Celkově tato disertace přináší hlubší porozumění vztahu mezi fyziologickými reakcemi, kognitivní zátěží, individuálními charakteristikami a klamavým chováním a zdůrazňuje, že jakékoli praktické využití těchto technologií musí zohledňovat širší psychologický a situační kontext.

14 LITERATURE

Aarts, L. A. M., Jeanne, V., Cleary, J. P., Lieber, C., Nelson, J. S., Bambang Oetomo, S., & Verkruysse, W. (2013). Non-contact heart rate monitoring utilizing camera photoplethysmography in the neonatal intensive care unit—A pilot study. *Early Human Development*, *89*(12), 943–948. https://doi.org/10.1016/j.earlhumdev.2013.09.016

Abdelrahman, Y., Velloso, E., Dingler, T., Schmidt, A., & Vetere, F. (2017). Cognitive heat: Exploring the usage of thermal imaging to unobtrusively estimate cognitive load. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *1*(3), 1–20. https://doi.org/10.1145/3130898

Abdulridha, F., & Albaker, B. M. (2024). Non-invasive real-time multimodal deception detection using machine learning and parallel computing techniques. *Social Network Analysis and Mining*, *14*(1), 97. https://doi.org/10.1007/s13278-024-01255-4

Abe, N. (2009). The neurobiology of deception: Evidence from neuroimaging and loss-of-function studies. *Current Opinion in Neurology*, *22*(6), 594–600. https://doi.org/10.1097/WCO.0b013e328332c3cf

Abeles, D., & Yuval-Greenberg, S. (2017). Just look away: Gaze aversions as an overt attentional disengagement mechanism. *Cognition*, *168*, 99–109. https://doi.org/10.1016/j.cognition.2017.06.021

Abouelenien, M., Burzo, M., Perez-Rosas, V., Mihalcea, R., Sun, H., & Zhao, B. (2019). Gender differences in multimodal contact-free deception detection. *IEEE MultiMedia*, *26*(3), 19–30. https://doi.org/10.1109/MMUL.2018.2883128

Abouelenien, M., Perez-Rosas, V., Mihalcea, R., & Burzo, M. (2017). Detecting deceptive behavior via integration of discriminative features from multiple modalities. *IEEE Transactions on Information Forensics and Security*, *12*(5), 1042–1055. https://doi.org/10.1109/TIFS.2016.2639344

Ahmad, M. I., Keller, I., Robb, D. A., & Lohan, K. S. (2023). A framework to estimate cognitive load using physiological data. *Personal and Ubiquitous Computing*, *27*(6), 2027–2041. https://doi.org/10.1007/s00779-020-01455-7

Ainsworth, M. D. S. (1978). The Bowlby-Ainsworth attachment theory. *Behavioral and Brain Sciences*, *1*(3), 436–438. https://doi.org/10.1017/S0140525X00075828

Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review*, *30*(2), 217–237. https://doi.org/10.1016/j.cpr.2009.11.004

Allen, M. T., Matthews, K. A., & Kenyon, K. L. (2000). The relationships of resting baroreflex sensitivity, heart rate variability and measures of impulse control in children and adolescents. *International Journal of Psychophysiology*, *37*(2), 185–194. https://doi.org/10.1016/S0167-8760(00)00089-1

Al-Naji, A., Gibson, K., Lee, S.-H., & Chahl, J. (2017). Monitoring of Cardiorespiratory Signal: Principles of Remote Measurements and Review of Methods. *IEEE Access*, *5*, 15776–15790. https://doi.org/10.1109/ACCESS.2017.2735419

Alshanskaia, E. I., Portnova, G. V., Liaukovich, K., & Martynova, O. V. (2024). Pupillometry and autonomic nervous system responses to cognitive load and false feedback: An unsupervised machine learning approach. *Frontiers in Neuroscience*, *18*, 1445697. https://doi.org/10.3389/fnins.2024.1445697

Alshanskaia, E., & Martynova, O. (2023). Eye Tracking and Autonomic Nervous System Responses. A Machine Learning Approach to Understanding Cognitive Stress. *2023 Fifth International Conference Neurotechnologies and Neurointerfaces (CNN)*, 8–11. https://doi.org/10.1109/CNN59923.2023.10275219

Amado, B. G., Arce, R., & Fariña, F. (2015). Undeutsch hypothesis and Criteria Based Content Analysis: A meta-analytic review. *The European Journal of Psychology Applied to Legal Context*, *7*(1), 3–12. https://doi.org/10.1016/j.ejpal.2014.11.002

Ambach, W., & Gamer, M. (2018). Physiological Measures in the Detection of Deception and Concealed Information. In *Detecting Concealed Information and Deception* (pp. 3–33). Elsevier. https://doi.org/10.1016/B978-0-12-812729-2.00001-X

Ambach, W., Stark, R., Peper, M., & Vaitl, D. (2008). An interfering Go/No-go task does not affect accuracy in a Concealed Information Test. *International Journal of Psychophysiology*, *68*(1), 6–16. https://doi.org/10.1016/j.ijpsycho.2007.11.004

Ammer, K. (2008). The Glamorgan Protocol for recording and evaluation of thermal images of the human body. *Thermology International*, *18*, 125–129.

Andreassi, J. L. (2010). *Psychophysiology* (0 ed.). Psychology Press. https://doi.org/10.4324/9780203880340

APA. (2024). *About the APA - American Polygraph Association*. https://www.polygraph.org/about_the_apa.php

Appelhans, B. M., & Luecken, L. J. (2006). Heart Rate Variability as an Index of Regulated Emotional Responding. *Review of General Psychology*, *10*(3), 229–240. https://doi.org/10.1037/1089-2680.10.3.229

Aristizabal-Tique, V. H., Henao-Pérez, M., López-Medina, D. C., Zambrano-Cruz, R., & Díaz-Londoño, G. (2023). Facial thermal and blood perfusion patterns of human emotions: Proof-of-Concept. *Journal of Thermal Biology*, *112*, 103464. https://doi.org/10.1016/j.jtherbio.2023.103464

Aron, A., Dutton, D. G., Aron, E. N., & Iverson, A. (1989). Experiences of Falling in Love. *Journal of Social and Personal Relationships*, *6*(3), 243–257. https://doi.org/10.1177/0265407589063001

Avola, D., Cascio, M., Cinque, L., Fagioli, A., & Foresti, G. L. (2021). LieToMe: An Ensemble Approach for Deception Detection from Facial Cues. *International Journal of Neural Systems*, *31*(02), 2050068. https://doi.org/10.1142/S0129065720500689

Avola, D., Cinque, L., Foresti, G. L., & Pannone, D. (2019). Automatic Deception Detection in RGB videos using Facial Action Units. *Proceedings of the 13th International Conference on Distributed Smart Cameras*, 1–6. https://doi.org/10.1145/3349801.3349806

Bagavathiappan, S., Saravanan, T., Philip, J., Jayakumar, T., Raj, B., Karunanithi, R., Panicker, T. M. R., Korath, Mp., & Jagadeesan, K. (2009). Infrared thermal imaging for

detection of peripheral vascular disorders. *Journal of Medical Physics*, *34*(1), 43. https://doi.org/10.4103/0971-6203.48720

Baima, N. R., & Paytas, T. (2020). True in Word and Deed: Plato on the Impossibility of Divine Deception. *Journal of the History of Philosophy*, *58*(2), 193–214. https://doi.org/10.1353/hph.2020.0036

Bakeman, R. (2005). Recommended effect size statistics for repeated measures designs. *Behavior Research Methods*, *37*(3), 379–384. https://doi.org/10.3758/BF03192707

Bangerter, A., Roulin, N., & König, C. J. (2012). Personnel selection as a signaling game. *Journal of Applied Psychology*, *97*(4), 719–738. https://doi.org/10.1037/a0026078

Barbosa Escobar, F., Velasco, C., Motoki, K., Byrne, D. V., & Wang, Q. J. (2021). The temperature of emotions. *PLOS ONE*, *16*(6), e0252408. https://doi.org/10.1371/journal.pone.0252408

Bartholomew, K., & Horowitz, L. M. (1991). Attachment styles among young adults: A test of a four-category model. *Journal of Personality and Social Psychology*, *61*(2), 226–244. https://doi.org/10.1037/0022-3514.61.2.226

Beaudry, O., Roy-Charland, A., Perron, M., Cormier, I., & Tapp, R. (2014). Featural processing in recognition of emotional facial expressions. *Cognition and Emotion*, *28*(3), 416–432. https://doi.org/10.1080/02699931.2013.833500

Belavadi, V., Zhou, Y., Bakdash, J. Z., Kantarcioglu, M., Krawczyk, D. C., Nguyen, L., Rakic, J., & Thuriasingham, B. (2020). MultiModal Deception Detection: Accuracy, Applicability and Generalizability. *2020 Second IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA)*, 99–106. https://doi.org/10.1109/TPS-ISA50397.2020.00023

Bell, B. E., & Loftus, E. F. (1989). Trivial persuasion in the courtroom: The power of (a few) minor details. *Journal of Personality and Social Psychology*, *56*(5), 669–679. https://doi.org/10.1037/0022-3514.56.5.669

Benedetto, S., Caldato, C., Greenwood, D. C., Bartoli, N., Pensabene, V., & Actis, P. (2019). Remote heart rate monitoring—Assessment of the Facereader rPPg by Noldus. *PLOS ONE*, *14*(11), e0225592. https://doi.org/10.1371/journal.pone.0225592

Ben-Shachar, M., Lüdecke, D., & Makowski, D. (2020). effectsize: Estimation of Effect Size Indices and Standardized Parameters. *Journal of Open Source Software*, *5*(56), 2815. https://doi.org/10.21105/joss.02815

Ben-Shakhar, G. (2008). The case against the use of polygraph examinations to monitor post-conviction sex offenders. *Legal and Criminological Psychology*, *13*(2), 191–207. https://doi.org/10.1348/135532508X298577

Ben-Shakhar, G., & Elaad, E. (2003). The validity of psychophysiological detection of information with the Guilty Knowledge Test: A meta-analytic review. *Journal of Applied Psychology*, *88*(1), 131–151. https://doi.org/10.1037/0021-9010.88.1.131

Berant, E., Mikulincer, M., & Florian, V. (2001). Attachment Style and Mental Health: A 1-Year Follow-Up Study of Mothers of Infants with Congenital Heart Disease. *Personality and Social Psychology Bulletin*, *27*(8), 956–968. https://doi.org/10.1177/0146167201278004

Bernard, V., Staffa, E., Mornstein, V., & Bourek, A. (2013). Infrared camera assessment of skin surface temperature – Effect of emissivity. *Physica Medica*, *29*(6), 583–591. https://doi.org/10.1016/j.ejmp.2012.09.003

Berntson, G. G., Quigley, K. S., Norman, G. J., & Lozano, D. L. (2017). Cardiovascular psychophysiology. In *Handbook of psychophysiology, 4th ed* (pp. 183–216). Cambridge University Press.

Bleil, M. E., Gianaros, P. J., Jennings, J. R., Flory, J. D., & Manuck, S. B. (2008). Trait Negative Affect: Toward an Integrated Model of Understanding Psychological Risk for Impairment in Cardiac Autonomic Function. *Psychosomatic Medicine*, *70*(3), 328–337. https://doi.org/10.1097/PSY.0b013e31816baefa

Bogaard, G., Colwell, K., & Crans, S. (2019). Using the Reality Interview improves the accuracy of the Criteria-Based Content Analysis and Reality Monitoring. *Applied Cognitive Psychology*, *33*(6), 1018–1031. https://doi.org/10.1002/acp.3537

Bogaard, G., Meijer, E. H., & Van der Plas, I. (2020). A model statement does not enhance the verifiability approach. *Applied Cognitive Psychology*, *34*(1), 96–105. https://doi.org/10.1002/acp.3596

Bogaard, G., Meijer, E. H., & Vrij, A. (2014). Using an Example Statement Increases Information but Does Not Increase Accuracy of CBCA, RM, and SCAN. *Journal of Investigative Psychology and Offender Profiling*, *11*(2), 151–163. https://doi.org /10.1002/jip.1409

Bogaard, G., Meijer, E. H., Vrij, A., Broers, N. J., & Merckelbach, H. (2014). Contextual Bias in Verbal Credibility Assessment: Criteria-Based Content Analysis, Reality Monitoring and Scientific Content Analysis. *Applied Cognitive Psychology*, *28*(1), 79–90. https://doi.org/10.1002/acp.2959

Bogaard, G., Meijer, E. H., Vrij, A., & Merckelbach, H. (2016). Scientific Content Analysis (SCAN) Cannot Distinguish Between Truthful and Fabricated Accounts of a Negative Event. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.00243

Bok, S. (1999). *Lying: Moral choice in public and private life* (2nd Vintage books ed). Vintage Books.

Bond, C. F., & DePaulo, B. M. (2006). Accuracy of Deception Judgments. *Personality and Social Psychology Review*, *10*(3), 214–234. https://doi.org/10.1207/s15327957 pspr1003_2

Bond, C. F., Levine, T. R., & Hartwig, M. (2014). New Findings in Non-Verbal Lie Detection. In P. A. Granhag, A. Vrij, & B. Verschuere (Eds.), *Detecting Deception* (1st ed., pp. 37–58). Wiley. https://doi.org/10.1002/9781118510001.ch2

Bonyad, A., Abdessalem, H. B., & Frasson, C. (2024). The Relation between Mental Workload and Face Temperature in Flight Simulation. *Journal of Behavioral and Brain Science*, *14*(02), 64–92. https://doi.org/10.4236/jbbs.2024.142006

Borza, D., Itu, R., & Danescu, R. (2018). In the Eye of the Deceiver: Analyzing Eye Movements as a Cue to Deception. *Journal of Imaging*, *4*(10), 120. https://doi.org/10.3390/jimaging4100120

Bouras, T., Stranjalis, G., & Sakas, D. E. (2007). Traumatic midbrain hematoma in a patient presenting with an isolated palsy of voluntary facial movements: Case report. *Journal of Neurosurgery*, *107*(1), 158–160. https://doi.org/10.3171/jns-07/07/0158

Bourdage, J. S., Roulin, N., & Levashina, J. (2017). Editorial: Impression Management and Faking in Job Interviews. *Frontiers in Psychology*, *8*, 1294. https://doi.org/10.3389/fpsyg.2017.01294

Bourdage, J. S., Roulin, N., & Tarraf, R. (2018). "I (might be) just that good": Honest and deceptive impression management in employment interviews. *Personnel Psychology*, *71*(4), 597–632. https://doi.org/10.1111/peps.12285

Bovik, A., Cormack, L., Van Der Linde, I., & Rajashekar, U. (2009). DOVES: A database of visual eye movements. *Spatial Vision*, *22*(2), 161–177. https://doi.org/10.1163/156856809787465636

Bowlby, J. (1982). Attachment and loss: Retrospect and prospect. *American Journal of Orthopsychiatry*, *52*(4), 664–678. https://doi.org/10.1111/j.19390025.1982.tb01456.x

Bradford, D., & Goodman-Delahunty, J. (2008). Detecting Deception in Police Investigations: Implications for False Confessions. *Psychiatry, Psychology and Law*, *15*(1), 105–118. https://doi.org/10.1080/13218710701873932

Bradley, M. M. (2009). Natural selective attention: Orienting and emotion. *Psychophysiology*, *46*(1), 1–11. https://doi.org/10.1111/j.1469-8986.2008.00702.x

Bradley, M. M., & Lang, P. J. (2000). Affective reactions to acoustic stimuli. *Psychophysiology*, *37*(2), 204–215.

Bradley, M. M., Miccoli, L., Escrig, M. A., & Lang, P. J. (2008). The pupil as a measure of emotional arousal and autonomic activation. *Psychophysiology*, *45*(4), 602–607. https://doi.org/10.1111/j.1469-8986.2008.00654.x

Brooks, P. (2005). The Future of Confession. *Law, Culture and the Humanities*, *1*(1), 53–74. https://doi.org/10.1191/1743872105lw005oa

Bryant, E. (2008). Real Lies, White Lies and Gray Lies: Towards a Typology of Deception. *Kaleidoscope*, *7*, 23–50.

Buchan, J. N., Paré, M., & Munhall, K. G. (2008). The effect of varying talker identity and listening conditions on gaze behavior during audiovisual speech perception. *Brain Research*, *1242*, 162–171. https://doi.org/10.1016/j.brainres.2008.06.083

Buller, D. B., & Burgoon, J. K. (1996). Interpersonal Deception Theory. *Communication Theory*, *6*(3), 203–242. https://doi.org/10.1111/j.1468-2885.1996.tb00127.x

Burgess, N., Becker, S., King, J. A., & O'Keefe, J. (2002). Memory for events and their spatial context: Models and experiments. In A. Baddeley, J. Aggleton, & M. Conway (Eds.), *Episodic Memory: New Directions in Research* (pp. 249–268). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780198508809.003.0014

Cabeza, R., & St Jacques, P. (2007). Functional neuroimaging of autobiographical memory. *Trends in Cognitive Sciences*, *11*(5), 219–227. https://doi.org/10.1016/j.tics.2007.02.005

Cacioppo, J. T., Berntson, G. G., Malarkey, W. B., Kiecolt-Glaser, J. K., Sheridan, J. F., Poehlmann, K. M., Burleson, M. H., Ernst, J. M., Hawkley, L. C., & Glaser, R. (1998). Autonomic, Neuroendocrine, and Immune Responses to Psychological Stress: The Reactivity Hypothesis [a]. *Annals of the New York Academy of Sciences*, *840*(1), 664–673. https://doi.org/10.1111/j.1749-6632.1998.tb09605.x

Calancie, O. G., Brien, D. C., Huang, J., Coe, B. C., Booij, L., Khalid-Khan, S., & Munoz, D. P. (2022). Maturation of Temporal Saccade Prediction from Childhood to Adulthood: Predictive Saccades, Reduced Pupil Size, and Blink Synchronization. *The Journal of Neuroscience*, *42*(1), 69–80. https://doi.org/10.1523/JNEUROSCI.0837-21.2021

Calvo, M. G., Fernández-Martín, A., Gutiérrez-García, A., & Lundqvist, D. (2018). Selective eye fixations on diagnostic face regions of dynamic emotional expressions: KDEF-dyn database. *Scientific Reports*, *8*(1), 17039. https://doi.org/10.1038/s41598-018-35259-w

Cardone, D., & Merla, A. (2017). New frontiers for applications of thermal infrared imaging devices: Computational psychopshysiology in the neurosciences. *Sensors*, *17*(5), 1042. https://doi.org/10.3390/s17051042

Carissimi, N., Beyan, C., & Murino, V. (2018). A Multi-View Learning Approach to Deception Detection. *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*, 599–606. https://doi.org/10.1109/FG.2018.00095

Carter, C. S., & van Veen, V. (2007). Anterior cingulate cortex and conflict detection: An update of theory and data. *Cognitive, Affective, & Behavioral Neuroscience*, *7*(4), 367–379. https://doi.org/10.3758/CABN.7.4.367

Cattaneo, L., & Pavesi, G. (2014). The facial motor system. *Neuroscience & Biobehavioral Reviews*, *38*, 135–159. https://doi.org/10.1016/j.neubiorev.2013.11.002

Causer, J., Vickers, J. N., Snelgrove, R., Arsenault, G., & Harvey, A. (2014). Performing under pressure: Quiet eye training improves surgical knot-tying performance. *Surgery*, *156*(5), 1089–1096. https://doi.org/10.1016/j.surg.2014.05.004

Chang, W.-Y., Hsu, S.-H., & Chien, J.-H. (2017). FATAUVA-Net: An Integrated Deep Learning Framework for Facial Attribute Recognition, Action Unit Detection, and Valence-Arousal Estimation. *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 1963–1971. https://doi.org/10.1109/CVPRW.2017.246

Chen, J., Van Den Bos, E., & Westenberg, P. M. (2020). A systematic review of visual avoidance of faces in socially anxious individuals: Influence of severity, type of social situation, and development. *Journal of Anxiety Disorders*, *70*, 102193. https://doi.org/10.1016/j.janxdis.2020.102193

Choi, K.-H., Kim, J., Kwon, O. S., Kim, M. J., Ryu, Y. H., & Park, J.-E. (2017). Is heart rate variability (HRV) an adequate tool for evaluating human emotions? – A focus on the use of the International Affective Picture System (IAPS). *Psychiatry Research*, *251*, 192–196. https://doi.org/10.1016/j.psychres.2017.02.025

Christ, S. E., Van Essen, D. C., Watson, J. M., Brubaker, L. E., & McDermott, K. B. (2009). The Contributions of Prefrontal Cortex and Executive Control to Deception: Evidence

from Activation Likelihood Estimate Meta-analyses. *Cerebral Cortex*, *19*(7), 1557–1566. https://doi.org/10.1093/cercor/bhn189

Chu, W.-S., De la Torre, F., & Cohn, J. F. (2017). Learning Spatial and Temporal Cues for Multi-Label Facial Action Unit Detection. *2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)*, 25–32. https://doi.org/10.1109/FG.2017.13

Clay-Warner, J., & Robinson, D. T. (2015). Infrared thermography as a measure of emotion response. *Emotion Review*, *7*(2), 157–162. https://doi.org/10.1177/1754073914554783

Clear, S. J., Gardner, A. A., Webb, H. J., & Zimmer-Gembeck, M. J. (2020). Common and Distinct Correlates of Depression, Anxiety, and Aggression: Attachment and Emotion Regulation of Sadness and Anger. *Journal of Adult Development*, *27*(3), 181–191. https://doi.org/10.1007/s10804-019-09333-0

Codispoti, M., Bradley, M. M., & Lang, P. J. (2001). Affective reactions to briefly presented pictures. *Psychophysiology*, *38*(3), 474–478.

Cohn, J. F., Ambadar, Z., & Ekman, P. (2007). Observer-based measurement of facial expression with the Facial Action Coding System. In *Handbook of emotion elicitation and assessment* (pp. 203–221). Oxford University Press.

Colwell, K., Hiscock-Anisman, C., & Fede, J. (2013). Assessment Criteria Indicative of Deception: An Example of the New Paradigm of Differential Recall Enhancement. In B. S. Cooper, D. Griesel, & M. Ternes (Eds.), *Applied Issues in Investigative Interviewing, Eyewitness Memory, and Credibility Assessment* (pp. 259–291). Springer New York. https://doi.org/10.1007/978-1-4614-5547-9_11

Colwell, K., Hiscock-Anisman, C. K., Memon, A., Taylor, L., & Prewett, J. (2007). Assessment Criteria Indicative of Deception (ACID): An integrated system of investigative interviewing and detecting deception. *Journal of Investigative Psychology and Offender Profiling*, *4*(3), 167–180. https://doi.org/10.1002/jip.73

Cook, A. E., Hacker, D. J., Webb, A. K., Osher, D., Kristjansson, S. D., Woltz, D. J., & Kircher, J. C. (2012). Lyin' eyes: Ocular-motor measures of reading reveal deception. *Journal*

of Experimental Psychology: Applied, *18*(3), 301–313. https://doi.org/10.1037/a0028307

Cooper, M. L., Shaver, P. R., & Collins, N. L. (1998). Attachment styles, emotion regulation, and adjustment in adolescence. *Journal of Personality and Social Psychology*, *74*(5), 1380–1397. https://doi.org/10.1037/0022-3514.74.5.1380

Costello, J. T., McInerney, C. D., Bleakley, C. M., Selfe, J., & Donnelly, A. E. (2012). The use of thermal imaging in assessing skin temperature following cryotherapy: A review. *Journal of Thermal Biology*, *37*(2), 103–110. https://doi.org/10.1016/j.jtherbio.2011.11.008

Cruz-Albarran, I. A., Benitez-Rangel, J. P., Osornio-Rios, R. A., & Morales-Hernandez, L. A. (2017). Human emotions detection based on a smart-thermal system of thermographic images. *Infrared Physics & Technology*, *81*, 250–261. https://doi.org/10.1016/j.infrared.2017.01.002

Curci, A., Lanciano, T., Battista, F., Guaragno, S., & Ribatti, R. M. (2019). Accuracy, Confidence, and Experiential Criteria for Lie Detection Through a Videotaped Interview. *Frontiers in Psychiatry*, *9*, 748. https://doi.org/10.3389/fpsyt.2018.00748

Daubert v. Merrell Dow Pharmaceuticals, Inc., 509 U.S. 579 (1993). (n.d.). Justia Law. Retrieved 25 October 2024, from https://supreme.justia.com/cases/federal/us/509/579/

Davatzikos, C., Ruparel, K., Fan, Y., Shen, D. G., Acharyya, M., Loughead, J. W., Gur, R. C., & Langleben, D. D. (2005). Classifying spatial patterns of brain activity with machine learning methods: Application to lie detection. *NeuroImage*, *28*(3), 663–668. https://doi.org/10.1016/j.neuroimage.2005.08.009

Day, B. L., & Fitzpatrick, R. C. (2005). The vestibular system. *Current Biology*, *15*(15), R583–R586. https://doi.org/10.1016/j.cub.2005.07.053

de Haan, G., & Jeanne, V. (2013). Robust Pulse Rate From Chrominance-Based rPPG. *IEEE Transactions on Biomedical Engineering*, *60*(10), 2878–2886. https://doi.org/10.1109/TBME.2013.2266196

De Rivecourt, M., Kuperus, M. N., Post, W. J., & Mulder, L. J. M. (2008). Cardiovascular and eye activity measures as indices for momentary changes in mental effort during simulated flight. *Ergonomics*, *51*(9), 1295–1319. https://doi.org/10.1080/00140130802120267

Deeb, H., Vrij, A., Leal, S., Giorgianni, D., Hypšová, P., & Mann, S. (2024). Exposing Suspects to Their Sketches in Repeated Interviews to Elicit Information and Veracity Cues. *The European Journal of Psychology Applied to Legal Context*, *16*(1), 1–15. https://doi.org/10.5093/ejpalc2024a1

Deeb, H., Vrij, A., Leal, S., & Mann, S. (2021). Combining the model statement and the sketching while narrating interview techniques to elicit information and detect lies in multiple interviews. *Applied Cognitive Psychology*, *35*(6), 1478–1491. https://doi.org/10.1002/acp.3880

Deeb, H., Vrij, A., Leal, S., Mann, S., & Burkhardt, J. (2022). The Model Sketch for Enhancing Lie Detection and Eliciting Information. *Brain Sciences*, *12*(9), 1180. https://doi.org/10.3390/brainsci12091180

Deeb, H., Vrij, A., Palena, N., Hypšová, P., Dib, G., Leal, S., & Mann, S. (2023). 'Honesty Repeats Itself: Comparing Manual and Automated Coding of Verbal Veracity Cues'. *Applied Psycholinguistics*, *45*(5), 934–962. https://doi.org/10.1017/S0142716424000298

Delgado, M. R., Gillis, M. M., & Phelps, E. A. (2008). Regulating the expectation of reward via cognitive strategies. *Nature Neuroscience*, *11*(8), 880–881. https://doi.org/10.1038/nn.2141

Delgado-Herrera, M., Reyes-Aguilar, A., & Giordano, M. (2021). What Deception Tasks Used in the Lab Really Do: Systematic Review and Meta-analysis of Ecological Validity of fMRI Deception Tasks. *Neuroscience*, *468*, 88–109. https://doi.org/10.1016/j.neuroscience.2021.06.005

Delmas, H., Denault, V., Burgoon, J. K., & Dunbar, N. E. (2024). A Review of Automatic Lie Detection from Facial Features. *Journal of Nonverbal Behavior*, *48*(1), 93–136. https://doi.org/10.1007/s10919-024-00451-2

DePaulo, B. M. (1992). Nonverbal behavior and self-presentation. *Psychological Bulletin*, *111*(2), 203–243. https://doi.org/10.1037/0033-2909.111.2.203

DePaulo, B. M., & Kashy, D. A. (1998). Everyday lies in close and casual relationships. *Journal of Personality and Social Psychology*, *74*(1), 63–79. https://doi.org/10.1037/0022-3514.74.1.63

DePaulo, B. M., Kashy, D. A., Kirkendol, S. E., Wyer, M. M., & Epstein, J. A. (1996). Lying in everyday life. *Journal of Personality and Social Psychology*, *70*(5), 979–995. https://doi.org/10.1037/0022-3514.70.5.979

DePaulo, B. M., Lanier, K., & Davis, T. (1983). Detecting the deceit of the motivated liar. *Journal of Personality and Social Psychology*, *45*(5), 1096–1103. https://doi.org/10.1037/0022-3514.45.5.1096

DePaulo, B. M., Lindsay, J. J., Malone, B. E., Muhlenbruck, L., Charlton, K., & Cooper, H. (2003). Cues to deception. *Psychological Bulletin*, *129*(1), 74–118. https://doi.org/10.1037/0033-2909.129.1.74

Derakhshan, A., Mikaeili, M., Gedeon, T., & Nasrabadi, A. M. (2020). Identifying the optimal features in multimodal deception detection. *Multimodal Technologies and Interaction*, *4*(2), 25. https://doi.org/10.3390/mti4020025

Di Battista, P. (1994). Effects of planning on performance of trust-violating versus tactful, white lies: How are familiar speech acts cognitively represented? *Communication Studies*, *45*(2), 174–186. https://doi.org/10.1080/10510979409368421

Diamond, L. M., Hicks, A. M., & Otter-Henderson, K. (2006). Physiological evidence for repressive coping among avoidantly attached adults. *Journal of Social and Personal Relationships*, *23*(2), 205–229. https://doi.org/10.1177/0265407506062470

Dianiska, R. E., Swanner, J. K., Brimbal, L., & Meissner, C. A. (2021). Using disclosure, common ground, and verification to build rapport and elicit information. *Psychology, Public Policy, and Law*, *27*(3), 341–353. https://doi.org/10.1037/law0000313

Dias, P., Soares, I., Klein, J., Cunha, J. P. S., & Roisman, G. I. (2011). Autonomic correlates of attachment insecurity in a sample of women with eating disorders. *Attachment & Human Development*, *13*(2), 155–167. https://doi.org/10.1080/14616734.2011.554005

Diaz-Piedra, C., Gomez-Milan, E., & Di Stasi, L. L. (2019). Nasal skin temperature reveals changes in arousal levels due to time on task: An experimental thermal infrared imaging study. *Applied Ergonomics*, *81*, 102870. https://doi.org/10.1016/j.apergo.2019.06.001

Diaz-Piedra, C., Sanchez-Carrion, J. M., Rieiro, H., & Di Stasi, L. L. (2017). Gaze-based Technology as a Tool for Surgical Skills Assessment and Training in Urology. *Urology*, *107*, 26–30. https://doi.org/10.1016/j.urology.2017.06.030

Dickerson, S. S., & Kemeny, M. E. (2004). Acute Stressors and Cortisol Responses: A Theoretical Integration and Synthesis of Laboratory Research. *Psychological Bulletin*, *130*(3), 355–391. https://doi.org/10.1037/0033-2909.130.3.355

Dimberg, U., & Petterson, M. (2000). Facial reactions to happy and angry facial expressions: Evidence for right hemisphere dominance. *Psychophysiology*, *37*(5), 693–696.

Dimitriev, D., Indeykina, O., & Dimitriev, A. (2023). The Effect of Auditory Stimulation on the Nonlinear Dynamics of Heart Rate: The Impact of Emotional Valence and Arousal. *Noise and Health*, *25*(118), 165–175. https://doi.org/10.4103/nah.nah_15_22

Dinges, L., Fiedler, M.-A., Al-Hamadi, A., Hempel, T., Abdelrahman, A., Weimann, J., Bershadskyy, D., & Steiner, J. (2024). Exploring facial cues: Automated deception detection using artificial intelligence. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-024-09811-x

Dionisio, D. P., Granholm, E., Hillix, W. A., & Perrine, W. F. (2001). Differentiation of deception using pupillary responses as an index of cognitive processing. *Psychophysiology*, *38*(2), 205–211. https://doi.org/10.1111/1469-8986.3820205

Doherty-Sneddon, G., Bruce, V., Bonner, L., Longbotham, S., & Doyle, C. (2002). Development of gaze aversion as disengagement from visual information.

Developmental Psychology, *38*(3), 438–445. https://doi.org/10.1037/0012-1649.38.3.438

Doherty-Sneddon, G., & Phelps, F. G. (2005). Gaze aversion: A response to cognitive or social difficulty? *Memory & Cognition*, *33*(4), 727–733. https://doi.org/10.3758/BF03195338

Donadio, V., Nolano, M., Provitera, V., Stancanelli, A., Lullo, F., Liguori, R., & Santoro, L. (2006). Skin sympathetic adrenergic innervation: An immunofluorescence confocal study. *Annals of Neurology*, *59*(2), 376–381. https://doi.org/10.1002/ana.20769

Dong, Z., Wang, G., Lu, S., Dai, L., Huang, S., & Liu, Y. (2022). Intentional-Deception Detection Based on Facial Muscle Movements in an Interactive Social Context. *Pattern Recognition Letters*, *164*, 30–39. https://doi.org/10.1016/j.patrec.2022.10.008

Dong, Z., Wang, G., Lu, S., Li, J., Yan, W., & Wang, S.-J. (2022). Spontaneous Facial Expressions and Micro-expressions Coding: From Brain to Face. *Frontiers in Psychology*, *12*, 784834. https://doi.org/10.3389/fpsyg.2021.784834

Donovan, J. J., Dwight, S. A., & Schneider, D. (2014). The impact of applicant faking on selection measures, hiring decisions, and employee performance. *Journal of Business and Psychology*, *29*(3), 479–493. https://doi.org/10.1007/s10869-013-9318-5

Drake, R. L., Vogl, W., Mitchell, A. W. M., & Gray, H. (2010). *Gray's anatomy for students* (2nd ed). Churchill Livingstone/Elsevier.

Drummond, P. D. (1994). Sweating and vascular responses in the face: Normal regulation and dysfunction in migraine, cluster headache and harlequin syndrome. *Clinical Autonomic Research*, *4*(5), 273–285. https://doi.org/10.1007/BF01827433

Duchowski, A. T. (2017). *Eye Tracking Methodology*. Springer International Publishing. https://doi.org/10.1007/978-3-319-57883-5

Dunbar, N. E., Fujiwara, K., & Bernhold, Q. S. (2023). Truth-tellers' and liars' synchrony during attitude-inconsistent conversations. *Frontiers in Communication*, *8*, 921446. https://doi.org/10.3389/fcomm.2023.921446

Dunbar, N. E., Giles, H., Bernhold, Q., Adams, A., Giles, M., Zamanzadeh, N., Gangi, K., Coveleski, S., & Fujiwara, K. (2020). Strategic Synchrony and Rhythmic Similarity in Lies About Ingroup Affiliation. *Journal of Nonverbal Behavior*, *44*(1), 153–172. https://doi.org/10.1007/s10919-019-00321-2

Ebisch, S. J., Aureli, T., Bafunno, D., Cardone, D., Romani, G. L., & Merla, A. (2012). Mother and child in synchrony: Thermal facial imprints of autonomic contagion. *Biological Psychology*, *89*(1), 123–129. https://doi.org/10.1016/j.biopsycho.2011.09.018

Ehrenthal, J. C., Friederich, H., & Schauenburg, H. (2011). Separation recall: Psychophysiological response-patterns in an attachment-related short-term stressor. *Stress and Health*, *27*(3), 251–255. https://doi.org/10.1002/smi.1326

Ekman, P. (2009). *Telling lies: Clues to deceit in the marketplace, politics, and marriage* (4th ed.). W.W. Norton.

Ekman, P., & Friesen, W. V. (1969). Nonverbal Leakage and Clues to Deception †. *Psychiatry*, *32*(1), 88–106. https://doi.org/10.1080/00332747.1969.11023575

Ekman, P., & Friesen, W. V. (1978). Facial Action Coding System (FACS). *Environmental Psychology & Nonverbal Behavior*. https://doi.org/10.1037/t27734-000

Ekman, P., Friesen, W. V., & Hager, J. C. (2002). *Facial Action Coding System*. Human Face.

Ekman, P., & O'Sullivan, M. (2006). From flawed self-assessment to blatant whoppers: The utility of voluntary and involuntary behavior in detecting deception. *Behavioral Sciences & the Law*, *24*(5), 673–686. https://doi.org/10.1002/bsl.729

Ekman, P., & Rosenberg, E. L. (2005). *What the Face RevealsBasic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS)*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195179644.001.0001

Ellis, A. P. J., West, B. J., Ryan, A. M., & DeShon, R. P. (2002). The use of impression management tactics in structured interviews: A function of question type? *Journal*

of Applied Psychology, *87*(6), 1200–1208. https://doi.org/10.1037/0021-9010.87.6.1200

Engert, V., Merla, A., Grant, J. A., Cardone, D., Tusche, A., & Singer, T. (2014). Exploring the Use of Thermal Infrared Imaging in Human Stress Research. *PLoS ONE*, *9*(3), e90782. https://doi.org/10.1371/journal.pone.0090782

Englehardt, E. E., & Pritchard, M. S. (2019). Moral Dimensions of Deceptive Communication. In T. Docan-Morgan (Ed.), *The Palgrave Handbook of Deceptive Communication* (pp. 91–106). Springer International Publishing. https://doi.org/10.1007/978-3-319-96334-1_5

Epstein, R. A., Parker, W. E., & Feiler, A. M. (2007). Where Am I Now? Distinct Roles for Parahippocampal and Retrosplenial Cortices in Place Recognition. *Journal of Neuroscience*, *27*(23), 6141–6149. https://doi.org/10.1523/JNEUROSCI.0799-07.2007

Fabes, R. A., & Eisenberg, N. (1997). Regulatory control and adults' stress-related responses to daily life events. *Journal of Personality and Social Psychology*, *73*(5), 1107–1117. https://doi.org/10.1037/0022-3514.73.5.1107

Fan, S., Shen, Z., Jiang, M., Koenig, B. L., Xu, J., Kankanhalli, M. S., & Zhao, Q. (2018). Emotional Attention: A Study of Image Sentiment and Visual Attention. *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 7521–7531. https://doi.org/10.1109/CVPR.2018.00785

Fernández-Cuevas, I., Bouzas Marins, J. C., Arnáiz Lastras, J., Gómez Carmona, P. M., Piñonosa Cano, S., García-Concepción, M. Á., & Sillero-Quintana, M. (2015). Classification of factors influencing the use of infrared thermography in humans: A review. *Infrared Physics & Technology*, *71*, 28–55. https://doi.org/10.1016/j.infrared.2015.02.007

Fiedler, K., Schmid, J., & Stahl, T. (2002). What Is the Current Truth About Polygraph Lie Detection? *Basic and Applied Social Psychology*, *24*(4), 313–324. https://doi.org/10.1207/S15324834BASP2404_6

Fischer, L. (2020). The Idea of Reading Someone's Thoughts in Contemporary Lie Detection Techniques. In L. Schlicht, C. Seemann, & C. Kassung (Eds.), *Mind Reading as a Cultural Practice* (pp. 109–137). Springer International Publishing. https://doi.org/10.1007/978-3-030-39419-6_6

Fisher, R. P., & Geiselman, R. E. (1992). *Memory-enhancing techniques for investigative interviewing: The cognitive interview*. Thomas.

Fluke. (2024). *What is Thermal Imaging? Thermal Cameras and How They Work*. https://www.fluke.com/en-us/learn/blog/thermal-imaging/how-infrared-cameras-work

Ford, E. B. (2006). Lie detection: Historical, neuropsychiatric and legal dimensions. *International Journal of Law and Psychiatry*, *29*(3), 159–177. https://doi.org/10.1016/j.ijlp.2005.07.001

Fox, J., Weisberg, S., & Price, B. (2001). *car: Companion to Applied Regression* (p. 3.1-3) [Dataset]. https://doi.org/10.32614/CRAN.package.car

Frank, M. G., & Ekman, P. (2004). Appearing truthful generalizes across different deception situations. *Journal of Personality and Social Psychology*, *86*(3), 486–495. https://doi.org/10.1037/0022-3514.86.3.486

Frank, R. H. (2015). *Microeconomics and behavior* (Ninth edition). McGraw-Hill Education.

Franzen, L., Cabugao, A., Grohmann, B., Elalouf, K., & Johnson, A. P. (2022). Individual pupil size changes as a robust indicator of cognitive familiarity differences. *PLOS ONE*, *17*(1), e0262753. https://doi.org/10.1371/journal.pone.0262753

Frías, M. T., Shaver, P. R., & Díaz-Loving, R. (2014). Individualism and collectivism as moderators of the association between attachment insecurities, coping, and social support. *Journal of Social and Personal Relationships*, *31*(1), 3–31. https://doi.org/10.1177/0265407513484631

Frijda, N. H. (2010). Impulsive action and motivation. *Biological Psychology*, *84*(3), 570–579. https://doi.org/10.1016/j.biopsycho.2010.01.005

Fumagalli, M., & Priori, A. (2012). Functional and clinical neuroanatomy of morality. *Brain*, *135*(7), 2006–2021. https://doi.org/10.1093/brain/awr334

Gallardo-Antolín, A., & Montero, J. M. (2021). Detecting Deception from Gaze and Speech Using a Multimodal Attention LSTM-Based Framework. *Applied Sciences*, *11*(14), 6393. https://doi.org/10.3390/app11146393

Gálvez-García, G., Fernández-Gómez, J., Bascour-Sandoval, C., Albayay, J., González-Quiñones, J. J., Moliné, A., Pérez-Luco, R., Boso, A., & Gómez-Milán, E. (2021). A trifactorial model of detection of deception using thermography. *Psychology, Crime & Law*, *27*(5), 405–426. https://doi.org/10.1080/1068316X.2020.1815198

Gamer, M. (2010). Does the Guilty Actions Test allow for differentiating guilty participants from informed innocents? A re-examination. *International Journal of Psychophysiology*, *76*(1), 19–24. https://doi.org/10.1016/j.ijpsycho.2010.01.009

Gamer, M. (2011). Detecting concealed information using autonomic measures. In B. Verschuere, G. Ben-Shakhar, & E. Meijer (Eds.), *Memory Detection* (1st ed., pp. 27–45). Cambridge University Press. https://doi.org/10.1017/CBO9780511975196.003

Gamer, M., Rill, H.-G., Vossel, G., & Gödert, H. W. (2006). Psychophysiological and vocal measures in the detection of guilty knowledge. *International Journal of Psychophysiology*, *60*(1), 76–87. https://doi.org/10.1016/j.ijpsycho.2005.05.006

Gamer, M., Verschuere, B., Crombez, G., & Vossel, G. (2008). Combining physiological measures in the detection of concealed information. *Physiology & Behavior*, *95*(3), 333–340. https://doi.org/10.1016/j.physbeh.2008.06.011

Gane, L., Power, S., Kushki, A., & Chau, T. (2011). Thermal Imaging of the Periorbital Regions during the Presentation of an Auditory Startle Stimulus. *PLoS ONE*, *6*(11), e27268. https://doi.org/10.1371/journal.pone.0027268

Ganis, G. (2014). Deception Detection Using Neuroimaging. In P. A. Granhag, A. Vrij, & B. Verschuere (Eds.), *Detecting Deception* (1st ed., pp. 105–121). Wiley. https://doi.org/10.1002/9781118510001.ch5

Ganis, G., & Keenan, J. P. (2009). The cognitive neuroscience of deception. *Social Neuroscience*, *4*(6), 465–472. https://doi.org/10.1080/17470910802507660

Garbey, M., Sun, N., Merla, A., & Pavlidis, I. (2007). Contact-Free Measurement of Cardiac Pulse Based on the Analysis of Thermal Imagery. *IEEE Transactions on Biomedical Engineering*, *54*(8), 1418–1426. https://doi.org/10.1109/TBME.2007.891930

Gasparini, F., Giltri, M., & Bandini, S. (2020). Discriminating affective state intensity using physiological responses. *Multimedia Tools and Applications*, *79*(47–48), 35845–35865. https://doi.org/10.1007/s11042-020-09114-y

Gegenfurtner, A., Lehtinen, E., Jarodzka, H., & Säljö, R. (2017). Effects of eye movement modeling examples on adaptive expertise in medical image diagnosis. *Computers & Education*, *113*, 212–225. https://doi.org/10.1016/j.compedu.2017.06.001

Gegenfurtner, A., Lehtinen, E., & Säljö, R. (2011). Expertise Differences in the Comprehension of Visualizations: A Meta-Analysis of Eye-Tracking Research in Professional Domains. *Educational Psychology Review*, *23*(4), 523–552. https://doi.org/10.1007/s10648-011-9174-7

Gelman, A., & Hill, J. (2006, December 18). *Data analysis using regression and multilevel/hierarchical models*. Higher Education from Cambridge University Press; Cambridge University Press. https://doi.org/10.1017/CBO9780511790942

George, J. F., & Robb, A. (2008). Deception and Computer-Mediated Communication in Daily Life. *Communication Reports*, *21*(2), 92–103. https://doi.org/10.1080/08934210802298108

Geven, L. M., Verschuere, B., Kindt, M., Vaknine, S., & Ben-Shakhar, G. (2022). Countering information leakage in the Concealed Information Test: The effects of item detailedness. *Psychophysiology*, *59*(2), e13957. https://doi.org/10.1111/psyp.13957

Gillath, O., Sesko, A. K., Shaver, P. R., & Chun, D. S. (2010). Attachment, authenticity, and honesty: Dispositional and experimentally induced security can reduce self- and other-deception. *Journal of Personality and Social Psychology*, *98*(5), 841–855. https://doi.org/10.1037/a0019206

Gillie, B. L., Vasey, M. W., & Thayer, J. F. (2014). Heart Rate Variability Predicts Control Over Memory Retrieval. *Psychological Science*, *25*(2), 458–465. https://doi.org/10.1177/0956797613508789

Gilman, T. L., Shaheen, R., Nylocks, K. M., Halachoff, D., Chapman, J., Flynn, J. J., Matt, L. M., & Coifman, K. G. (2017). A film set for the elicitation of emotion in research: A comprehensive catalog derived from four decades of investigation. *Behavior Research Methods*, *49*(6), 2061–2082. https://doi.org/10.3758/s13428-016-0842-x

Ginton, A. (2017). Examining different types of comparison questions in a field study of CQT polygraph technique: Theoretical and practical implications. *Journal of Investigative Psychology and Offender Profiling*, *14*(3), 281–293. https://doi.org/10.1002/jip.1475

Gioia, F., Nardelli, M., Scilingo, E. P., & Greco, A. (2023). Autonomic Regulation of Facial Temperature during Stress: A Cross-Mapping Analysis. *Sensors*, *23*(14), 6403. https://doi.org/10.3390/s23146403

Gödert, H. W., Rill, H.-G., & Vossel, G. (2001). Psychophysiological differentiation of deception: The effects of electrodermal lability and mode of responding on skin conductance and heart rate. *International Journal of Psychophysiology*, *40*(1), 61–75. https://doi.org/10.1016/S0167-8760(00)00149-5

Gołaszewski, M., Zajac, P., & Widacki, J. (2015). Thermal vision as a method of detection of deception: A review of experiences. *European Polygraph*, *9*(1), 5–24. https://doi.org/10.1515/ep-2015-0001

Gordon, N. J. (2016). *Essentials of Polygraph and Polygraph Testing*. CRC Press.

Granhag, P. A., & Hartwig, M. (2014). The Strategic Use of Evidence Technique: A Conceptual Overview. In P. A. Granhag, A. Vrij, & B. Verschuere (Eds.), *Detecting Deception* (1st ed., pp. 231–251). Wiley. https://doi.org/10.1002/9781118510001.ch10

Granhag, P. A., & Hartwig, M. (2008). A new theoretical perspective on deception detection: On the psychology of instrumental mind-reading. *Psychology, Crime & Law*, *14*(3), 189–200. https://doi.org/10.1080/10683160701645181

Granhag, P. A., & Vrij, A. (2005). Deception Detection. In *Psychology and law: An empirical perspective* (Vol. 2005, pp. 43–92). The Guilford Press.

Granhag, P. A., Vrij, A., & Verschuere, B. (Eds.). (2015). *Detecting deception: Current challenges and cognitive approaches*. Wiley Blackwell.

Green, M., Williams, L., & Davidson, D. (2003). In the face of danger: Specific viewing strategies for facial expressions of threat? *Cognition and Emotion*, *17*, 779–786.

Green, S. (2004). *Lying, Misleading, and Falsely Denying: How Moral Concepts Inform the Law of Perjury, Fraud, and False Statements*. *53*.

Green, S. P. (2015). Lying and Law. In J. Meibauer (Ed.), *The Oxford handbook of lying (OUP, forthcoming).* https://papers.ssrn.com/abstract=2690413

Greene, J. D., Nystrom, L. E., Engell, A. D., Darley, J. M., & Cohen, J. D. (2004). The Neural Bases of Cognitive Conflict and Control in Moral Judgment. *Neuron*, *44*(2), 389–400. https://doi.org/10.1016/j.neuron.2004.09.027

Griffin, Z. M., & Oppenheimer, D. M. (2006). Speakers gaze at objects while preparing intentionally inaccurate labels for them. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*(4), 943–948. https://doi.org/10.1037/0278-7393.32.4.943

Gross, J. J. (2015). Emotion Regulation: Current Status and Future Prospects. *Psychological Inquiry*, *26*(1), 1–26. https://doi.org/10.1080/1047840X.2014.940781

Gross, J. J., & John, O. P. (1998). Mapping the domain of expressivity: Multimethod evidence for a hierarchical model. *Journal of Personality and Social Psychology*, *74*(1), 170–191. https://doi.org/10.1037/0022-3514.74.1.170

Gross, J. J., & John, O. P. (2003). Individual differences in two emotion regulation processes: Implications for affect, relationships, and well-being. *Journal of Personality and Social Psychology*, *85*(2), 348–362. https://doi.org/10.1037/0022-3514.85.2.348

Grubin, D. (2010). The polygraph and forensic psychiatry. *Journal of the American Academy of Psychiatry and the Law*, *38*(4), 446–451.

Grubin, D., & Madsen, L. (2005). Lie detection and the polygraph: A historical review. *Journal of Forensic Psychiatry & Psychology*, *16*(2), 357–369. https://doi.org/10.1080/14789940412331337353

Gu, S., Jiang, Y., Liu, M., Li, Y., Liang, Y., Feng, R., Xu, M., Wang, F., & Huang, J. H. (2023). Eye movements and ERP biomarkers for face processing problems in avoidant attachment-style individuals. *Frontiers in Behavioral Neuroscience*, *17*, 1135909. https://doi.org/10.3389/fnbeh.2023.1135909

Gudi, A., Bittner, M., & van Gemert, J. (2020). Real-Time Webcam Heart-Rate and Variability Estimation with Clean Ground Truth for Evaluation. *Applied Sciences*, *10*(23), 8630. https://doi.org/10.3390/app10238630

Gudjonsson, G. H. (2003). *The Psychology of Interrogations and Confessions: A Handbook*. John Wiley & Sons.

Guendelman, S., Kaltwasser, L., Bayer, M., Gallese, V., & Dziobek, I. (2024). Brain mechanisms underlying the modulation of heart rate variability when accepting and reappraising emotions. *Scientific Reports*, *14*(1), 18756. https://doi.org /10.1038/s41598-024-68352-4

Gullett, N., Zajkowska, Z., Walsh, A., Harper, R., & Mondelli, V. (2023). Heart rate variability (HRV) as a way to understand associations between the autonomic nervous system (ANS) and affective states: A critical review of the literature. *International Journal of Psychophysiology*, *192*, 35–42. https://doi.org/10.1016/j.ijpsycho.2023.08.001

Hall, J. A., Andrzejewski, S. A., & Yopchick, J. E. (2009). Psychosocial Correlates of Interpersonal Sensitivity: A Meta-Analysis. *Journal of Nonverbal Behavior*, *33*(3), 149–180. https://doi.org/10.1007/s10919-009-0070-5

Hancock, J. T., Thom-Santelli, J., & Ritchie, T. (2004). Deception and design: The impact of communication technology on lying behavior. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 129–134. https://doi.org/10.1145 /985692.985709

Hanhart, P., & Ebrahimi, T. (2014). EYEC3D: 3D video eye tracking dataset. *2014 Sixth International Workshop on Quality of Multimedia Experience (QoMEX)*, 55–56. https://doi.org/10.1109/QoMEX.2014.6982290

Hansen, A. L., Johnsen, B. H., & Thayer, J. F. (2003). Vagal influence on working memory and attention. *International Journal of Psychophysiology*, *48*(3), 263–274. https://doi.org/10.1016/S0167-8760(03)00073-4

Harker, M. (2013). Psychological Sweating: A Systematic Review Focused on Aetiology and Cutaneous Response. *Skin Pharmacology and Physiology*, *26*(2), 92–100. https://doi.org/10.1159/000346930

Hartwig, M., Anders Granhag, P., & Strömwall, L. A. (2007). Guilty and innocent suspects' strategies during police interrogations. *Psychology, Crime & Law*, *13*(2), 213–227. https://doi.org/10.1080/10683160600750264

Hartwig, M., Granhag, P. A., & Luke, T. (2014). Strategic Use of Evidence During Investigative Interviews. In *Credibility Assessment* (pp. 1–36). Elsevier. https://doi.org/10.1016/B978-0-12-394433-7.00001-4

Harvey, A. C., Vrij, A., Leal, S., Hope, L., & Mann, S. (2017). Deception and decay: Verbal lie detection as a function of delay and encoding quality. *Journal of Applied Research in Memory and Cognition*, *6*(3), 306–318. https://doi.org/10.1037/h0101812

Hasan, K., Rahman, W., Gerstner, L., Sen, T., Lee, S., Haut, K. G., & Hoque, M. (2019). Facial Expression Based Imagination Index and a Transfer Learning Approach to Detect Deception. *2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*, 634–640. https://doi.org/10.1109/ACII.2019.8925473

Hayano, J., & Yuda, E. (2019). Pitfalls of assessment of autonomic function by heart rate variability. *Journal of Physiological Anthropology*, *38*(1), 3. https://doi.org/10.1186/s40101-019-0193-2

He, X., Wang, L., Gao, X., & Chen, Y. (2012). The eye activity measurement of mental workload based on basic flight task. *IEEE 10th International Conference on Industrial Informatics*, 502–507. https://doi.org/10.1109/INDIN.2012.6301203

Hermanowicz, E. T. (2018). Augustine on Lying. *Speculum*, *93*(3), 699–727. https://doi.org/10.1086/698318

Hessels, R. S., Holleman, G. A., Cornelissen, T. H. W., Hooge, I. T. C., & Kemner, C. (2018). Eye contact takes two – autistic and social anxiety traits predict gaze behavior in dyadic interaction. *Journal of Experimental Psychopathology*, *9*(2), jep.062917. https://doi.org/10.5127/jep.062917

Higgins, C. A., & Judge, T. A. (2004). The Effect of Applicant Influence Tactics on Recruiter Perceptions of Fit and Hiring Recommendations: A Field Study. *Journal of Applied Psychology*, *89*(4), 622–632. https://doi.org/10.1037/0021-9010.89.4.622

Hilgendorf, E. L., & Irving, B. (1981). A Decision-Making Model of Confessions. In S. M. A. Lloyd-Bostock (Ed.), *Psychology in Legal Contexts* (pp. 67–84). Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-04917-2_5

Hochman, G., Glöckner, A., Fiedler, S., & Ayal, S. (2016). "I can see it in your eyes": Biased Processing and Increased Arousal in Dishonest Responses. *Journal of Behavioral Decision Making*, *29*(2–3), 322–335. https://doi.org/10.1002/bdm.1932

Holleman, G. A., Hessels, R. S., Kemner, C., & Hooge, I. T. C. (2020). Implying social interaction and its influence on gaze behavior to the eyes. *PLOS ONE*, *15*(2), e0229203. https://doi.org/10.1371/journal.pone.0229203

Holmberg, D., Lomore, C. D., Takacs, T. A., & Price, E. L. (2011). Adult attachment styles and stressor severity as moderators of the coping sequence. *Personal Relationships*, *18*(3), 502–517. https://doi.org/10.1111/j.1475-6811.2010.01318.x

Holst, G. C. (2000). *Common sense approach to thermal imaging*. JCD Publ.

Holstege, G. (2002). Emotional innervation of facial musculature. *Movement Disorders*, *17*(S2), S12–S16. https://doi.org/10.1002/mds.10050

Houston, P. (Ed.). (2012). *Spy the lie: Former CIA officers show you how to detect deception* (1st ed). St. Martin's Press.

Hu, M., Qian, F., Wang, X., He, L., Guo, D., & Ren, F. (2022). Robust Heart Rate Estimation With Spatial–Temporal Attention Network From Facial Videos. *IEEE Transactions on*

Cognitive and Developmental Systems, *14*(2), 639–647. https://doi.org/10.1109/TCDS.2021.3062370

Hugenberg, K., McConnell, A. R., Kunstman, J. W., Lloyd, E. P., & Humphrey, B. (2017). *Miami University Deception Detection Database.* [Dataset].

Hunnius, S., De Wit, T. C. J., Vrins, S., & Von Hofsten, C. (2011). Facing threat: Infants' and adults' visual scanning of faces with neutral, happy, sad, angry, and fearful emotional expressions. *Cognition & Emotion*, *25*(2), 193–205. https://doi.org/10.1080/15298861003771189

Hurley, C. M., & Frank, M. G. (2011). Executing Facial Control During Deception Situations. *Journal of Nonverbal Behavior*, *35*(2), 119–131. https://doi.org/10.1007/s10919-010-0102-1

Hypšová, P., & Seitl, M. (2022). *Infračervené termovizní snímání a analýza mimiky při detekci úmyslného zkreslování informací—Případová studie*. https://doi.org/10.13140/RG.2.2.12916.42885

Hypšová, P., Seitl, M., Popelka, S., & Dostál, D. (2024). Infrared thermal imaging and eye-tracking for deception detection: A laboratory study. *Current Psychology*. https://doi.org/10.1007/s12144-024-06840-6

Iacono, W. G. (2008). Effective Policing: Understanding How Polygraph Tests Work and Are Used. *Criminal Justice and Behavior*, *35*(10), 1295–1308. https://doi.org/10.1177/0093854808321529

Iacono, W. G., & Ben-Shakhar, G. (2019). Current status of forensic lie detection with the comparison question technique: An update of the 2003 National Academy of Sciences report on polygraph testing. *Law and Human Behavior*, *43*(1), 86–98. https://doi.org/10.1037/lhb0000307

Ikuenobe, P. (2002). The Meta-Ethical Issue of the Nature of Lying: Implications for Moral Education. *Studies in Philosophy and Education*, *21*(1), 37–63. https://doi.org/10.1023/A:1014446323547

Ioannidis, C. A., & Siegling, A. B. (2015). Criterion and incremental validity of the emotion regulation questionnaire. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00247

Ioannou, S., Gallese, V., & Merla, A. (2014). Thermal infrared imaging in psychophysiology: Potentialities and limits. *Psychophysiology*, *51*(10), 951–963. https://doi.org/10.1111/psyp.12243

Ioannou, S., Morris, P. H., Baker, M., Reddy, V., & Gallese, V. (2017). Seeing a Blush on the Visible and Invisible Spectrum: A Functional Thermal Infrared Imaging Study. *Frontiers in Human Neuroscience*, *11*, 525. https://doi.org/10.3389/fnhum.2017.00525

Ioannou, S., Morris, P., Mercer, H., Baker, M., Gallese, V., & Reddy, V. (2014). Proximity and gaze influences facial temperature: A thermal infrared imaging study. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.00845

Ioannou, S., Morris, P., Terry, S., Baker, M., Gallese, V., & Reddy, V. (2016). Sympathy crying: Insights from infrared thermal imaging on a female sample. *PLOS ONE*, *11*(10), e0162749. https://doi.org/10.1371/journal.pone.0162749

Isbilir, E., Cakir, M., Acarturk, C., & Tekerek, S. (2018). Towards a Multimodal Model of Cognitive Workload through Synchronous Optical Brain Imaging and Eye Tracking Measures. *Frontiers in Human Neuroscience*, *12*. https://doi.org/10.3389/conf.fnhum.2018.227.00089

Itier, R. J., & Batty, M. (2009). Neural bases of eye and gaze processing: The core of social cognition. *Neuroscience & Biobehavioral Reviews*, *33*(6), 843–863. https://doi.org/10.1016/j.neubiorev.2009.02.004

Izard, C. E. (2013). *Human Emotions*. Springer.

Izard, C. E., & Weiss, M. (1979). *Maximally discriminative facial movement coding system*. University of Delaware, instructional resources Center.

Jackson, D. C., Malmstadt, J. R., Larson, C. L., & Davidson, R. J. (2000). Suppression and enhancement of emotional responses to unpleasant pictures. *Psychophysiology*, *37*(4), 515–522.

Jain, U., Tan, B., & Li, Q. (2012). Concealed knowledge identification using facial thermal imaging. *2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 1677–1680. https://doi.org/10.1109/ICASSP.2012.6288219

Jaiswal, M., Tabibu, S., & Bajpai, R. (2016). The Truth and Nothing But the Truth: Multimodal Analysis for Deception Detection. *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*, 938–943. https://doi.org/10.1109/ICDMW.2016.0137

Jansen, A., König, C. J., Stadelmann, E. H., & Kleinmann, M. (2012). Applicants' Self-Presentational Behavior: What Do Recruiters Expect and What Do They Get? *Journal of Personnel Psychology*, *11*(2), 77–85. https://doi.org/10.1027/1866-5888/a000046

Jian, B.-L., Chen, C.-L., Huang, M.-W., & Yau, H.-T. (2019). Emotion-Specific Facial Activation Maps Based on Infrared Thermal Image Sequences. *IEEE Access*, *7*, 48046–48052. https://doi.org/10.1109/ACCESS.2019.2908819

Johnsen, B. H., Thayer, J. F., Laberg, J. C., Wormnes, B., Raadal, M., Skaret, E., Kvale, G., & Berg, E. (2003). Attentional and physiological characteristics of patients with dental anxiety. *Journal of Anxiety Disorders*, *17*(1), 75–87. https://doi.org/10.1016/S0887-6185(02)00178-0

Johnson, J. M., & Kellogg, D. L. (2018). Skin vasoconstriction as a heat conservation thermoeffector. In *Handbook of Clinical Neurology* (Vol. 156, pp. 175–192). Elsevier. https://doi.org/10.1016/B978-0-444-63912-7.00011-4

Johnson, J. M., Minson, C. T., & Kellogg, D. L. (2014). Cutaneous Vasodilator and Vasoconstrictor Mechanisms in Temperature Regulation. In R. Terjung (Ed.), *Comprehensive Physiology* (1st ed., pp. 33–89). Wiley. https://doi.org/10.1002/cphy.c130015

Johnson, M. K., & Raye, C. L. (1981). Reality monitoring. *Psychological Review*, *88*(1), 67–85. https://doi.org/10.1037/0033-295X.88.1.67

Kalbfleisch, P. J., & Docan-Morgan, T. (2019). Defining Truthfulness, Deception, and Related Concepts. In T. Docan-Morgan (Ed.), *The Palgrave Handbook of Deceptive Communication* (pp. 29–39). Springer International Publishing. https://doi.org/10.1007/978-3-319-96334-1_2

Kan, Y., Wang, X., Chen, X., Zhao, H., Lan, J., & Duan, H. (2021). Acute stress reduces the emotional attentional blink: Evidence from human electrophysiology. *Cognitive, Affective, & Behavioral Neuroscience*, *21*(1), 58–73. https://doi.org /10.3758/s13415-020-00847-9

Kassambara, A., & Mundt, F. (2016). *factoextra: Extract and Visualize the Results of Multivariate Data Analyses* (p. 1.0.7) [Dataset]. https://doi.org/10.32614 /CRAN.package.factoextra

Kassin, S. M. (2005). On the Psychology of Confessions: Does Innocence Put Innocents at Risk? *American Psychologist*, *60*(3), 215–228. https://doi.org/10.1037/0003-066X.60.3.215

Kassin, S. M. (2014). False Confessions: Causes, Consequences, and Implications for Reform. *Policy Insights from the Behavioral and Brain Sciences*, *1*(1), 112–121. https://doi.org/10.1177/2372732214548678

Kassin, S. M., Dror, I. E., & Kukucka, J. (2013). The forensic confirmation bias: Problems, perspectives, and proposed solutions. *Journal of Applied Research in Memory and Cognition*, *2*(1), 42–52. https://doi.org/10.1016/j.jarmac.2013.01.001

Kassin, S. M., & Gudjonsson, G. H. (2004). The Psychology of Confessions: A Review of the Literature and Issues. *Psychological Science in the Public Interest*, *5*(2), 33–67. https://doi.org/10.1111/j.1529-1006.2004.00016.x

Kenny, D. A., & Judd, C. M. (1986). Consequences of violating the independence assumption in analysis of variance. *Psychological Bulletin*, *99*(3), 422–431. https://doi.org /10.1037/0033-2909.99.3.422

Keskin, M., Ooms, K., Dogru, A. O., & De Maeyer, P. (2020). Exploring the Cognitive Load of Expert and Novice Map Users Using EEG and Eye Tracking. *ISPRS International Journal of Geo-Information*, *9*(7), 429. https://doi.org/10.3390/ijgi9070429

Khorrami, P., Paine, T. L., & Huang, T. S. (2015). Do Deep Neural Networks Learn Facial Action Units When Doing Expression Recognition? *2015 IEEE International Conference on Computer Vision Workshop (ICCVW)*, 19–27. https://doi.org/10.1109/ICCVW.2015.12

Kim, K., Lee, Y., Kim, H.-T., & Lee, J.-H. (2019). Detecting deception: Effect of auditory and visual stimuli on pupil dilation. *Social Behavior and Personality: An International Journal*, *47*(3), 1–10. https://doi.org/10.2224/sbp.7454

Kim, S. Y., Park, H., Kim, H., Kim, J., & Seo, K. (2022). Technostress causes cognitive overload in high-stress people: Eye tracking analysis in a virtual kiosk test. *Information Processing & Management*, *59*(6), 103093. https://doi.org/10.1016/j.ipm.2022.103093

Kim, Y. (2006). Gender, attachment, and relationship duration on cardiovascular reactivity to stress in a laboratory study of dating couples. *Personal Relationships*, *13*(1), 103–114. https://doi.org/10.1111/j.1475-6811.2006.00107.x

Kinner, V. L., Kuchinke, L., Dierolf, A. M., Merz, C. J., Otto, T., & Wolf, O. T. (2017). What our eyes tell us about feelings: Tracking pupillary responses during emotion regulation processes. *Psychophysiology*, *54*(4), 508–518. https://doi.org/10.1111/psyp.12816

Kistler, A., Mariauzouls, C., & von Berlepsch, K. (1998). Fingertip temperature as an indicator for sympathetic responses. *International Journal of Psychophysiology*, *29*(1), 35–41. https://doi.org/10.1016/S0167-8760(97)00087-1

Kleinberg, B., van der Toolen, Y., Vrij, A., Arntz, A., & Verschuere, B. (2018). Automated verbal credibility assessment of intentions: The model statement technique and predictive modeling. *Applied Cognitive Psychology*, *32*(3), 354–366. https://doi.org/10.1002/acp.3407

Knapp, M. L., Griffin, D. J., Earnest, W., & McGlone, M. S. (2016). *Lying and deception in human interaction* (Second edition). Kendall Hunt Publishing Company.

Koelstra, S., Muhl, C., Soleymani, M., Jong-Seok Lee, Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., & Patras, I. (2012). DEAP: A Database for Emotion Analysis ;Using

Physiological Signals. *IEEE Transactions on Affective Computing*, *3*(1), 18–31. https://doi.org/10.1109/T-AFFC.2011.15

Köhnken, G. (2004). Statement Validity Analysis and the 'detection of the truth'. In P. A. Granhag & L. A. Strömwall (Eds.), *The Detection of Deception in Forensic Contexts* (1st ed., pp. 41–63). Cambridge University Press. https://doi.org/10.1017/CBO9780511490071.003

Kop, W. J., Synowski, S. J., Newell, M. E., Schmidt, L. A., Waldstein, S. R., & Fox, N. A. (2011). Autonomic nervous system reactivity to positive and negative mood induction: The role of acute psychological responses and frontal electrocortical activity. *Biological Psychology*, *86*(3), 230–238. https://doi.org/10.1016/j.biopsycho.2010.12.003

Kosonogov, V., De Zorzi, L., Honoré, J., Martínez-Velázquez, E. S., Nandrino, J.-L., Martinez-Selva, J. M., & Sequeira, H. (2017). Facial thermal variations: A new marker of emotional arousal. *PLOS ONE*, *12*(9), e0183592. https://doi.org/10.1371/journal.pone.0183592

Kozel, F. A., Johnson, K. A., Laken, S. J., Grenesko, E. L., Smith, J. A., Walker, J., & George, M. S. (2009). Can simultaneously acquired electrodermal activity improve accuracy of fMRI detection of deception? *Social Neuroscience*, *4*(6), 510–517. https://doi.org/10.1080/17470910801907168

Krejtz, K., Duchowski, A. T., Niedzielska, A., Biele, C., & Krejtz, I. (2018). Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze. *PLOS ONE*, *13*(9), e0203629. https://doi.org/10.1371/journal.pone.0203629

Kreyßig, N., & Krautz, A. E. (2019). Lying and perception of lies by bilingual speakers. *Applied Psycholinguistics*, *40*(05), 1313–1329. https://doi.org/10.1017/S0142716419000286

Kring, A. M., & Sloan, D. M. (2007). The Facial Expression Coding System (FACES): Development, validation, and utility. *Psychological Assessment*, *19*(2), 210–224. https://doi.org/10.1037/1040-3590.19.2.210

Kristensen, M., & Hansen, T. (2004). Statistical analyses of repeated measures in physiological research: A tutorial. *Advances in Physiology Education*, *28*(1), 2–14. https://doi.org/10.1152/advan.00042.2003

Kristof-Brown, A., Barrick, M. R., & Franke, M. (2002). Applicant Impression Management: Dispositional Influences and Consequences for Recruiter Perceptions of Fit and Similarity. *Journal of Management*, *28*(1), 27–46. https://doi.org/10.1177/014920630202800103

Ktistakis, E., Skaramagkas, V., Manousos, D., Tachos, N. S., Tripoliti, E., Fotiadis, D. I., & Tsiknakis, M. (2022). COLET: A dataset for COgnitive workLoad estimation based on eye-tracking. *Computer Methods and Programs in Biomedicine*, *224*, 106989. https://doi.org/10.1016/j.cmpb.2022.106989

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*(13). https://doi.org/10.18637/jss.v082.i13

Kyriacou, P. A., & Chatterjee, S. (2022). The origin of photoplethysmography. In *Photoplethysmography: Technology, Signal Analysis and Applications* (pp. 17–43). Elsevier. https://doi.org/10.1016/B978-0-12-823374-0.00004-9

Iacono, W. G. (2017). Detection of deception. In *Handbook of psychophysiology, 4th ed* (pp. 565–580). Cambridge University Press.

Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*. https://doi.org/10.3389/fpsyg.2013.00863

Lancaster, G. L. J., Vrij, A., Hope, L., & Waller, B. (2013). Sorting the liars from the truth tellers: The benefits of asking unanticipated questions on lie detection. *Applied Cognitive Psychology*, *27*(1), 107–114. https://doi.org/10.1002/acp.2879

Land, M. F., & Furneaux, S. (1997). The knowledge base of the oculomotor system. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *352*(1358), 1231–1239. https://doi.org/10.1098/rstb.1997.0105

Lane, R., Mcrae, K., Reiman, E., Chen, K., Ahern, G., & Thayer, J. (2009). Neural correlates of heart rate variability during emotion. *NeuroImage*, *44*(1), 213–222. https://doi.org/10.1016/j.neuroimage.2008.07.056

Langleben, D. D. (2008). Detection of deception with fMRI: Are we there yet? *Legal and Criminological Psychology*, *13*(1), 1–9. https://doi.org/10.1348/135532507X251641

Langleben, D. D., Loughead, J. W., Bilker, W. B., Ruparel, K., Childress, A. R., Busch, S. I., & Gur, R. C. (2005). Telling truth from lie in individual subjects with fast event-related fMRI. *Human Brain Mapping*, *26*(4), 262–272. https://doi.org/10.1002/hbm.20191

Langleben, D. D., & Moriarty, J. C. (2013). Using brain imaging for lie detection: Where science, law, and policy collide. *Psychology, Public Policy, and Law*, *19*(2), 222–234. https://doi.org/10.1037/a0028841

Larsen, J. T., Norris, C. J., & Cacioppo, J. T. (2003). Effects of positive and negative affect on electromyographic activity over zygomaticus major and corrugator supercilii. *Psychophysiology*, *40*(5), 776–785. https://doi.org/10.1111/1469-8986.00078

Law, S. J., Bourdage, J., & O'Neill, T. A. (2016). To fake or not to fake: Antecedents to interview faking, warning instructions, and its impact on applicant reactions. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01771

Leal, S., & Vrij, A. (2010). The occurrence of eye blinks during a guilty knowledge test. *Psychology, Crime & Law*, *16*(4), 349–357. https://doi.org/10.1080/10683160902776843

Leal, S., Vrij, A., Deeb, H., & Jupe, L. (2018). Using the model statement to elicit verbal differences between truth tellers and liars: The benefit of examining core and peripheral details. *Journal of Applied Research in Memory and Cognition*, *7*(4), 610–617. https://doi.org/10.1016/j.jarmac.2018.07.001

Leal, S., Vrij, A., Vernham, Z., Dalton, G., Jupe, L., Harvey, A., & Nahari, G. (2018). Cross-cultural verbal deception. *Legal and Criminological Psychology*, *23*(2), 192–213. https://doi.org/10.1111/lcrp.12131

Leary, M. R., & Kowalski, R. M. (1990). Impression management: A literature review and two-component model. *Psychological Bulletin*, *107*(1), 34–47. https://doi.org/10.1037/0033-2909.107.1.34

Lečbych, M., & Pospíšilíková, K. (2012). Česká verze čkály Experiences in Close Relationships (ECR): Pilotní posouzení vztahové vazby v dospělosti. *E-psychologie*, *6*(3), 1–11.

Lee, E., Chen, E., & Lee, C.-Y. (2020). Meta-rPPG: Remote Heart Rate Estimation Using a Transductive Meta-learner. In A. Vedaldi, H. Bischof, T. Brox, & J.-M. Frahm (Eds.), *Computer Vision – ECCV 2020* (Vol. 12372, pp. 392–409). Springer International Publishing. https://doi.org/10.1007/978-3-030-58583-9_24

Lee, T. M. C., Liu, H., Tan, L., Chan, C. C. H., Mahankali, S., Feng, C., Hou, J., Fox, P. T., & Gao, J. (2002). Lie detection by functional magnetic resonance imaging. *Human Brain Mapping*, *15*(3), 157–164. https://doi.org/10.1002/hbm.10020

Lenth, R. V. (2017). *emmeans: Estimated Marginal Means, aka Least-Squares Means* (p. 1.11.0) [Dataset]. https://doi.org/10.32614/CRAN.package.emmeans

Levashina, J., & Campion, M. A. (2006). A model of faking likelihood in the employment interview. *International Journal of Selection and Assessment*, *14*(4), 299–316. https://doi.org/10.1111/j.1468-2389.2006.00353.x

Levashina, J., & Campion, M. A. (2007). Measuring faking in the employment interview: Development and validation of an interview faking behavior scale. *Journal of Applied Psychology*, *92*(6), 1638–1656. https://doi.org/10.1037/0021-9010.92.6.1638

Levine, T. R. (2014). Truth-Default Theory (TDT): A Theory of Human Deception and Deception Detection. *Journal of Language and Social Psychology*, *33*(4), 378–392. https://doi.org/10.1177/0261927X14535916

Li, Y., Bian, J., & Song, R. (2024). Video-based deception detection using wrapper-based feature selection. *2024 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*, 1–5. https://doi.org/10.1109/CIVEMSA58715.2024.10586610

Lisofsky, N., Kazzer, P., Heekeren, H. R., & Prehn, K. (2014). Investigating socio-cognitive processes in deception: A quantitative meta-analysis of neuroimaging studies. *Neuropsychologia*, *61*, 113–122. https://doi.org/10.1016/j.neuropsychologia.2014.06.001

Liu, P., Han, S., Meng, Z., & Tong, Y. (2014). Facial Expression Recognition via a Boosted Deep Belief Network. *2014 IEEE Conference on Computer Vision and Pattern Recognition*, 1805–1812. https://doi.org/10.1109/CVPR.2014.233

Liu, Y., Prati, L. M., Perrewé, P. L., & Brymer, R. A. (2010). Individual Differences in Emotion Regulation, Emotional Experiences at Work, and Work-related Outcomes: A Two-Study Investigation. *Journal of Applied Social Psychology*, *40*(6), 1515–1538. https://doi.org/10.1111/j.1559-1816.2010.00627.x

L.Knapp, M., & Comaden, M. E. (1979). Telling it like it isn't: A review of theory and research on deceptive communications. *Human Communication Research*, *5*(3), 270–285. https://doi.org/10.1111/j.1468-2958.1979.tb00640.x

Lu, H., & Han, H. (2021). NAS-HR: Neural architecture search for heart rate estimation from face videos. *Virtual Reality & Intelligent Hardware*, *3*(1), 33–42. https://doi.org/10.1016/j.vrih.2020.10.002

Luber, B., Fisher, C., Appelbaum, P. S., Ploesser, M., & Lisanby, S. H. (2009). Non-invasive brain stimulation in the detection of deception: Scientific challenges and ethical consequences. *Behavioral Sciences & the Law*, *27*(2), 191–208. https://doi.org/10.1002/bsl.860

Lüdecke, D., Ben-Shachar, M., Patil, I., Waggoner, P., & Makowski, D. (2021). performance: An R Package for Assessment, Comparison and Testing of Statistical Models. *Journal of Open Source Software*, *6*(60), 3139. https://doi.org/10.21105/joss.03139

Luque-Casado, A., Perales, J. C., Cárdenas, D., & Sanabria, D. (2016). Heart rate variability and cognitive processing: The autonomic response to task demands. *Biological Psychology*, *113*, 83–90. https://doi.org/10.1016/j.biopsycho.2015.11.013

Lykken, D. T. (1959). The GSR in the detection of guilt. *Journal of Applied Psychology*, *43*(6), 385–388. https://doi.org/10.1037/h0046060

Mac Giolla, E., & Luke, T. J. (2021). Does the cognitive approach to lie detection improve the accuracy of human observers? *Applied Cognitive Psychology*, *35*(2), 385–392. https://doi.org/10.1002/acp.3777

Machado-Moreira, C. A., & Taylor, N. A. S. (2012). Psychological sweating from glabrous and nonglabrous skin surfaces under thermoneutral conditions. *Psychophysiology*, *49*(3), 369–374. https://doi.org/10.1111/j.1469-8986.2011.01309.x

MacIntyre, A. (1994). *Truthfulness, Lies, and Moral Philosophers: What Can We Learn From Mill and Kant?*

Maechler, M., Rousseeuw, P., Struyf, A., & Hubert, M. (1999). *cluster: 'Finding Groups in Data': Cluster Analysis Extended Rousseeuw et al.* (p. 2.1.8.1) [Dataset]. https://doi.org/10.32614/CRAN.package.cluster

Mahanama, B., Jayawardana, Y., Rengarajan, S., Jayawardena, G., Chukoskie, L., Snider, J., & Jayarathna, S. (2022). Eye Movement and Pupil Measures: A Review. *Frontiers in Computer Science*, *3*, 733531. https://doi.org/10.3389/fcomp.2021.733531

Mahon, J. E. (2018). Classic Philosophical Approaches to Lying and Deception. In J. Meibauer (Ed.), *The Oxford Handbook of Lying* (1st ed., pp. 13–31). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780198736578.013.2

Mann, S., Ewens, S., Shaw, D., Vrij, A., Leal, S., & Hillman, J. (2013). Lying Eyes: Why Liars Seek Deliberate Eye Contact. *Psychiatry, Psychology and Law*, *20*(3), 452–461. https://doi.org/10.1080/13218719.2013.791218

Mar, R. A. (2011). The Neural Bases of Social Cognition and Story Comprehension. *Annual Review of Psychology*, *62*(1), 103–134. https://doi.org/10.1146/annurev-psych-120709-145406

Marchak, F. M. (2013). Detecting false intent using eye blink measures. *Frontiers in Psychology*, *4*. https://doi.org/10.3389/fpsyg.2013.00736

Markowitz, D. M., Hancock, J. T., Woodworth, M. T., & Ely, M. (2023). Contextual considerations for deception production and detection in forensic interviews. *Frontiers in Psychology*, *14*, 1134052. https://doi.org/10.3389/fpsyg.2023.1134052

Marqués-Sánchez, P., Liébana-Presa, C., Benítez-Andrades, J. A., Gundín-Gallego, R., Álvarez-Barrio, L., & Rodríguez-Gonzálvez, P. (2020). Thermal Infrared Imaging to Evaluate Emotional Competences in Nursing Students: A First Approach through a Case Study. *Sensors*, *20*(9), 2502. https://doi.org/10.3390/s20092502

Martinez-Conde, S., & Macknik, S. L. (2015). From Exploration to Fixation: An Integrative View of Yarbus's Vision. *Perception*, *44*(8–9), 884–899. https://doi.org /10.1177/0301006615594963

Masip, J., Sporer, S. L., Garrido, E., & Herrero, C. (2005). The detection of deception with the reality monitoring approach: A review of the empirical evidence. *Psychology, Crime & Law*, *11*(1), 99–122. https://doi.org/10.1080/10683160410001726356

Mathôt, S. (2018). Pupillometry: Psychology, Physiology, and Function. *Journal of Cognition*, *1*(1), 16. https://doi.org/10.5334/joc.18

Mathôt, S., & Vilotijević, A. (2022). Methods in cognitive pupillometry: Design, preprocessing, and statistical analysis. *Behavior Research Methods*, *55*(6), 3055–3077. https://doi.org/10.3758/s13428-022-01957-7

Mathur, L., & Matarić, M. J. (2020). *Introducing Representations of Facial Affect in Automated Multimodal Deception Detection*. https://doi.org/10.48550/ARXIV. 2008.13369

Matsuda, I., Ogawa, T., & Tsuneoka, M. (2019). Broadening the Use of the Concealed Information Test in the Field. *Frontiers in Psychiatry*, *10*, 24. https://doi.org/10.3389/fpsyt.2019.00024

Matsukawa, K., Endo, K., Ishii, K., Ito, M., & Liang, N. (2018). Facial skin blood flow responses during exposures to emotionally charged movies. *The Journal of Physiological Sciences*, *68*(2), 175–190. https://doi.org/10.1007/s12576-017-0522-3

Matsumoto, D., & Hwang, H. C. (2018). Microexpressions Differentiate Truths From Lies About Future Malicious Intent. *Frontiers in Psychology*, *9*, 2545. https://doi.org/10.3389/fpsyg.2018.02545

Matsumoto, D., Keltner, D., Shiota, M. N., O'Sullivan, M., & Frank, M. (2008). Facial expressions of emotion. In *Handbook of emotions, 3rd ed* (pp. 211–234). The Guilford Press.

Maunder, R. G., Lancee, W. J., Nolan, R. P., Hunter, J. J., & Tannenbaum, D. W. (2006). The relationship of attachment insecurity to subjective stress and autonomic function during standardized acute stress in healthy adults. *Journal of Psychosomatic Research*, *60*(3), 283–290. https://doi.org/10.1016/j.jpsychores.2005.08.013

Mazar, N., Amir, O., & Ariely, D. (2008). The Dishonesty of Honest People: A Theory of Self-Concept Maintenance. *Journal of Marketing Research*, *45*(6), 633–644. https://doi.org/10.1509/jmkr.45.6.633

McCarthy, A., Lee, K., Itakura, S., & Muir, D. W. (2006). Cultural Display Rules Drive Eye Gaze During Thinking. *Journal of Cross-Cultural Psychology*, *37*(6), 717–722. https://doi.org/10.1177/0022022106292079

McDuff, D., Wander, M., Liu, X., Hill, B. L., Hernandez, J., Lester, J., & Baltrusaitis, T. (2022). *SCAMPS: Synthetics for Camera Measurement of Physiological Signals* (Version 1). arXiv. https://doi.org/10.48550/ARXIV.2206.04197

McGlone, M. S., & Knapp, M. L. (2019). Historical Perspectives on the Study of Lying and Deception. In T. Docan-Morgan (Ed.), *The Palgrave Handbook of Deceptive Communication* (pp. 3–28). Springer International Publishing. https://doi.org /10.1007/978-3-319-96334-1_1

Meijer, E. H., & Verschuere, B. (2014). The Polygraph: Current Practice and New Approaches. In P. A. Granhag, A. Vrij, & B. Verschuere (Eds.), *Detecting Deception* (1st ed., pp. 59–80). Wiley. https://doi.org/10.1002/9781118510001.ch3

Meijer, E. H., & Verschuere, B. (2017). Deception detection based on neuroimaging: Better than the polygraph? *Journal of Forensic Radiology and Imaging*, *8*, 17–21. https://doi.org/10.1016/j.jofri.2017.03.003

Meijer, E. H., Verschuere, B., Gamer, M., Merckelbach, H., & Ben-Shakhar, G. (2016). Deception detection with behavioral, autonomic, and neural measures: Conceptual

and methodological considerations that warrant modesty. *Psychophysiology*, *53*(5), 593–604. https://doi.org/10.1111/psyp.12609

Meissner, C. A., & Kassin, S. M. (2004). "You're Guilty, So Just Confess!" In G. D. Lassiter (Ed.), *Interrogations, Confessions, and Entrapment* (pp. 85–106). Springer US. https://doi.org/10.1007/978-0-387-38598-3_4

Melchers, K. G., Roulin, N., & Buehl, A. (2020). A review of applicant faking in selection interviews. *International Journal of Selection and Assessment*, *28*(2), 123–142. https://doi.org/10.1111/ijsa.12280

Menekse Dalveren, G. G., & Cagiltay, N. E. (2018). Insights from surgeons' eye-movement data in a virtual simulation surgical training environment: Effect of experience level and hand conditions. *Behaviour & Information Technology*, *37*(5), 517–537. https://doi.org/10.1080/0144929X.2018.1460399

Meyer, P. (2010). *Liespotting: Proven Techniques to Detect Deception*. St. Martin's Publishing Group.

Mikulincer, M. (1998). Adult attachment style and individual differences in functional versus dysfunctional experiences of anger. *Journal of Personality and Social Psychology*, *74*(2), 513–524. https://doi.org/10.1037/0022-3514.74.2.513

Mikulincer, M., Gillath, O., & Shaver, P. R. (2002). Activation of the attachment system in adulthood: Threat-related primes increase the accessibility of mental representations of attachment figures. *Journal of Personality and Social Psychology*, *83*(4), 881–895. https://doi.org/10.1037/0022-3514.83.4.881

Mikulincer, M., & Shaver, P. R. (2007). *Attachment in adulthood: Structure, dynamics, and change* (p. 578). The Guilford Press.

Mikulincer, M., & Shaver, P. R. (2019). Attachment orientations and emotion regulation. *Current Opinion in Psychology*, *25*, 6–10. https://doi.org/10.1016/j.copsyc.2018.02.006

Millen, A. E., & Hancock, P. J. B. (2019). Eye see through you! Eye tracking unmasks concealed face recognition despite countermeasures. *Cognitive Research: Principles and Implications*, *4*(1), 23. https://doi.org/10.1186/s41235-019-0169-0

Mirsadikov, A., & George, J. (2023). Can you see me lying? Investigating the role of deception on gaze behavior. *International Journal of Human-Computer Studies*, *174*, 103010. https://doi.org/10.1016/j.ijhcs.2023.103010

Moliné, A., Dominguez, E., Salazar-López, E., Gálvez-García, G., Fernández-Gómez, J., De la Fuente, J., Iborra, O., Tornay, F. J., & Gómez Milán, E. (2018). The mental nose and the Pinocchio effect: Thermography, planning, anxiety, and lies. *Journal of Investigative Psychology and Offender Profiling*, *15*(2), 234–248. https://doi.org/10.1002/jip.1505

Moliné, A., Gálvez-García, G., Fernández-Gómez, J., De la Fuente, J., Iborra, O., Tornay, F., Mata Martín, J. L., Puertollano, M., & Gómez Milán, E. (2017). The Pinocchio effect and the Cold Stress Test: Lies and thermography. *Psychophysiology*, *54*(11), 1621–1631. https://doi.org/10.1111/psyp.12956

Monaro, M., Capuozzo, P., Ragucci, F., Maffei, A., Curci, A., Scarpazza, C., Angrilli, A., & Sartori, G. (2020). Using Blink Rate to Detect Deception: A Study to Validate an Automatic Blink Detector and a New Dataset of Videos from Liars and Truth-Tellers. In M. Kurosu (Ed.), *Human-Computer Interaction. Human Values and Quality of Life* (Vol. 12183, pp. 494–509). Springer International Publishing. https://doi.org/10.1007/978-3-030-49065-2_35

Monaro, M., Gamberini, L., & Sartori, G. (2017). The detection of faked identity using unexpected questions and mouse dynamics. *PLOS ONE*, *12*(5), e0177851. https://doi.org/10.1371/journal.pone.0177851

Monaro, M., Maldera, S., Scarpazza, C., Sartori, G., & Navarin, N. (2022). Detecting deception through facial expressions in a dataset of videotaped interviews: A comparison between human judges and machine learning models. *Computers in Human Behavior*, *127*, 107063. https://doi.org/10.1016/j.chb.2021.107063

Monaro, M., Spolaor, R., Li, Q., Conti, M., Gamberini, L., & Sartori, G. (2017). Type Me the Truth!: Detecting Deceitful Users via Keystroke Dynamics. *Proceedings of the 12th International Conference on Availability, Reliability and Security*, 1–6. https://doi.org/10.1145/3098954.3104047

Monin, B., & Merritt, A. (2012). Moral hypocrisy, moral inconsistency, and the struggle for moral integrity. In M. Mikulincer & P. R. Shaver (Eds.), *The social psychology of morality: Exploring the causes of good and evil.* (pp. 167–184). American Psychological Association. https://doi.org/10.1037/13091-009

Moreira, D. G., Costello, J. T., Brito, C. J., Adamczyk, J. G., Ammer, K., Bach, A. J. E., Costa, C. M. A., Eglin, C., Fernandes, A. A., Fernández-Cuevas, I., Ferreira, J. J. A., Formenti, D., Fournet, D., Havenith, G., Howell, K., Jung, A., Kenny, G. P., Kolosovas-Machuca, E. S., Maley, M. J., … Sillero-Quintana, M. (2017). Thermographic imaging in sports and exercise medicine: A Delphi study and consensus statement on the measurement of human skin temperature. *Journal of Thermal Biology*, *69*, 155–162. https://doi.org/10.1016/j.jtherbio.2017.07.006

Murad, U., & Malkawi, M. (2012). Artificial neuro fuzzy logic system for detecting human emotions. *2012 International Conference on Computer, Information and Telecommunication Systems (CITS)*, 1–4. https://doi.org/10.1109/CITS.2012.6220388

Nahari, G. (2018). The Applicability of the Verifiability Approach to the Real World. In *Detecting Concealed Information and Deception* (pp. 329–349). Elsevier. https://doi.org/10.1016/B978-0-12-812729-2.00014-8

Nahari, G. (2023). Meta-Research Perspectives on Verbal Lie Detection. *Brain Sciences*, *13*(3), 392. https://doi.org/10.3390/brainsci13030392

Nahari, G., Ashkenazi, T., Fisher, R. P., Granhag, P., Hershkowitz, I., Masip, J., Meijer, E. H., Nisin, Z., Sarid, N., Taylor, P. J., Verschuere, B., & Vrij, A. (2019). 'Language of lies': Urgent issues and prospects in verbal lie detection research. *Legal and Criminological Psychology*, *24*(1), 1–23. https://doi.org/10.1111/lcrp.12148

Nahari, G., Vrij, A., & Fisher, R. P. (2012). Does the truth come out in the writing? Scan as a lie detection tool. *Law and Human Behavior*, *36*(1), 68–76. https://doi.org/10.1037/h0093965

Nahari, G., Vrij, A., & Fisher, R. P. (2014a). Exploiting liars' verbal strategies by examining the verifiability of details. *Legal and Criminological Psychology*, *19*(2), 227–239. https://doi.org/10.1111/j.2044-8333.2012.02069.x

Nahari, G., Vrij, A., & Fisher, R. P. (2014b). The Verifiability Approach: Countermeasures Facilitate its Ability to Discriminate Between Truths and Lies. *Applied Cognitive Psychology*, *28*(1), 122–128. https://doi.org/10.1002/acp.2974

Nakai, K., Kurosawa, M., Kirimoto, T., Matsui, T., Abe, S., Suzuki, S., & Sun, G. (2024). Performance enhancement of thermal image analysis for noncontact cardiopulmonary signal extraction. *Infrared Physics & Technology*, *138*, 105244. https://doi.org/10.1016/j.infrared.2024.105244

Nam, B., Kim, J. Y., Bark, B., Kim, Y., Kim, J., So, S. W., Choi, H. Y., & Kim, I. Y. (2023). FacialCueNet: Unmasking deception - an interpretable model for criminal interrogation using facial expressions. *Applied Intelligence*, *53*(22), 27413–27427. https://doi.org/10.1007/s10489-023-04968-9

National Research Council. (2003). *The polygraph and lie detection*. National Academies Press. https://doi.org/10.17226/10420

Nhan, B. R., & Chau, T. (2010). Classifying Affective States Using Thermal Infrared Imaging of the Human Face. *IEEE Transactions on Biomedical Engineering*, *57*(4), 979–987. https://doi.org/10.1109/TBME.2009.2035926

Nikolopoulos, S., Petrantonakis, P. C., Georgiadis, K., Kalaganis, F., Liaros, G., Lazarou, I., Adam, K., Papazoglou-Chalikias, A., Chatzilari, E., Oikonomou, V. P., Kumar, C., Menges, R., Staab, S., Müller, D., Sengupta, K., Bostantjopoulou, S., Katsarou, Z., Zeilig, G., Plotnik, M., … Kompatsiaris, I. (2017). A multimodal dataset for authoring and editing multimedia content: The MAMEM project. *Data in Brief*, *15*, 1048–1056. https://doi.org/10.1016/j.dib.2017.10.072

Niu, X., Han, H., Shan, S., & Chen, X. (2018). SynRhythm: Learning a Deep Heart Rate Estimator from General to Specific. *2018 24th International Conference on Pattern Recognition (ICPR)*, 3580–3585. https://doi.org/10.1109/ICPR.2018.8546321

Niu, X., Han, H., Shan, S., & Chen, X. (2019). VIPL-HR: A Multi-modal Database for Pulse Estimation from Less-Constrained Face Video. In C. V. Jawahar, H. Li, G. Mori, & K. Schindler (Eds.), *Computer Vision – ACCV 2018* (Vol. 11365, pp. 562–576). Springer International Publishing. https://doi.org/10.1007/978-3-030-20873-8_36

Niu, X., Yu, Z., Han, H., Li, X., Shan, S., & Zhao, G. (2020). Video-Based Remote Physiological Measurement via Cross-Verified Feature Disentangling. In A. Vedaldi, H. Bischof, T. Brox, & J.-M. Frahm (Eds.), *Computer Vision – ECCV 2020* (Vol. 12347, pp. 295–310). Springer International Publishing. https://doi.org/10.1007/978-3-030-58536-5_18

Nortje, A., & Tredoux, C. (2019). How good are we at detecting deception? A review of current techniques and theories. *South African Journal of Psychology*, *49*(4), 491–504. https://doi.org/10.1177/0081246318822953

Novotny, E., Frank, M. G., & Grizzard, M. (2021). A Laboratory Study Comparing the Effectiveness of Verbal and Nonverbal Rapport-Building Techniques in Interviews. *Communication Studies*, *72*(5), 819–833. https://doi.org/10.1080/10510974.2021.1975141

Nozawa, A., & Tacano, M. (2009). Correlation analysis on alpha attenuation and nasal skin temperature. *Journal of Statistical Mechanics: Theory and Experiment*, *2009*(01), P01007. https://doi.org/10.1088/1742-5468/2009/01/P01007

Nurçin, F. V., Imanov, E., Işın, A., & Ozsahin, D. U. (2017). Lie detection on pupil size by back propagation neural network. *Procedia Computer Science*, *120*, 417–421. https://doi.org/10.1016/j.procs.2017.11.258

Oberlader, V. A., Naefgen, C., Koppehele-Gossel, J., Quinten, L., Banse, R., & Schmidt, A. F. (2016). Validity of content-based techniques to distinguish true and fabricated statements: A meta-analysis. *Law and Human Behavior*, *40*(4), 440–457. https://doi.org/10.1037/lhb0000193

Ofshe, R. J., & Leo, R. A. (1996). The Decision to Confess Falsely: Rational Choice and Irrational Action Symposium on Coercion: An Interdisciplinary Examination of Coercion, Exploitation, and the Law: II. Coerced Confessions. *Denver University Law Review*, *74*(4), 979–1122.

Oksol, E. M., & O'Donohue, W. T. (2004). A Critical Analysis of the Polygraph. In *Handbook of Forensic Psychology* (pp. 601–634). Elsevier. https://doi.org/10.1016/B978-012524196-0/50026-7

O'Neill, T. A., Lee, N. M., Radan, J., Law, S. J., Lewis, R. J., & Carswell, J. J. (2013). The impact of "non-targeted traits" on personality test faking, hiring, and workplace deviance. *Personality and Individual Differences*, *55*(2), 162–168. https://doi.org/10.1016/j.paid.2013.02.027

O'Neill, T. A., Lewis, R. J., Law, S. J., Larson, N., Hancock, S., Radan, J., Lee, N., & Carswell, J. J. (2017). Forced-choice pre-employment personality assessment: Construct validity and resistance to faking. *Personality and Individual Differences*, *115*, 120–127. https://doi.org/10.1016/j.paid.2016.03.075

Or, C. K. L., & Duffy, V. G. (2007). Development of a facial skin temperature-based methodology for non-intrusive mental workload measurement. *Occupational Ergonomics*, *7*(2), 83–94. https://doi.org/10.3233/OER-2007-7202

Owens, A. P. (2020). The Role of Heart Rate Variability in the Future of Remote Digital Biomarkers. *Frontiers in Neuroscience*, *14*, 582145. https://doi.org/10.3389/fnins.2020.582145

Paige, L. E., Wolf, J. M., & Gutchess, A. (2022). Evaluating heart rate variability as a predictor of the influence of lying on memory. *Memory*, *30*(7), 785–795. https://doi.org/10.1080/09658211.2020.1849307

Palena, N., Caso, L., Vrij, A., & Nahari, G. (2021). The verifiability approach: A meta-analysis. *Journal of Applied Research in Memory and Cognition*, *10*(1), 155–166. https://doi.org/10.1037/h0101785

Palinko, O., Kun, A. L., Shyrokov, A., & Heeman, P. (2010). Estimating cognitive load using remote eye tracking in a driving simulator. *Proceedings of the 2010 Symposium on*

Eye-Tracking Research & Applications - ETRA '10, 141. https://doi.org/10.1145/1743666.1743701

Panasiti, M. S., Cardone, D., Pavone, E. F., Mancini, A., Merla, A., & Aglioti, S. M. (2016). Thermal signatures of voluntary deception in ecological conditions. *Scientific Reports*, *6*(1), 35174. https://doi.org/10.1038/srep35174

Pandzic, I. S., & Forchheimer, R. (Eds.). (2002). *MPEG-4 Facial Animation: The Standard, Implementation And Applications* (1st ed.). Wiley. https://doi.org/10.1002/0470854626

Paolini, D., Alparone, F. R., Cardone, D., van Beest, I., & Merla, A. (2016). "The face of ostracism": The impact of the social categorization on the thermal facial responses of the target and the observer. *Acta Psychologica*, *163*, 65–73. https://doi.org/10.1016/j.actpsy.2015.11.001

Paré, M., Richler, R. C., Ten Hove, M., & Munhall, K. G. (2003). Gaze behavior in audiovisual speech perception: The influence of ocular fixations on the McGurk effect. *Perception & Psychophysics*, *65*(4), 553–567. https://doi.org/10.3758/BF03194582

Park, K. K., Suk, H. W., Hwang, H., & Lee, J.-H. (2013). A functional analysis of deception detection of a mock crime using infrared thermal imaging and the Concealed Information Test. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00070

Partala, T., & Surakka, V. (2003). Pupil size variation as an indication of affective processing. *International Journal of Human-Computer Studies*, *59*(1–2), 185–198. https://doi.org/10.1016/S1071-5819(03)00017-X

Pascuzzo, K., Cyr, C., & Moss, E. (2013). Longitudinal association between adolescent attachment, adult romantic attachment, and emotion regulation strategies. *Attachment & Human Development*, *15*(1), 83–103. https://doi.org/10.1080/14616734.2013.745713

Pavlidis, I., Eberhardt, N. L., & Levine, J. A. (2002). Seeing through the face of deception. *Nature*, *415*(6867), 35–35. https://doi.org/10.1038/415035a

Pavlidis, I., & Levine, J. (2002). Thermal image analysis for polygraph testing. *IEEE Engineering in Medicine and Biology Magazine*, *21*(6), 56–64. https://doi.org/10.1109/MEMB.2002.1175139

Pavlidis, I., Levine, J., & Baukol, P. (2001). Thermal image analysis for anxiety detection. *Proceedings 2001 International Conference on Image Processing (Cat. No.01CH37205)*, *2*, 315–318. https://doi.org/10.1109/ICIP.2001.958491

Pavlidis, I., Tsiamyrtzis, P., Shastri, D., Wesley, A., Zhou, Y., Lindner, P., Buddharaju, P., Joseph, R., Mandapati, A., Dunkin, B., & Bass, B. (2012). Fast by Nature—How Stress Patterns Define Human Experience and Performance in Dexterous Tasks. *Scientific Reports*, *2*(1), 305. https://doi.org/10.1038/srep00305

Pedrotti, M., Mirzaei, M. A., Tedesco, A., Chardonnet, J.-R., Mérienne, F., Benedetto, S., & Baccino, T. (2014). Automatic Stress Classification With Pupil Diameter Analysis. *International Journal of Human-Computer Interaction*, *30*(3), 220–236. https://doi.org/10.1080/10447318.2013.848320

Pérez-Rosas, V., Abouelenien, M., Mihalcea, R., & Burzo, M. (2015). Deception Detection using Real-life Trial Data. *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction*, 59–66. https://doi.org/10.1145/2818346.2820758

Peterson, M. H., Griffith, R. L., Isaacson, J. A., O'Connell, M. S., & Mangos, P. M. (2011). Applicant faking, social desirability, and the prediction of counterproductive work behaviors. *Human Performance*, *24*(3), 270–290. https://doi.org/10.1080/08959285.2011.580808

Peth, J., Kim, J. S. C., & Gamer, M. (2013). Fixations and eye-blinks allow for detecting concealed crime related memories. *International Journal of Psychophysiology*, *88*(1), 96–103. https://doi.org/10.1016/j.ijpsycho.2013.03.003

Poh, M.-Z., McDuff, D. J., & Picard, R. W. (2010). Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. *Optics Express*, *18*(10), 10762. https://doi.org/10.1364/OE.18.010762

Pollina, D. A., Dollins, A. B., Senter, S. M., Brown, T. E., Pavlidis, I., Levine, J. A., & Ryan, A. H. (2006). Facial skin surface temperature changes during a "Concealed

Information" Test. *Annals of Biomedical Engineering*, *34*(7), 1182–1189. https://doi.org/10.1007/s10439-006-9143-3

Pollina, D. A., & Ryan, A. H. (2004). Relationship Between Facial Skin Surface Temperature Reactivity and Traditional Polygraph Measures Used in the Psychophysiological Detection of Deception: A Preliminary Investigation. *Polygraph*, *33*(3), 143–155.

Pollina, D. A., Senter, S. M., & Cutlip, R. (2015). Hemifacial skin temperature changes related to deception: Blood flow or thermal capacitance? *Journal of Global Research in Computer Sciences*, *6*, 1–9.

Porter, S., Brinke, L. T., Baker, A., & Wallace, B. (2011). Would I lie to you? "Leakage" in deceptive facial expressions relates to psychopathy and emotional intelligence. *Personality and Individual Differences*, *51*(2), 133–137. https://doi.org /10.1016/j.paid.2011.03.031

Porter, S., & ten Brinke, L. (2008). Reading Between the Lies: Identifying Concealed and Falsified Emotions in Universal Facial Expressions. *Psychological Science*, *19*(5), 508–514. https://doi.org/10.1111/j.1467-9280.2008.02116.x

Porter, S., ten Brinke, L., & Wallace, B. (2012). Secrets and Lies: Involuntary Leakage in Deceptive Facial Expressions as a Function of Emotional Intensity. *Journal of Nonverbal Behavior*, *36*(1), 23–37. https://doi.org/10.1007/s10919-011-0120-7

Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, *17*(03). https://doi.org /10.1017/S0954579405050340

Prabhakar, G., Mukhopadhyay, A., Murthy, L., Modiksha, M., Sachin, D., & Biswas, P. (2020). Cognitive load estimation using ocular parameters in automotive. *Transportation Engineering*, *2*, 100008. https://doi.org/10.1016/j.treng.2020.100008

Proudfoot, J. G., Jenkins, J. L., Burgoon, J. K., & Nunamaker, J. F. (2015). Deception is in the eye of the communicator: Investigating pupil diameter variations in automated deception detection interviews. *2015 IEEE International Conference on Intelligence and Security Informatics (ISI)*, 97–102. https://doi.org/10.1109/ISI.2015.7165946

Proudfoot, J. G., Jenkins, J. L., Burgoon, J. K., & Nunamaker, J. F. (2016). More Than Meets the Eye: How Oculometric Behaviors Evolve Over the Course of Automated Deception Detection Interactions. *Journal of Management Information Systems*, *33*(2), 332–360. https://doi.org/10.1080/07421222.2016.1205929

Puri, C., Olson, L., Pavlidis, I., Levine, J., & Starren, J. (2005). StressCam: Non-contact measurement of users' emotional states through thermal imaging. *CHI '05 Extended Abstracts on Human Factors in Computing Systems*, 1725–1728. https://doi.org/10.1145/1056808.1057007

Qi, H., Guo, Z., Chen, X., Shen, Z., & Jane Wang, Z. (2017). Video-based human heart rate measurement using joint blind source separation. *Biomedical Signal Processing and Control*, *31*, 309–320. https://doi.org/10.1016/j.bspc.2016.08.020

Qiu, Y., Liu, Y., Arteaga-Falconi, J., Dong, H., & El Saddik, A. (2019). EVM-CNN: Real-Time Contactless Heart Rate Estimation From Facial Video. *IEEE Transactions on Multimedia*, *21*(7), 1778–1787. https://doi.org/10.1109/TMM.2018.2883866

Rahman, S., Habel, M., & Contrada, R. J. (2018). Poincaré plot indices as measures of sympathetic cardiac regulation: Responses to psychological stress and associations with pre-ejection period. *International Journal of Psychophysiology*, *133*, 79–90. https://doi.org/10.1016/j.ijpsycho.2018.08.005

Rajoub, B. A., & Zwiggelaar, R. (2014). Thermal facial analysis for deception detection. *IEEE Transactions on Information Forensics and Security*, *9*(6), 1015–1023. https://doi.org/10.1109/TIFS.2014.2317309

Raskin, D. C., & Honts, C. R. (2002). The comparison question test. In *Handbook of polygraph testing* (pp. 1–47). Academic Press.

Raskin, D. C., & Kircher, J. C. (2014). Validity of Polygraph Techniques and Decision Methods. In *Credibility Assessment* (pp. 63–129). Elsevier. https://doi.org/10.1016/B978-0-12-394433-7.00003-8

Ren, P., Barreto, A., Gao, Y., & Adjouadi, M. (2013). Affective Assessment by Digital Processing of the Pupil Diameter. *IEEE Transactions on Affective Computing*, *4*(1), 2–14. https://doi.org/10.1109/T-AFFC.2012.25

Revanur, A., Li, Z., Ciftci, U. A., Yin, L., & Jeni, L. A. (2021). The First Vision For Vitals (V4V) Challenge for Non-Contact Video-Based Physiological Estimation. *2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, 2760–2767. https://doi.org/10.1109/ICCVW54120.2021.00310

Rill-Garcia, R., Escalante, H. J., Villasenor-Pineda, L., & Reyes-Meza, V. (2019). High-Level Features for Multimodal Deception Detection in Videos. *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 1565–1573. https://doi.org/10.1109/CVPRW.2019.00198

Ring, E. F. J., & Ammer, K. (2012). Infrared thermal imaging in medicine. *Physiological Measurement*, *33*(3), R33–R46. https://doi.org/10.1088/0967-3334/33/3/R33

Robinson, D. T., Clay-Warner, J., Moore, C. D., Everett, T., Watts, A., Tucker, T. N., & Thai, C. (2012). Toward an Unobtrusive Measure of Emotion During Interaction: Thermal Imaging Techniques. In W. Kalkhoff, S. R. Thye, & E. J. Lawler (Eds.), *Advances in Group Processes* (Vol. 29, pp. 225–266). Emerald Group Publishing Limited. https://doi.org/10.1108/S0882-6145(2012)0000029011

Rogalski, A. (2002). Infrared detectors: An overview. *Infrared Physics & Technology*, *43*(3–5), 187–210. https://doi.org/10.1016/S1350-4495(02)00140-8

Rogalski, A. (2010). *Infrared Detectors* (0 ed.). CRC Press. https://doi.org/10.1201/b10319

Rosenblum, L. D., Miller, R. M., & Sanchez, K. (2007). Lip-Read Me Now, Hear Me Better Later. *Psychological Science*, *18*(5), 392–396. https://doi.org/10.1111/j.1467-9280.2007.01911.x

Roulin, N. (2016). Individual differences predicting impression management detection in job interviews. *Personnel Assessment and Decisions*, *2*(1). https://doi.org/10.25035/pad.2016.001

Roulin, N., Bangerter, A., & Levashina, J. (2014). Interviewers' perceptions of impression management in employment interviews. *Journal of Managerial Psychology*, *29*(2), 141–163. https://doi.org/10.1108/JMP-10-2012-0295

Roulin, N., Bangerter, A., & Levashina, J. (2015). Honest and deceptive impression management in the employment interview: Can it be detected and how does it impact evaluations? *Personnel Psychology*, *68*(2), 395–444. https://doi.org/10.1111/peps.12079

Roulin, N., & Bourdage, J. S. (2017). Once an Impression Manager, Always an Impression Manager? Antecedents of Honest and Deceptive Impression Management Use and Variability across Multiple Job Interviews. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00029

Roulin, N., & Krings, F. (2016). When Winning is Everything: The Relationship between Competitive Worldviews and Job Applicant Faking. *Applied Psychology*, *65*(4), 643–670. https://doi.org/10.1111/apps.12072

Roulin, N., & Krings, F. (2020). Faking to fit in: Applicants' response strategies to match organizational culture. *Journal of Applied Psychology*, *105*(2), 130–145. https://doi.org/10.1037/apl0000431

Roulin, N., & Powell, D. M. (2018). Identifying applicant faking in job interviews: Examining the role of criterion-based content analysis and storytelling. *Journal of Personnel Psychology*, *17*(3), 143–154. https://doi.org/10.1027/1866-5888/a000207

Ruiz Puentes, P., Soberanis-Mukul, R. D., Acar, A., Gupta, I., Bhowmick, J., Li, Y., Ghazi, A., Kazanzides, P., Ying Wu, J., & Unberath, M. (2023). Pupillometry in telerobotic surgery: A comparative evaluation of algorithms for cognitive effort estimation. *Medical Robotics*, *1*. https://doi.org/10.54844/mr.2023.0420

Sabatino DiCriscio, A., Hu, Y., & Troiani, V. (2018). Task-induced pupil response and visual perception in adults. *PLOS ONE*, *13*(12), e0209556. https://doi.org/10.1371/journal.pone.0209556

Saladin, K. S., Gan, C. A., & Cushman, H. N. (2018). *Anatomy & physiology: The unity of form and function* (Eighth edition). McGraw-Hill Education.

Salazar-López, E., Domínguez, E., Juárez Ramos, V., de la Fuente, J., Meins, A., Iborra, O., Gálvez, G., Rodríguez-Artacho, M. A., & Gómez-Milán, E. (2015). The mental and

subjective skin: Emotion, empathy, feelings and thermography. *Consciousness and Cognition*, *34*, 149–162. https://doi.org/10.1016/j.concog.2015.04.003

Salvi, C., & Bowden, E. M. (2016). Looking for Creativity: Where Do We Look When We Look for New Ideas? *Frontiers in Psychology*, *7*. https://doi.org/10.3389 /fpsyg.2016.00161

Santa Clara Police Department. (n.d.). Santa Clara Police Department. Retrieved 26 August 2024, from https://iamscpd.org

Santas, G. (Ed.). (2006). *The Blackwell Guide to Plato's Republic* (1st ed.). Wiley. https://doi.org/10.1002/9780470776414

Sapir, A. (2005). *The Lsi Course on Scientific Content Analysis (Scan).* Phoenix, AZ: Laboratory for Scientific Interrogation.

Satpathi, S., Arafath, K. M. I. Y., Routray, A., & Satpathi, P. S. (2024). Analysis of thermal videos for detection of lie during interrogation. *EURASIP Journal on Image and Video Processing*, *2024*(1), 9. https://doi.org/10.1186/s13640-024-00624-5

Saxe, L. (1991). Lying: Thoughts of an applied social psychologist. *American Psychologist*, *46*(4), 409–415. https://doi.org/10.1037/0003-066X.46.4.409

Scalise, L. (2012). Non Contact Heart Monitoring. In R. M. Millis (Ed.), *Advances in Electrocardiograms_ Methods and Analysis* (Vol. 4, pp. 81–106). InTech.

Scarpazza, C., & Sartori, G. (2020). Editorial: Deception in Court—Open Issues and Detection Techniques. *Frontiers in Psychiatry*, *11*, 476. https://doi.org /10.3389/fpsyt.2020.00476

Schrumpf, F., Frenzel, P., Aust, C., Osterhoff, G., & Fuchs, M. (2021). Assessment of deep learning based blood pressure prediction from PPG and rPPG signals. *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 3815–3825. https://doi.org/10.1109/CVPRW53098.2021.00423

Schudlik, K., Reinhard, M., & Müller, P. (2021). Prepared to fake? The relationship between applicants' job interview preparation and faking. *International Journal of Selection and Assessment*, *29*(1), 29–54. https://doi.org/10.1111/ijsa.12317

Schutte, M., Bogaard, G., Mac Giolla, E., Warmelink, L., Kleinberg, B., & Verschuere, B. (2021). *Man versus Machine: Comparing manual with LIWC coding of perceptual and contextual details for verbal lie detection*. https://doi.org /10.31234/osf.io/cth58

Schweitzer, M. E., Brodt, S. E., & Croson, R. T. A. (2002). Seeing and believing: visual access and the strategic use of deception. *International Journal of Conflict Management*, *13*(3), 258–375. https://doi.org/10.1108/eb022876

Sciaraffa, N., Borghini, G., Di Flumeri, G., Cincotti, F., Babiloni, F., & Aricò, P. (2021). Joint Analysis of Eye Blinks and Brain Activity to Investigate Attentional Demand during a Visual Search Task. *Brain Sciences*, *11*(5), 562. https://doi.org/10.3390 /brainsci11050562

Seitl, M., Manuoglu, E., & Krám, T. (2024). Personal integrity and faking in the workplace: When competition matters. *Current Psychology*, *43*(9), 7719–7730. https://doi.org/10.1007/s12144-023-04880-y

Seitl, M., Omastová, E., Sulejmanov, F., Hess, U., Hareli, S., Dostál, D., Hypsova, P., & Kafetsios, K. (2023). An Emotional Experience of Work. *Studia Psychologica*, *65*(4), 307–319. https://doi.org/10.31577/sp.2023.04.882

Sen, M. U., Perez-Rosas, V., Yanikoglu, B., Abouelenien, M., Burzo, M., & Mihalcea, R. (2022). Multimodal Deception Detection Using Real-Life Trial Data. *IEEE Transactions on Affective Computing*, *13*(1), 306–319. https://doi.org /10.1109/TAFFC.2020.3015684

Serota, K. B., Levine, T. R., & Boster, F. J. (2010). The Prevalence of Lying in America: Three Studies of Self-Reported Lies. *Human Communication Research*, *36*(1), 2–25. https://doi.org/10.1111/j.1468-2958.2009.01366.x

Servais, A., Préa, N., Hurter, C., & Barbeau, E. J. (2023). Why and when do you look away when trying to remember? Gaze aversion as a marker of the attentional switch to the internal world during memory retrieval. *Acta Psychologica*, *240*, 104041. https://doi.org/10.1016/j.actpsy.2023.104041

Seymour, T. L., Baker, C. A., & Gaunt, J. T. (2013). Combining Blink, Pupil, and Response Time Measures in a Concealed Knowledge Test. *Frontiers in Psychology*, *3*. https://doi.org/10.3389/fpsyg.2012.00614

Shaffer, F., & Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms. *Frontiers in Public Health*, *5*, 258. https://doi.org/10.3389/fpubh.2017.00258

Shaffer, F., McCraty, R., & Zerr, C. L. (2014). A healthy heart is not a metronome: An integrative review of the heart's anatomy and heart rate variability. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.01040

Shallcross, S. L., Frazier, P. A., & Anders, S. L. (2014). Social resources mediate the relations between attachment dimensions and distress following potentially traumatic events. *Journal of Counseling Psychology*, *61*(3), 352–362. https://doi.org/10.1037/a0036583

Sharma, S., Gangadhara, K. G., Xu, F., Slowe, A. S., Frank, M. G., & Nwogu, I. (2021). Coupled Systems for Modeling Rapport Between Interlocutors. *2021 16th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2021)*, 1–8. https://doi.org/10.1109/FG52635.2021.9667067

Shastri, D., Merla, A., Tsiamyrtzis, P., & Pavlidis, I. (2009). Imaging Facial Signs of Neurophysiological Responses. *IEEE Transactions on Biomedical Engineering*, *56*(2), 477–484. https://doi.org/10.1109/TBME.2008.2003265

Shearn, D., Bergman, E., Hill, K., Abel, A., & Hinds, L. (1990). Facial coloration and temperature responses in blushing. *Psychophysiology*, *27*(6), 687–693. https://doi.org/10.1111/j.1469-8986.1990.tb03194.x

Shen, X., Fan, G., Niu, C., & Chen, Z. (2021). Catching a Liar Through Facial Expression of Fear. *Frontiers in Psychology*, *12*, 675097. https://doi.org/10.3389/fpsyg.2021.675097

Shi, H., Yang, L., Zhao, L., Su, Z., Mao, X., Zhang, L., & Liu, C. (2017). Differences of Heart Rate Variability Between Happiness and Sadness Emotion States: A Pilot Study.

Journal of Medical and Biological Engineering, *37*(4), 527–539. https://doi.org/10.1007/s40846-017-0238-0

Simonovic, B., Stupple, E. J. N., Gale, M., & Sheffield, D. (2018). Performance Under Stress: An Eye-Tracking Investigation of the Iowa Gambling Task (IGT). *Frontiers in Behavioral Neuroscience*, *12*, 217. https://doi.org/10.3389/fnbeh.2018.00217

Sin, N. L., Sloan, R. P., McKinley, P. S., & Almeida, D. M. (2016). Linking Daily Stress Processes and Laboratory-Based Heart Rate Variability in a National Sample of Midlife and Older Adults. *Psychosomatic Medicine*, *78*(5), 573–582. https://doi.org /10.1097/PSY.0000000000000306

Sip, K. E., Lynge, M., Wallentin, M., McGregor, W. B., Frith, C. D., & Roepstorff, A. (2010). The production and detection of deception in an interactive game. *Neuropsychologia*, *48*(12), 3619–3626. https://doi.org/10.1016 /j.neuropsychologia.2010.08.013

Sip, K. E., Skewes, J. C., Marchant, J. L., McGregor, W. B., Roepstorff, A., & Frith, C. D. (2012). What if I Get Busted? Deception, Choice, and Decision-Making in Social Interaction. *Frontiers in Neuroscience*, *6*. https://doi.org/10.3389/fnins.2012.00058

Skaramagkas, V., Giannakakis, G., Ktistakis, E., Manousos, D., Karatzanis, I., Tachos, N., Tripoliti, E., Marias, K., Fotiadis, D. I., & Tsiknakis, M. (2023). Review of Eye Tracking Metrics Involved in Emotional and Cognitive Processes. *IEEE Reviews in Biomedical Engineering*, *16*, 260–277. https://doi.org/10.1109/RBME.2021.3066072

Sokol-Hessner, P., Hsu, M., Curley, N. G., Delgado, M. R., Camerer, C. F., & Phelps, E. A. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *Proceedings of the National Academy of Sciences*, *106*(13), 5035–5040. https://doi.org/10.1073/pnas.0806761106

Sokolov, E. N. (1990). The orienting response, and future directions of its development. *The Pavlovian Journal of Biological Science*, *25*(3), 142–150. https://doi.org/10.1007/BF02974268

Solbu, A., Frank, M. G., Xu, F., Nwogu, I., & Neurohr, M. (2024). The Effect of Synchrony of Happiness on Facial Expression of Negative Emotion When Lying. *Journal of Nonverbal Behavior*, *48*(1), 73–92. https://doi.org/10.1007/s10919-023-00447-4

Somsen, R. J. M., Jennings, J. R., & Van der Molen, M. W. (2004). The cardiac cycle time effect revisited: Temporal dynamics of the central-vagal modulation of heart rate in human reaction time tasks. *Psychophysiology*, *41*(6), 941–953. https://doi.org/10.1111/j.1469-8986.2004.00241.x

Spence, S. A., Farrow, T. F. D., Herford, A. E., Wilkinson, I. D., Zheng, Y., & Woodruff, P. W. R. (2001). Behavioural and functional anatomical correlates of deception in humans: *Neuroreport*, *12*(13), 2849–2853. https://doi.org/10.1097/00001756-200109170-00019

Speth, J., Vance, N., Czajka, A., Bowyer, K. W., Wright, D., & Flynn, P. (2021). Deception detection and remote physiological monitoring: A dataset and baseline experimental results. *2021 IEEE International Joint Conference on Biometrics (IJCB)*, 1–8. https://doi.org/10.1109/IJCB52358.2021.9484409

Sporer, S. L. (2016). Deception and Cognitive Load: Expanding Our Horizon with a Working Memory Model. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.00420

Sporer, S. L., & Schwandt, B. (2007). Moderators of nonverbal indicators of deception: A meta-analytic synthesis. *Psychology, Public Policy, and Law*, *13*(1), 1–34. https://doi.org/10.1037/1076-8971.13.1.1

Sporer, S. L., & Sharman, S. J. (2006). Should I believe this? Reality monitoring of accounts of self-experienced and invented recent and distant autobiographical events. *Applied Cognitive Psychology*, *20*(6), 837–854. https://doi.org/10.1002/acp.1234

Steinhauer, S. R., Bradley, M. M., Siegle, G. J., Roecklein, K. A., & Dix, A. (2022). Publication guidelines and recommendations for pupillary measurement in psychophysiological studies. *Psychophysiology*, *59*(4), e14035. https://doi.org/10.1111/psyp.14035

Steinhauer, S. R., Siegle, G. J., Condray, R., & Pless, M. (2004). Sympathetic and parasympathetic innervation of pupillary dilation during sustained processing.

International Journal of Psychophysiology, *52*(1), 77–86. https://doi.org/10.1016/j.ijpsycho.2003.12.005

Strömwall, L., & Granhag, P. A. (2003). How to Detect Deception? Arresting the Beliefs of Police Officers, Prosecutors and Judges. *Psychology, Crime & Law*, *9*(1), 19–36. https://doi.org/10.1080/10683160308138

Strotzer, M. (2009). One Century of Brain Mapping Using Brodmann Areas*. *Clinical Neuroradiology*, *19*(3), 179–186. https://doi.org/10.1007/s00062-009-9002-3

Su, L., & Levine, M. (2016). Does "lie to me" lie to you? An evaluation of facial clues to high-stakes deception. *Computer Vision and Image Understanding*, *147*, 52–68. https://doi.org/10.1016/j.cviu.2016.01.009

Subhash, H. M., Ofoegbuna, T., Oliveira, A., Pierce, M. C., & Pillai, S. (2024). *Infrared Thermal Imaging for Assessing Human Perspiration and Evaluating Antiperspirant Product Efficacy*. https://doi.org/10.21203/rs.3.rs-4706772/v1

Sugano, Y., Matsushita, Y., & Sato, Y. (2014). Learning-by-Synthesis for Appearance-Based 3D Gaze Estimation. *2014 IEEE Conference on Computer Vision and Pattern Recognition*, 1821–1828. https://doi.org/10.1109/CVPR.2014.235

Suzuki, K., Laohakangvalvit, T., Matsubara, R., & Sugaya, M. (2021). Constructing an Emotion Estimation Model Based on EEG/HRV Indexes Using Feature Extraction and Feature Selection Algorithms. *Sensors*, *21*(9), 2910. https://doi.org/10.3390/s21092910

Syed, F., Khan, S., & Toma, M. (2023). Modeling Dynamics of the Cardiovascular System Using Fluid-Structure Interaction Methods. *Biology*, *12*(7), 1026. https://doi.org/10.3390/biology12071026

Synnott, J., Dietzel, D., & Ioannou, M. (2015). A review of the polygraph: History, methodology and current status. *Crime Psychology Review*, *1*(1), 59–83. https://doi.org/10.1080/23744006.2015.1060080

ten Brinke, L., & Porter, S. (2012). Cry me a river: Identifying the behavioral consequences of extremely high-stakes interpersonal deception. *Law and Human Behavior*, *36*(6), 469–477. https://doi.org/10.1037/h0093929

Thannoon, H. H., Ali, W. H., & Hashim, I. A. (2018). Detection of Deception Using Facial Expressions Based on Different Classification Algorithms. *2018 Third Scientific Conference of Electrical Engineering (SCEE)*, 51–56. https://doi.org/10.1109/SCEE.2018.8684170

Thayer, J. F., Åhs, F., Fredrikson, M., Sollers, J. J., & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. *Neuroscience & Biobehavioral Reviews*, *36*(2), 747–756. https://doi.org/10.1016/j.neubiorev.2011.11.009

Thomas, B. L., Claassen, N., Becker, P., & Viljoen, M. (2019). Validity of Commonly Used Heart Rate Variability Markers of Autonomic Nervous System Function. *Neuropsychobiology*, *78*(1), 14–26. https://doi.org/10.1159/000495519

Tominaga, S. (1994). Dichromatic reflection models for a variety of materials. *Color Research & Application*, *19*(4), 277–285. https://doi.org/10.1002/col.5080190408

Török-Suri, K., Németh, K., Baradits, M., & Csukly, G. (2025). Investigating Eye Movements to Examine Attachment-Related Differences in Facial Emotion Perception and Face Memory. *Journal of Imaging*, *11*(2), 60. https://doi.org/10.3390/jimaging11020060

Trifiletti, E., D'Ascenzo, S., Lugli, L., Cocco, V. M., Di Bernardo, G. A., Iani, C., Rubichi, S., Nicoletti, R., & Vezzali, L. (2020). Truth and lies in your eyes: Pupil dilation of White participants in truthful and deceptive responses to White and Black partners. *PLOS ONE*, *15*(10), e0239512. https://doi.org/10.1371/journal.pone.0239512

Trovillo, P. V. (1939). A History of Lie Detection. *Journal of Criminal Law and Criminology (1931-1951)*, *29*(6), 848. https://doi.org/10.2307/1136489

Tsiamyrtzis, P., Dowdall, J., Shastri, D., Pavlidis, I. T., Frank, M. G., & Ekman, P. (2007). Imaging Facial Physiology for the Detection of Deceit. *International Journal of Computer Vision*, *71*(2), 197–214. https://doi.org/10.1007/s11263-006-6106-y

Twyman, N. W., Lowry, P. B., Burgoon, J. K., & Nunamaker, J. F. (2014). Autonomous Scientifically Controlled Screening Systems for Detecting Information Purposely Concealed by Individuals. *Journal of Management Information Systems*, *31*(3), 106–137. https://doi.org/10.1080/07421222.2014.995535

Uccula, A., Mercante, B., Barone, L., & Enrico, P. (2022). Adult Avoidant Attachment, Attention Bias, and Emotional Regulation Patterns: An Eye-Tracking Study. *Behavioral Sciences*, *13*(1), 11. https://doi.org/10.3390/bs13010011

Unsworth, N., & Robison, M. K. (2015). Individual differences in the allocation of attention to items in working memory: Evidence from pupillometry. *Psychonomic Bulletin & Review*, *22*(3), 757–765. https://doi.org/10.3758/s13423-014-0747-6

Valenza, G., Citi, L., Saul, J. P., & Barbieri, R. (2018). Measures of sympathetic and parasympathetic autonomic outflow from heartbeat dynamics. *Journal of Applied Physiology*, *125*(1), 19–39. https://doi.org/10.1152/japplphysiol.00842.2017

van der Kooij, K. M., & Naber, M. (2019). An open-source remote heart rate imaging method with practical apparatus and algorithms. *Behavior Research Methods*, *51*(5), 2106–2119. https://doi.org/10.3758/s13428-019-01256-8

Vance, N., Speth, J., Khan, S., Czajka, A., Bowyer, K. W., Wright, D., & Flynn, P. (2022). Deception Detection and Remote Physiological Monitoring: A Dataset and Baseline Experimental Results. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, *4*(4), 522–532. https://doi.org/10.1109/TBIOM.2022.3218956

Vanderhallen, M., Jaspaert, E., & Vervaeke, G. (2016). SCAN as an investigative tool. *Police Practice and Research*, *17*(3), 279–293. https://doi.org/10.1080/15614263.2015.1008479

Vehlen, A., Belopolsky, A. V., & Domes, G. (2024). Gaze behavior in response to affect during natural social interactions. *Frontiers in Psychology*, *15*, 1433483. https://doi.org/10.3389/fpsyg.2024.1433483

Verschuere, B., & Ben-Shakhar, G. (2011). *Theory of the Concealed Information Test*. Cambridge University Press. https://dare.uva.nl/search?identifier=19d20e8f-4817-4c89-bf1a-4cdba93903d0

Verschuere, B., Ben-Shakhar, G., & Meijer, E. (Eds.). (2011). *Memory Detection: Theory and Application of the Concealed Information Test* (1st ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511975196

Verschuere, B., & Crombez, G. (2008). Déjà vu! The effect of previewing test items on the validity of the Concealed Information polygraph Test. *Psychology, Crime & Law*, *14*(4), 287–297. https://doi.org/10.1080/10683160701786407

Verschuere, B., Crombez, G., De Clercq, A., & Koster, E. H. W. (2004). Autonomic and behavioral responding to concealed information: Differentiating orienting and defensive responses. *Psychophysiology*, *41*(3), 461–466. https://doi.org /10.1111/j.1469-8986.00167.x

Verschuere, B., Crombez, G., & Koster, E. (2004). Orienting to guilty knowledge. *Cognition and Emotion*, *18*(2), 265–279. https://doi.org/10.1080/02699930341000095

Verschuere, B., Crombez, G., Smolders, L., & De Clercq, A. (2009). Differentiating Orienting and Defensive Responses to Concealed Information: The Role of Verbalization. *Applied Psychophysiology and Biofeedback*, *34*(3), 237–244. https://doi.org/10.1007/s10484-009-9093-2

Verschuere, B., Meijer, E., & De Clercq, A. (2011). Concealed information under stress: A test of the orienting theory in real-life police interrogations. *Legal and Criminological Psychology*, *16*(2), 348–356. https://doi.org/10.1348 /135532510X521755

Vine, S. J., McGrath, J. S., Bright, E., Dutton, T., Clark, J., & Wilson, M. R. (2014). Assessing visual control during simulated and live operations: Gathering evidence for the content validity of simulation using eye movement metrics. *Surgical Endoscopy*, *28*(6), 1788–1793. https://doi.org/10.1007/s00464-013-3387-4

Viola, P., & Jones, M. J. (2004). Robust real-time face detection. *International Journal of Computer Vision*, *57*(2), 137–154. https://doi.org/10.1023/B:VISI.000 0013087.49260.fb

Vollmer, M., & Möllmann, K.-P. (2018). *Infrared thermal imaging: Fundamentals, research and applications* (Second edition). Wiley-VCH Verlag GmbH & Co. KGaA.

Volz, K. G., Vogeley, K., Tittgemeyer, M., von Cramon, D. Y., & Sutter, M. (2015). The neural basis of deception in strategic interactions. *Frontiers in Behavioral Neuroscience*, *9*. https://doi.org/10.3389/fnbeh.2015.00027

Vrij, A. (2000). *Detecting lies and deceit: The psychology of lying and the implications for professional practice*. John Wiley.

Vrij, A. (2005). Criteria-Based Content Analysis: A Qualitative Review of the First 37 Studies. *Psychology, Public Policy, and Law*, *11*(1), 3–41. https://doi.org/10.1037/1076-8971.11.1.3

Vrij, A. (2009). *Detecting lies and deceit: Pitfalls and opportunities* (2. ed., repr). Wiley.

Vrij, A. (2015a). Deception detection. In B. L. Cutler & P. A. Zapf (Eds.), *APA handbook of forensic psychology, Vol. 2: Criminal investigation, adjudication, and sentencing outcomes.* (pp. 225–244). American Psychological Association. https://doi.org/10.1037/14462-008

Vrij, A. (2015b). Verbal Lie Detection Tools: Statement Validity Analysis, Reality Monitoring and Scientific Content Analysis. In P. A. Granhag, A. Vrij, & B. Verschuere (Eds.), *Detecting Deception* (1st ed., pp. 1–35). Wiley. https://doi.org/10.1002/9781118510001.ch1

Vrij, A. (2018). Verbal Lie Detection Tools From an Applied Perspective. In *Detecting Concealed Information and Deception* (pp. 297–327). Elsevier. https://doi.org/10.1016/B978-0-12-812729-2.00013-6

Vrij, A., Akehurst, L., & Knight, S. (2006). Police officers', social workers', teachers' and the general public's beliefs about deception in children, adolescents and adults. *Legal and Criminological Psychology*, *11*(2), 297–312. https://doi.org/10.1348/135532505X60816

Vrij, A., Edward, K., Roberts, K. P., & Bull, R. (2000). Detecting Deceit via Analysis of Verbal and Nonverbal Behavior. *Journal of Nonverbal Behavior*, *24*(4), 239–263. https://doi.org/10.1023/A:1006610329284

Vrij, A., Fisher, R., Mann, S., & Leal, S. (2008). A cognitive load approach to lie detection. *Journal of Investigative Psychology and Offender Profiling*, *5*(1–2), 39–43. https://doi.org/10.1002/jip.82

Vrij, A., Fisher, R. P., & Blank, H. (2017). A cognitive approach to lie detection: A meta-analysis. *Legal and Criminological Psychology*, *22*(1), 1–21. https://doi.org /10.1111/lcrp.12088

Vrij, A., & Ganis, G. (2014). Theories in Deception and Lie Detection. In *Credibility Assessment* (pp. 301–374). Elsevier. https://doi.org/10.1016/B978-0-12-394433-7.00007-5

Vrij, A., & Granhag, P. A. (2006). Interviewing to Detect Deception. In S. Å. Christianson (Ed.), *Offenders' Memories of Violent Crimes* (1st ed., pp. 279–304). Wiley. https://doi.org/10.1002/9780470713082.ch12

Vrij, A., & Granhag, P. A. (2012). Eliciting cues to deception and truth: What matters are the questions asked. *Journal of Applied Research in Memory and Cognition*, *1*(2), 110–117. https://doi.org/10.1016/j.jarmac.2012.02.004

Vrij, A., Granhag, P. A., Ashkenazi, T., Ganis, G., Leal, S., & Fisher, R. P. (2022). Verbal Lie Detection: Its Past, Present and Future. *Brain Sciences*, *12*(12), 1644. https://doi.org/10.3390/brainsci12121644

Vrij, A., Granhag, P. A., Leal, S., Fisher, R. P., Kleinman, S. M., & Ashkenazi, T. (2023). The Present and Future of Verbal Lie Detection. In D. DeMatteo & K. C. Scherr (Eds.), *The Oxford Handbook of Psychology and Law* (1st ed., pp. 565–581). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780197649138.013.33

Vrij, A., Granhag, P. A., Mann, S., & Leal, S. (2011). Outsmarting the liars: Toward a cognitive lie detection approach. *Current Directions in Psychological Science*, *20*(1), 28–32. https://doi.org/10.1177/0963721410391245

Vrij, A., Granhag, P. A., & Porter, S. (2010). Pitfalls and Opportunities in Nonverbal and Verbal Lie Detection. *Psychological Science in the Public Interest*, *11*(3), 89–121. https://doi.org/10.1177/1529100610390861

Vrij, A., Hartwig, M., & Granhag, P. A. (2019). Reading Lies: Nonverbal Communication and Deception. *Annual Review of Psychology*, *70*(1), 295–317. https://doi.org/10.1146/annurev-psych-010418-103135

Vrij, A., Leal, S., & Fisher, R. P. (2018). Verbal Deception and the Model Statement as a Lie Detection Tool. *Frontiers in Psychiatry*, *9*, 492. https://doi.org/10.3389/fpsyt.2018.00492

Vrij, A., Leal, S., Granhag, P. A., Mann, S., Fisher, R. P., Hillman, J., & Sperry, K. (2009). Outsmarting the liars: The benefit of asking unanticipated questions. *Law and Human Behavior*, *33*(2), 159–166. https://doi.org/10.1007/s10979-008-9143-y

Vrij, A., Mann, S. A., Fisher, R. P., Leal, S., Milne, R., & Bull, R. (2008). Increasing cognitive load to facilitate lie detection: The benefit of recalling an event in reverse order. *Law and Human Behavior*, *32*(3), 253–265. https://doi.org/10.1007/s10979-007-9103-y

Vrij, A., Mann, S., & Fisher, R. P. (2006). An Empirical Test of the Behaviour Analysis Interview. *Law and Human Behavior*, *30*(3), 329–345. https://doi.org/10.1007/s10979-006-9014-3

Vrij, A., Mann, S., Leal, S., & Fisher, R. (2010). 'Look into my eyes': Can an instruction to maintain eye contact facilitate lie detection? *Psychology, Crime & Law*, *16*(4), 327–348. https://doi.org/10.1080/10683160902740633

Vrij, A., Meissner, C. A., Fisher, R. P., Kassin, S. M., Morgan, C. A., & Kleinman, S. M. (2017). Psychological Perspectives on Interrogation. *Perspectives on Psychological Science*, *12*(6), 927–955. https://doi.org/10.1177/1745691617706515

Vrij, A., Oliveira, J., Hammond, A., & Ehrlichman, H. (2015). Saccadic eye movement rate as a cue to deceit. *Journal of Applied Research in Memory and Cognition*, *4*(1), 15–19. https://doi.org/10.1016/j.jarmac.2014.07.005

Vrtička, P., Bondolfi, G., Sander, D., & Vuilleumier, P. (2012). The neural substrates of social emotion perception and regulation are modulated by adult attachment style. *Social Neuroscience*, *7*(5), 473–493. https://doi.org/10.1080/17470919.2011.647410

Wade, M. G., & Jones, G. (1997). The Role of Vision and Spatial Orientation in the Maintenance of Posture. *Physical Therapy*, *77*(6), 619–628. https://doi.org/10.1093/ptj/77.6.619

Walczyk, J. J., Roper, K. S., Seemann, E., & Humphrey, A. M. (2003). Cognitive mechanisms underlying lying to questions: Response time as a cue to deception. *Applied Cognitive Psychology*, *17*(7), 755–774. https://doi.org/10.1002/acp.914

Wang, C.-A., & Munoz, D. P. (2015). A circuit for pupil orienting responses: Implications for cognitive modulation of pupil size. *Current Opinion in Neurobiology*, *33*, 134–140. https://doi.org/10.1016/j.conb.2015.03.018

Wang, J. T., Spezio, M., & Camerer, C. F. (2010). Pinocchio's Pupil: Using Eyetracking and Pupil Dilation to Understand Truth Telling and Deception in Sender-Receiver Games. *American Economic Review*, *100*(3), 984–1007. https://doi.org/10.1257/aer.100.3.984

Wang, W., den Brinker, A. C., Stuijk, S., & de Haan, G. (2017). Algorithmic Principles of Remote PPG. *IEEE Transactions on Biomedical Engineering*, *64*(7), 1479–1491. https://doi.org/10.1109/TBME.2016.2609282

Wang, W., Stuijk, S., & de Haan, G. (2016). A Novel Algorithm for Remote Photoplethysmography: Spatial Subspace Rotation. *IEEE Transactions on Biomedical Engineering*, *63*(9), 1974–1984. https://doi.org/10.1109/TBME.2015.2508602

Wang, X., Li, D., Menassa, C. C., & Kamat, V. R. (2019). Can infrared facial thermography disclose mental workload in indoor thermal environments? *Proceedings of the 1st ACM International Workshop on Urban Building Energy Sensing, Controls, Big Data Analysis, and Visualization*, 87–96. https://doi.org/10.1145/3363459.3363528

Wang, Y.-P., Cheng, R.-H., He, Y., & Mu, L.-Z. (2022). Thermal Analysis of Blood Flow Alterations in Human Hand and Foot Based on Vascular-Porous Media Model. *Frontiers in Bioengineering and Biotechnology*, *9*, 786615. https://doi.org/10.3389/fbioe.2021.786615

Warmelink, L., Subramanian, A., Tkacheva, D., & McLatchie, N. (2019). Unexpected questions in deception detection interviews: Does question order matter? *Legal and Criminological Psychology*, *24*(2), 258–272. https://doi.org/10.1111/lcrp.12151

Warmelink, L., Vrij, A., Mann, S., Jundi, S., & Granhag, P. A. (2012). The effect of question expectedness and experience on lying about intentions. *Acta Psychologica*, *141*(2), 178–183. https://doi.org/10.1016/j.actpsy.2012.07.011

Warmelink, L., Vrij, A., Mann, S., Leal, S., Forrester, D., & Fisher, R. P. (2011). Thermal imaging as a lie detection tool at airports. *Law and Human Behavior*, *35*(1), 40–48. https://doi.org/10.1007/s10979-010-9251-3

Webb, A. K., Hacker, D. J., Osher, D., Cook, A. E., Woltz, D. J., Kristjansson, S., & Kircher, J. C. (2009). Eye Movements and Pupil Size Reveal Deception in Computer Administered Questionnaires. In D. D. Schmorrow, I. V. Estabrooke, & M. Grootjen (Eds.), *Foundations of Augmented Cognition. Neuroergonomics and Operational Neuroscience* (Vol. 5638, pp. 553–562). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-02812-0_64

Webb, A. K., Honts, C. R., Kircher, J. C., Bernhardt, P., & Cook, A. E. (2009). Effectiveness of pupil diameter in a probable-lie comparison question test for deception. *Legal and Criminological Psychology*, *14*(2), 279–292. https://doi.org/10.1348/135532508X398602

Wei, M., Vogel, D. L., Ku, T.-Y., & Zakalik, R. A. (2005). Adult Attachment, Affect Regulation, Negative Mood, and Interpersonal Problems: The Mediating Roles of Emotional Reactivity and Emotional Cutoff. *Journal of Counseling Psychology*, *52*(1), 14–24. https://doi.org/10.1037/0022-0167.52.1.14

Weiss, B., & Feldman, R. S. (2006). Looking good and lying to do it: Deception as an impression management strategy in job interviews. *Journal of Applied Social Psychology*, *36*(4), 1070–1086. https://doi.org/10.1111/j.0021-9029.2006.00055.x

Westcott, E. B., & Segal, S. S. (2013). Perivascular Innervation: A Multiplicity of Roles in Vasomotor Control and Myoendothelial Signaling. *Microcirculation*, *20*(3), 217–238. https://doi.org/10.1111/micc.12035

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., … Yutani, H. (2019). Welcome to the Tidyverse. *Journal of Open Source Software*, *4*(43), 1686. https://doi.org/10.21105/joss.01686

Wickham, H., François, R., Henry, L., Müller, K., & Vaughan, D. (2023). *Dplyr: A Grammar of Data Manipulation. R package version 1.1.4*. https://github.com/tidyverse/dplyr

Wilson, M. R., Vine, S. J., Bright, E., Masters, R. S. W., Defriend, D., & McGrath, J. S. (2011). Gaze training enhances laparoscopic technical skill acquisition and multi-tasking performance: A randomized, controlled study. *Surgical Endoscopy*, *25*(12), 3731–3739. https://doi.org/10.1007/s00464-011-1802-2

Wright, G. R. T., Berry, C. J., & Bird, G. (2013). Deceptively simple … The "deception-general" ability and the need to put the liar under the spotlight. *Frontiers in Neuroscience*, *7*. https://doi.org/10.3389/fnins.2013.00152

Wright, K. W. (2006). Anatomy and Physiology of Eye Movements. In K. W. Wright, P. H. Spiegel, & L. S. Thompson (Eds.), *Handbook of Pediatric Strabismus and Amblyopia* (pp. 24–69). Springer New York. https://doi.org/10.1007/0-387-27925-3_2

Wu, C., Liu, Y., Guo, X., Zhu, T., & Bao, Z. (2022). Enhancing the feasibility of cognitive load recognition in remote learning using physiological measures and an adaptive feature recalibration convolutional neural network. *Medical & Biological Engineering & Computing*, *60*(12), 3447–3460. https://doi.org/10.1007/s11517-022-02670-5

Wu, Y., Gu, R., Yang, Q., & Luo, Y. (2019). How Do Amusement, Anger and Fear Influence Heart Rate and Heart Rate Variability? *Frontiers in Neuroscience*, *13*, 1131. https://doi.org/10.3389/fnins.2019.01131

Wu, Z., Singh, B., Davis, L., & Subrahmanian, V. (2018). Deception Detection in Videos. *Proceedings of the AAAI Conference on Artificial Intelligence*, *32*(1). https://doi.org/10.1609/aaai.v32i1.11502

Xia, C., Ren, M., Wang, B., Dong, M., Xu, G., Xie, J., & Zhang, C. (2021). Infrared thermography-based diagnostics on power equipment: State-of-the-art. *High Voltage*, *6*(3), 387–407. https://doi.org/10.1049/hve2.12023

Xiao, H., Liu, T., Sun, Y., Li, Y., Zhao, S., & Avolio, A. (2024). Remote photoplethysmography for heart rate measurement: A review. *Biomedical Signal Processing and Control*, *88*, 105608. https://doi.org/10.1016/j.bspc.2023.105608

Yamuza, M. T. V., Bolea, J., Orini, M., Laguna, P., Orrite, C., Vallverdu, M., & Bailon, R. (2019). Human Emotion Characterization by Heart Rate Variability Analysis Guided by Respiration. *IEEE Journal of Biomedical and Health Informatics*, *23*(6), 2446–2454. https://doi.org/10.1109/JBHI.2019.2895589

Yildirim, S., Chimeumanu, M. S., & Rana, Z. A. (2023). The influence of micro-expressions on deception detection. *Multimedia Tools and Applications*, *82*(19), 29115–29133. https://doi.org/10.1007/s11042-023-14551-6

Yin, L., Hu, Y., Dynowski, D., Li, J., & Weber, B. (2017). The good lies: Altruistic goals modulate processing of deception in the anterior insula. *Human Brain Mapping*, *38*(7), 3675–3690. https://doi.org/10.1002/hbm.23623

Yin, L., Reuter, M., & Weber, B. (2016). Let the man choose what to do: Neural correlates of spontaneous lying and truth-telling. *Brain and Cognition*, *102*, 13–25. https://doi.org/10.1016/j.bandc.2015.11.007

Yoo, K., Ahn, J., & Lee, S.-H. (2021). The confounding effects of eye blinking on pupillometry, and their remedy. *PLOS ONE*, *16*(12), e0261463. https://doi.org/10.1371/journal.pone.0261463

Young, H. A., Cousins, A. L., Watkins, H. T., & Benton, D. (2017). Is the link between depressed mood and heart rate variability explained by disinhibited eating and diet? *Biological Psychology*, *123*, 94–102. https://doi.org/10.1016/j.biopsycho.2016.12.001

Yu, J., Tao, Q., Zhang, R., Chan, C. C. H., & Lee, T. M. C. (2019). Can fMRI discriminate between deception and false memory? A meta-analytic comparison between

deception and false memory studies. *Neuroscience & Biobehavioral Reviews*, *104*, 43–55. https://doi.org/10.1016/j.neubiorev.2019.06.027

Zembaty, J. S. (1993). Aristotle on Lying. *Journal of the History of Philosophy*, *31*(1), 7–29. https://doi.org/10.1353/hph.1993.0008

Zhao, G., Li, X., Li, Y., & Pietikäinen, M. (2023). Facial Micro-Expressions: An Overview. *Proceedings of the IEEE*, *111*(10), 1215–1235. https://doi.org/10.1109/JPROC.2023.3275192

Zheltyakova, M., Kireev, M., Korotkov, A., & Medvedev, S. (2020). Neural mechanisms of deception in a social context: An fMRI replication study. *Scientific Reports*, *10*(1), 10713. https://doi.org/10.1038/s41598-020-67721-z

Zhi, R., Liu, M., & Zhang, D. (2020). A comprehensive survey on automatic facial action unit analysis. *The Visual Computer*, *36*(5), 1067–1093. https://doi.org/10.1007/s00371-019-01707-5

Zhou, Y., Ghassemi, P., Chen, M., McBride, D., Casamento, J. P., Pfefer, T. J., & Wang, Q. (2020). Clinical evaluation of fever-screening thermography: Impact of consensus guidelines and facial measurement location. *Journal of Biomedical Optics*, *25*(9), 097002. https://doi.org/10.1117/1.JBO.25.9.097002

Zhu, Z., Tsiamyrtzis, P., & Pavlidis, I. (2007). Forehead thermal signature extraction in lie detection. *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 243–246. https://doi.org/10.1109/IEMBS.2007.4352269

Zloteanu, M., Bull, P., Krumhuber, E. G., & Richardson, D. C. (2021). Veracity judgement, not accuracy: Reconsidering the role of facial expressions, empathy, and emotion recognition training on deception detection. *Quarterly Journal of Experimental Psychology*, *74*(5), 910–927. https://doi.org/10.1177/1747021820978851

Zloteanu, M., & Vuorre, M. (2024). A tutorial for deception detection analysis or: How I learned to stop aggregating veracity judgments and embraced signal detection theory mixed models. *Journal of Nonverbal Behavior*, *48*(1), 161–185. https://doi.org/10.1007/s10919-024-00456-x

Zlotenaou, M. (2020). Reconsidering facial expressions and deception detection. In A. Freitas-Magalhaes & J. Borod (Eds.), *Handbook of Facial Expression of Emotion* (Vol. 2020, pp. 238–283). FEELab Science Books.

Zuckerman, M., DePaulo, B. M., & Rosenthal, R. (1981). Verbal and Nonverbal Communication of Deception. In *Advances in Experimental Social Psychology* (Vol. 14, pp. 1–59). Elsevier. https://doi.org/10.1016/S0065-2601(08)60369-X

SUPPLEMENTARY MATERIALS

List of supplementary materials:

1. English abstract of the doctoral thesis
2. Czech abstract of the doctoral thesis
3. Original approval of the FF UP Ethics Panel for Research

ABSTRACT OF THE DOCTORAL THESIS

Name of the thesis: Validity of Non-Invasive Methods for Measuring Behavioural and Physiological Changes in Deception Detection

Author: Mgr. Petra Hypšová

Supervisor: doc. PhDr. Martin Seitl, Ph.D.

Number of pages and characters: 291 pages; 567 005 characters

Number of attachments: 3

Number of used references: 585

Abstract:

This dissertation investigates the validity of non-invasive methods for deception detection using functional infrared thermal imaging (fITI), remote photoplethysmography (rPPG), facial expression analysis, and eye-tracking. A case study (N = 1), two pilot studies (N_1 = 15; N_2 = 27) and a main experiment (N ≈ 100) explored deception under different levels of cognitive load (spontaneous vs. rehearsed), veracity (truth vs. lie), and interactions (all conditions including baseline) with attention to moderating role of attachment avoidance. To improve methodological precision, two automated systems for processing thermal data were developed. The results showed an increased heart rate during deception, especially during spontaneous lying, while facial temperature and gaze patterns reflected general task-related demands not deception per se. Emotional valence and arousal varied according to cognitive load, with greater engagement during spontaneous responses. Attachment avoidance moderated physiological responses and gaze behaviour, but not emotional arousal or valence. These findings challenge the notion of universal deception cues and support a context-sensitive, person-centred approach based on individual characteristics and situational factors.

Key words: attachment avoidance; cognitive load; deception detection; eye-tracking; functional infrared thermal imaging (fITI); non-invasive deception detection; remote photoplethysmography (rPPG)

CZECH ABSTRACT OF THE DOCTORAL THESIS

Název práce: Validita neinvazivních metod měření behaviorálních a fyziologických změn při detekci úmyslného zkreslování informací

Autor: Mgr. Petra Hypšová

Vedoucí práce: doc. PhDr. Martin Seitl, Ph.D.

Počet stran a znaků: 291 stran; 567 005 znaků

Počet příloh: 3

Počet titulů použité literatury: 585

Abstrakt:

Tato disertační práce se zabývá validitou neinvazivní detekce klamání pomocí funkčního infračerveného termovizního snímání (fITI), dálkové fotopletysmografie (rPPG), analýzy obličejové emoční exprese a eye-trackingu. Případová studie (N = 1), dvě pilotní studie (N_1 = 15; N_2 = 27) a hlavní experiment (N ≈ 100), zkoumaly projevy klamání v podmínkách různé kognitivní zátěže (spontánní vs. připravené odpovědi), odlišné pravdivosti výpovědí (pravda vs. lež) a různých interakcí (všechny podmínky včetně baseline), s důrazem na možnou moderující roli vztahové vyhýbavosti. Pro zvýšení metodologické přesnosti byly vyvinuty dva automatizované systémy pro zpracování termovizních dat. Výsledky ukázaly zvýšenou srdeční frekvenci během klamání, zejména při spontánním lhaní, zatímco teplota obličeje a vzorce pohledu odrážely spíše obecné požadavky spojené s plněním úkolu než klamání per se. Emoční valence a arousal se lišily v závislosti na kognitivní zátěži, přičemž spontánní odpovědi byly spojeny s vyšší mírou zapojení. Vztahová vyhýbavost se ukázala jako statisticky významný moderátor fyziologických reakcí a očních fixací, nikoli však emočního arousalu ani valence. Tato zjištění zpochybňují představu univerzálních ukazatelů klamání a podporují kontextově citlivý, na osobu zaměřený přístup, který zohledňuje individuální charakteristiky a situační faktory.

Klíčová slova: detekce lži; eye-tracking; funkční infračervené termovizní snímání (fITI); kognitivní zátěž; nekontaktní detekce lži; vzdálená fotopletysmografie (rPPG); vztahová vyhýbavost

ORIGINAL APPROVAL OF THE FF UP ETHICS PANEL FOR RESEARCH

Opinion of the FF UP Ethics Panel for Research

Panel composition:

doc. Mgr. Ivona Barešová, Ph.D.
PhDr. Ondřej Bláha, Ph.D. PhDr.
Olga Pechová, Ph.D.
doc. PhDr. Matúš Šucha, Ph.D. (chairman)
doc. PhDr. Daniel Topinka, Ph.D. Mgr.
Elizabeth Allyn Woock, Ph.D. doc. PhDr.
Lenka Křupková, Ph.D.

The submitted project has been approved by the Ethics Panel under reference number: 03/2023 on: 31. 5. 2023

The FF UP Ethics Panel for Research evaluated the submitted project and found no contradictions with the applicable principles, regulations and international guidelines for research involving human participants.

The project solver fulfilled the conditions necessary to obtain the approval of the Ethics Panel of the Faculty of Arts UP for
Research.

UNIVERZITA PALACKÉHO V OLOMOUCI 13

Doc. PhDr. MATÚŠ ŠUCHA, PhD.

Digitally signed by Doc. PhDr. MATÚŠ ŠUCHA, PhD. Date: 2023.05.31 08:42:06 +02'00'

.....

signature of the Chairman