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Online Deception: The Impact of Language in Text-Based Deception Detection

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ONLINE DECEPTION: THE IMPACT OF LANGUAGE IN

TEXT-BASED DECEPTION DETECTION

by

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ABSTRACT

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The proliferation of misinformation and deception online poses significant risks, from election interference to public health crises. Yet, research on text-based deception remains limited. This work helps to advance the understanding of how individuals discern deception in online communications, focusing on the perception of linguistic errors and anomalies. Across three studies, I explored how syntactic mistakes and unusual word choices influence judgments of truthfulness and deceit. The first study examined the impact of syntactic errors on participants' perceptions of deception in short vignettes, finding that such mistakes led participants to view statements as more deceptive when they were supposed to be truthful and less so in deceptive statements. The second study extended this investigation to include unusual word choices, observing that both linguistic features significantly altered deception judgments, mirroring the patterns found in the first study. The third study delved into the neural mechanisms of deception detection, specifically analyzing the N400 and P600 ERP components in response to the same linguistic manipulations. This revealed a novel ERP component associated with semantic veracity differences, suggesting a distinct neurophysiological response to deceptive versus truthful statements. These findings elucidate the complex interplay between linguistic cues and deception perception, highlighting the importance of syntactic and semantic processing in discerning online deceit. Identifying a novel ERP component further enriches our neuroscientific understanding of these mechanisms by illuminating that specific cognitive processes are involved in the perception of deception. Collectively, this research underscores the nuanced role of language in deception detection and offers a foundational step toward developing more effective tools for identifying misinformation online.

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PUBLIC ABSTRACT

Online Deception: The Impact of Language in Text-Based Deception Detection

Stephanie Dayle Avila

In today's digital age, spreading false information online can have serious consequences, from affecting elections to undermining public health efforts. Despite the issue's importance, there's been relatively little research into better understanding how people make decisions about lies and misinformation online. My project dives into this challenge by exploring how specific language cues, like grammar errors or unusual word choices, influence people's perception of statements in terms of deceit online. I examined how people react to these cues through three separate but related studies when reading truthful and deceptive statements. The first two studies showed that true statements with grammatical errors and unusual word choices were seen as more deceitful, and lie statements with the same language were seen as less deceptive. The third part of my research took a closer look at what's happening in the brain. By measuring brain activity, I discovered a new brain response that is sensitive to the difference between perceived truths and lies. This research sheds light on how language influences how we perceive deception, primarily online.

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Chapter I – Introduction

The internet has seen a significant rise in misinformation over the last decade (Alharbi et al., 2021). Misinformation involves disseminating false or misleading information, directly impacting how individuals perceive and interact with the world around them, and 50.5% of online misinformation is spread via social media (Loukas et al., 2020). Misinformation has significant societal implications, including eroding trust, altering perceptions, and increasing polarization, leading to widespread social unrest and hindering effective communication and problem-solving (Metzger et al., 2021). This was demonstrated during events like the 2020 U.S. Presidential Election and subsequent Capitol insurrection. The misinformation spread through social media resulted in 65% of Republicans believing the election was stolen (Agiesta & Edwards-Levy, 2021) and five fatalities (Soto-Vasquez, 2021). Recognizing misinformation online is essential for professionals, such as legal personnel, healthcare workers, recruiters, and laypeople, as it significantly influences decision-making, maintains professional integrity, and ensures accurate and safe navigation of daily information.

Understanding the dynamics of misinformation necessitates an exploration of the intentions and motivations behind its spread because it helps develop targeted strategies to combat misinformation effectively. Not every individual who disseminates misinformation does so with the intent to deceive. Misinformation broadly encompasses all false or inaccurate information, irrespective of the intention behind its spread (Vraga & Bode, 2020). Conversely, deception specifically involves an intentional act by the communicator (or sender) to lead others to accept as true what the communicator considers to be false or misleading (Crank & Curtis, 2020; Levine, 2014; Vrij, 2008).

Deception is a phenomenon that permeates various aspects of modern life, notably in politics, business, and social media. In politics, it manifests in propaganda and spin – a form of deception that involves presenting information in a biased manner (Mattes et al., 2023); in business, it can be misleading advertising and corporate espionage (FTC, 2023). In social media, deception becomes even more nuanced as it intertwines with personal interactions and public discourse (Qureshi et al., 2022). For example, online dating apps have been directly linked to over 16,000 abductions, 100 murders, and yearly sexual assault counts in the thousands (Valentine, 2022), illustrating the real-world, life-threatening consequences of deception in digital spaces.

The proliferation of misinformation and deception in digital environments can be attributed to the limited efficacy of individuals in accurately discerning deceptive content. The average success rate for truth-lie discrimination - the ability to distinguish truthful statements from deceptive statements – is 54% (Bond Jr. & DePaulo, 2006). This low success rate is alarming because it indicates that even in a "coin toss" scenario, individuals are only slightly better than chance at identifying deception. The issue is compounded by the tendency toward overconfidence in personal lie detection abilities, showing that individuals often overestimate their capacity to identify lies (Slessor et al., 2014). Such overconfidence is not limited to interpersonal interactions but extends to digital communication. Wang et al. (2010) demonstrated this through their findings on email scams, where individuals displayed misplaced confidence in their ability to identify phishing emails. This confidence did not correlate with their actual accuracy. Moreover, reliance on popular but scientifically dubious methods, like the belief that liars look down and to the left (Lauffer, 2021; Park et al., 2002), further impairs deception detection.

Though widely believed, such misconceptions are only loosely based on scientific findings and, thus, can impair effective deception detection. Taken together, these findings beg the question: “Why are we so bad at detecting lies?” And by extension: “what factors influence judgements of veracity?”

Detecting deception online is challenging due to the absence of cues like facial expressions, body language, and tone of voice, which are often relied upon in traditional lie detection. This makes differentiating truth from falsehoods in online communication more difficult, impacting the interpretation of information. Research adds layers to this complexity by exploring both the execution and identification of deceptive behavior. Despite its extensiveness, this research shows inconsistent results (e.g., Bond Jr. & DePaulo, 2006; Curtis & Hart, 2015; Masip & Herrero, 2015) and a narrow focus. A significant limitation is the research focuses on bald-faced or outright lies (BFL; e.g., Bond Jr. & DePaulo, 2006; McCornack et al., 2014). This type of lie, exemplified by scenarios such as Sally denying taking a cookie despite having done so, represents a straightforward case of factual contradiction. Yet, deception is often more nuanced, involving complex scenarios like misleading literal truths (MLTs). In MLTs, statements are factually true but designed to deceive by omission or implication, such as suggesting someone else could have taken the cookie to divert suspicion.

Furthermore, deception research has concentrated chiefly on face-to-face or audio-visual contexts, where behavioral and verbal cues are accessible. This focus creates a notable knowledge gap regarding text-based deception, especially in cue-absent digital mediums like social media and email. Moreover, the existing literature mainly focuses on the act of deceiving and its cues, with less emphasis on perceptions of deception and misleading communication. Factors like biases and source credibility influence these perceptions. For instance, during the 2020 U.S. Presidential election, some perceived Donald Trump’s tweets as truthful despite evidence to the contrary, illustrating how factual information is filtered through personal belief systems. This example highlights the need for a broader approach in deception research that considers both deceit mechanisms and the complex ways individuals perceive and interpret deceptive communication, which is essential for developing more effective strategies against the challenges of misinformation.

Psychological and Behavioral Theories of Deception

Examining deception through psychological and behavioral lenses involves exploring theories about the motives, processes of lying, and cues used to judge potential deception. These theories delve into the cognitive effort required to fabricate lies and the social-psychological factors that drive deception.

Interpersonal Deception Theory

Buller' and Burgoon's (1996) interpersonal deception theory provides a framework for understanding deception during interpersonal communication, emphasizing the role of social, psychological, and interactive factors in face-to-face contexts. It differentiates between strategic manipulation and non-strategic behaviors like involuntary nervous gestures. The theory highlights the interactive aspects of deception, where the sender manages the interaction for success. At the same time, the receiver actively interprets messages and may seek more information to confirm or deny their suspicions. Feedback is crucial because it influences the sender’s behavior adjustments to evade detection. For example, Buller et al. (1996) assigned participants roles in a simulated job interview, where one group (the receiver) was covertly signaled to be suspicious of the other group (the sender), who were instructed to deceive after an initial truthful response. This setup was designed to manipulate the level of suspicion on the fly and observe resultant changes in communication. They found that the receiver's suspicion provoked linguistic non-immediacy (i.e., fewer self-references and greater group references) from the sender in deceptive interactions. Thus, there was a significant shift in the complexity and fluency of responses, with senders being less verbally immediate and specific when deceiving than when telling the truth. This finding indicates that linguistic patterns are variable and dynamic during deception (Buller et al., 1996). Interpersonal deception theory illuminates the dynamic adjustments of deceptive strategies in real-time interactions, yet its application to online, text-based communication is still unexplored.

Information Manipulation Theory 2

The Information Manipulation Theory (McCornack, 1992) and its enhancement, Information Manipulation Theory 2 (McCornack et al., 2014), explain how individuals deceive by manipulating information during communication. The original theory suggests that deception often involves subtly altering truthful information by modifying its quantity, quality, relevance, or presentation, introducing the concept of MLTs. The updated theory integrates cognitive aspects, examining how cognitive load and memory impact deceptive discourse, applicable to in-person and online interactions. Examples could include omitting critical details in texts or emails (i.e., quantity), mixing truths in online posts for credibility (i.e., quality), adding irrelevant information for distraction (i.e., relevance), or using ambiguous language to mislead (i.e., presentation). A significant contribution of Information Manipulation Theory 2 is the application of Zipf's Principle of Least Effort to deception, which can be exemplified by someone choosing to say "I'm working late" when lying about their whereabouts, as it is easier and less effortful to maintain than fabricating a complex story. This challenges the conventional view by proposing that deception might sometimes be selected for efficiency, suggesting that it is not always more complex or cognitively taxing than truth-telling.

Activation-Decision-Construction-Action Theory (ADCAT)

The ADCAT is a cognitive framework for understanding serious deception (Walczyk et al., 2014), integrating elements from the dual-process theory (Wason & Evans, 1974). The dual-process theory outlines two systems in deceptive communication: automatic processing, involving intuitive and quick cognitive processes for simple and immediate lies (Walczyk et al., 2003), and controlled processing, which requires deliberate effort for complex lies (Walczyk et al., 2003). Walczyk et al. (2014) identify four stages in the deception process: activation (recognizing the expectation of a truthful response and retrieving or constructing this truth), decision (deciding whether to deceive, considering cost and benefits), construction (manipulating information with attention to plausibility and consistency), and action (delivering the deceptive message). Walczyk et al. support each of these stages by referencing research on working memory and the theory of mind. Researchers collected self-report data on participants' decisions to lie or tell the truth based on various scenarios and associated consequences. They found that the decision to lie often depends more on the consequences of telling the truth than those of lying (Masip et al., 2016). In online communication, the tendency towards controlled processing is likely higher due to the availability of time for constructing and revising messages.

Truth Default Theory

The truth-default theory provides a novel view of deception in communication (Levine, 2014). It posits that people usually operate under a “truth-default” state, inherently assuming others are honest unless there is strong evidence to doubt their honesty. This *truth bias* is a practical approach to communication, reflecting honesty in most daily interactions (Levine, 2014). Additionally, Levine (2014) argues that the cost of wrongfully accusing someone of lying is often perceived as higher than the cost of believing a lie. The truth bias has been established and evidenced by Bond and DePaulo’s (2006) meta-analysis (see Deception Detection Accuracy below) and a study that found that altering the truth-lie base rate affects accuracy (Levine et al., 1999). In their study, Levine et al. (1999) created videos with both truthful and deceptive statements. They manipulated the truth-lie base rate by deleting specific segments of the tapes, then had participants view the tapes and judge each segment as truthful or deceptive. They found that truth-lie discrimination accuracy was highest in the 75% honest condition, with a discrimination accuracy of 59.48%, and lowest in the 25% honest condition, with a discrimination accuracy of 39.83%. Thus, a truth bias was evident across conditions as participants were more likely to judge messages as truthful. This theory explains the prevalence and success of online deception, as individuals naturally lean towards believing the things they read or hear are true.

The Theory of Self-Presentation

The theory of self-presentation views deception as a tool for managing self-image (Baumeister & Hutton, 1987). It examines how individuals manipulate information to create favorable impressions, driven by the motivation to maintain or enhance their self-image (Von Hippel & Trivers, 2011). In social contexts, this concern about perception can lead to strategic deception, especially when self-image is at risk or can be improved (Baumeister & Hutton, 1987). Forms of deception include exaggeration, omission, fabrication, and minimization, all rooted in the human need for self-esteem and social approval (Hipple & Trivers, 2011). In online text-based communication, deception for impression management is particularly relevant. In a study by Ellison et al. (2006), individuals with active online dating profiles were interviewed on how they presented themselves. They discovered that individuals primarily focused on balancing authenticity, impression management, and credibility when creating profiles. This can include selecting photos and creating descriptions that reflect their interests and personality, while also strategically highlighting their most appealing qualities and accomplishments. viewing these elements as key to their self-presentation. Thus, the digital realm provides a platform for individuals to craft and present idealized versions of themselves.

Deception Detection

Deception detection research spans psychology, communication, criminal justice, computer science, and linguistics. Initially, studies focused on physical deception indicators, like facial expressions and body language (e.g., Brougham, 1992; Buller & Aune, 1987; Ekman & Friesen, 1974; Vrij et al., 2019; Zuckerman et al., 1981). A major shift occurred with technology-assisted methods, beginning with the polygraph's introduction in 1921 (Synnott et al., 2015). The polygraph, measuring physiological responses such as blood pressure and heart rate, was deemed highly accurate in lie detection (Geddes, 2002). Advancements continued with electroencephalography (EEG) applications, like the 1991 'Brain Fingerprinting Method' by Farwell and Donchin, which analyzes brainwave patterns for deception detection. Brain Fingerprinting is a technique that employs the guilty knowledge test to analyze the P300 Event-Related Potential (ERP). These concepts are detailed in the *Cognitive Load and Reaction Time* and *Electroencephalogram (EEG)* sections below.

Deception Detection Accuracy

Bond Jr. and DePaulo's (2006) meta-analysis across 206 studies involving 24,483 participants, including college students and legal professionals, investigated deception detection accuracy using video and audio recordings focusing on aspects such as sender motivation, receiver exposure, and sender preparation, rather than directly examining deception cues. Overall, they discovered that Secret Service agents had the highest accuracy rate at 64.12%, while college students had the lowest at 52.82%, with polygraphers slightly higher at 55.67%. These findings reveal a prevalent truth bias (see *Truth-Default Theory* above), where individuals are more inclined to consider statements as truthful. Additionally, motivation, exposure and preparation had little effect on accuracy ratings. The average receiver's truth-lie discrimination was 53.43% when the sender had no motivation to lie and 53.27% when the sender had motivation. The average receiver's truth-lie discrimination was 53.13% when the sender was more prepared for deception and 53.75% when the sender was less prepared for deception. The average receiver's truth-lie discrimination was 53.06% when the receiver had no exposure to the sender and 54.55% when they had been exposed to the sender before. This trend remained consistent across studies, indicating a widespread difficulty in detecting deception. In contrast, research by Masip and Herrero (2015) specifically emphasized physical cues in deception detection. Participants were asked how they believed lies can be detected, and results indicated that most people (86%) rely on physical rather than verbal cues for deception detection, with an overwhelming 95.45% of police officers believing in the presence of physical cues in liars.

Vrij and Mann (2001) demonstrated that reliance solely on physical cues diminishes truth-lie discrimination. In their study, 65 police officers watched videos of convicted murderers making truthful and deceptive statements. The officers were more accurate at identifying truths (70% hit rate) than lies (57% hit rate), with those considering both physical and verbal cues outperforming those focusing only on physical signs. Blair et al. (2010) further found that individuals focusing on verbal cues of deception achieved up to a 47% higher accuracy rate compared to those relying solely on physical cues. The highest accuracy, between 75% to 81%, was observed in those who assessed both contextual information (i.e., knowledge about the situation and the sender) and verbal cues. Additionally, Vrij and Mann (2001) reported that top-performing police officers (18 of the 65 participants) in deception detection often relied more on contextual contradictions than their less successful counterparts.

Furthermore, DePaulo et al. (1996) uncovered a notable gap between perceived and actual deception detection abilities. Their research showed that people often overrate their skills in detecting lies, leading to an overconfidence bias, with no significant correlation between confidence and actual accuracy in detecting deception. This overconfidence is concerning, particularly in today's digital landscape where misinformation is prevalent and can lead to serious events like the January 6, 2020, insurrection. Additionally, misinformation in the digital age is often text-based, eliminating the ability of people to use verbal or physical cues, such as the tonal inflection of a voice (Kirchhübel & Howard, 2013; Sondhi et al., 2016), or unusually long pauses (Suchotzki et al., 2017a), which can be indicative of deception. This highlights the importance of reevaluating our approach to recognizing deception in digital text, as the evolving nature of online communication demand more sophisticated and adaptive methods to discern and counteract misleading and deceptive information.

Deceptive Cues

Physical Cues. Until recently, the dominant view in both science and popular culture was that liars display body language and facial expression cues, herein referred to as physical cues when engaging in deception. One of the most commonly known forms of physical cues is avoiding eye contact (Buller & Aune, 1987; Ekman & Friesen, 1974; Zuckerman et al., 1981). Additional physical cues associated with engaging in deceptive behavior include blinking excessively (Zuckerman et al., 1981), covering the mouth or nose (Brougham, 1992), fidgeting (Ekman & Friesen, 1974; Zuckerman et al., 1981), and displaying facial micro-expressions (Ekman & Friesen, 1974). Micro-expressions are small, split-second facial details that putatively cannot be faked during deceptive communication. For example, if an individual were to lie about being mad, they may try to hide the anger on their face. In doing so, uncontrollable and minute facial movements, such as a slight pursing of the lips, would give away the individual's genuine emotions (Ekman, 2001). Some research has shown that relying on physical cues can lead to decent deception detection accuracy (Brougham, 1992; Masip & Herrero, 2015; Vrij & Lochun, 1997). However, other research indicates that these physical cues are not consistently valid indicators of deception (Bond Jr. & DePaulo, 2006; Curtis & Hart, 2015; Sporer & Schwandt, 2006; Suchotzki et al., 2017a; Vrij, 2008; Vrij & Mann, 2001). Thus, putative physical cues of deception are at best unreliable, and in any case are not available in the majority of online interactions which are text-based or involve static images.

Verbal Communication Cues. Research on voice pitch changes as cues in deceptive speech (Kirchhübel & Howard, 2013; Sondhi et al., 2016; Srivastava & Dubey, 2018) has produced mixed results. Kirchhübel & Howard (2013) used a mock-theft setup to analyze if voice pitch could predict truthful or deceptive responses. Participants were informed that the nature of the study was to test a new security system at the university, and they instructed participants to take money off a desk. A security actor then interviewed the participants, and the participants were informed that they could keep the full amount of money if they could convince the interviewer that they did not take the money. Krichhübel and Howard (2013) examined the sound frequency composition of the participants' voices to test if voice pitch was predictive of truthful versus deceptive interview answers. They found no significant effects. In contrast, Sondhi et al. (2016) recorded suspects' responses during police interrogations on phone thefts and found a notable increase in high-frequency sounds in the voices of those later found guilty. Their results suggested that increased pitch could indicate deception. The Sondhi et al. study's real-world setting suggests that verbal cues, like voice pitch changes, might be reliable indicators of deception in in-person or audio communications. However, in the realm of online communication, which predominantly relies on static text, the relationship between textual discrepancies and perceived deception remains unclear.

Cognitive Load and Reaction Time. Cognitive load refers to the amount of information processed in working memory at a given time (Sporer & Schwandt, 2006; Sweller, 1988; Walczyk et al., 2014). In deception research, it's measured by the response time during deceptive behavior (Suchotzki et al., 2017a; Verschuere et al., 2018). Various tests assess reaction times in deception scenarios, including the concealed information test, the autobiographical implicit association test, the Sheffield lie test, and the differentiation of deception test. The concealed information test is based on the premise that a criminal will react to stimuli related to the crime (e.g., a knife; MacLaren, 2001), while the autobiographical test measures reaction to personal involvement in an incident (e.g. longer time to answer a question related to the crime; Sartori et al., 2008). The Sheffield lie test involves telling truths and lies about the same stimuli to establish a baseline for reactions (Spence et al., 2001). The differentiation test requires participants to alternate between lying and truth-telling about different stimuli (e.g., lie when the stimulus is new and tell the truth when the stimulus is old; Furedy et al., 1988). These methods aim to enhance lie detection, particularly in police interrogations.

Suchotzki et al. (2017) analyzed reaction time data across 114 deception detection studies using the tests described above. Suchotzki et al. calculated the effect size of reaction time differences across studies. They used the standardized paired difference (Cohen’s d for paired data) by subtracting the mean reaction time of truths from the mean reaction time of lies and dividing by the pooled standard deviation. Suchotzki et al. found that individuals who engage in deceptive behavior have an average delayed reaction time of 115 milliseconds across tests. Reaction time for the concealed information test was lowest at 49 milliseconds, followed by the differentiation of deception test at 106 milliseconds, the Sheffield lie test at 149 milliseconds, and the autobiographical implicit association test at 180 milliseconds. In a second meta-analysis study, Verschuere et al. (2018) analyzed 21 published and unpublished studies examining the effects of additional cognitive load (e.g., time pressure, sleep deprivation, and foreign language) on the reaction time difference between truth-telling and deceptive communication. The studies examined included all the deception tests listed above except the Sheffield lie test. Verschuere et al. standardized reaction time by subtracting the reaction time of the control conditions (no additional cognitive load) from the load conditions and dividing by the corrected inter-correlation standard error term. While their analysis resulted in a mean reaction time difference of 186 milliseconds between truth-telling and deception, no evidence suggests additional cognitive load impacted reaction time across conditions (Verschuere et al., 2018).

Yin et al. (2016) examined reaction times for spontaneous lies by asking participants to play a modified version of the Asian dice game, *sic bo*. In *sic bo*, players roll three dice and bet on the sum. In this modified version, Yin et al. created 342 random dice images as outcomes for participants to bet on. Predictions were made on a binary scale - “big” if they predicted the sum of the three dice to be 11 or greater and “small” if they predicted the sum of the three dice to be 10 or fewer. After participants bet, they viewed the image of the three dice and reported if their prediction was correct. Yin et al. informed participants that there was no punishment for untrue reports, and their reports determined their final payoff. Computer software tracked participants’ responses, which allowed Yin et al. to determine when participants gave false reports. Yin et al. recorded participant reaction times as well, and reaction time increased when participants had a high incentive (more significant payoff) to respond deceptively. Additionally, Zhu et al. (2019) found a significant effect on reaction time in conditions of a high deception incentive compared to a low deception incentive and in conditions of a low deceptive incentive compared to an honest incentive.

Combined Cues. In his comprehensive review, Levine (2018) synthesized findings from three meta-analysis studies conducted between 1981 to 2007 to evaluate the effectiveness of various cues in detecting deception. These studies encompassed a wide range of cues, including but not limited to nervousness, vocal tension, vocal pitch, speech rate, head movements, and hand movements. Levine's analysis aimed to quantify the efficacy of each of these cues on identifying deceptive behavior. A key finding from Levine's review was the significant role of verbal cues in indicating deception. Among these, the number of details provided, and the level of verbal uncertainty, emerged as the most predictive factors. Specifically, an effect size of -0.3 for the number of details suggested that fewer details in a narrative were strongly indicative of deception. Similarly, an effect size of 0.3 for verbal-vocal uncertainty, such as vocal effort and hesitation disfluencies, implied that higher levels of uncertainty in speech were associated with deceptive statements. Additionally, vocal cues like tension and pitch were also found to be reasonably predictive of deception, with effect sizes of 0.27 and 0.26, respectively. This indicated that vocal tension and pitch increases could be potential markers of deceptive behavior. In contrast, physical cues such as head movements and eye contact were found to have minimal predictive power. The effect sizes for these cues were near zero, suggesting they are unreliable indicators of deception. Levine's review underscores a notable limitation in extending findings from face-to-face interactions, where verbal and vocal cues are moderately effective, to digital communication, as these cues do not easily translate to online, text-based environments, necessitating exploration of alternative methods for detecting deception.

Psychophysiological Cues

The polygraph was utilized in criminal trials for many decades until the landmark case *United States v. Scheffer* (1998). Scheffer was a member of the Air Force and suspected of using drugs. A urinalysis indicated that Scheffer was lying when he denied the drug use, directly contradicting the polygrapher's report. Supreme Court Justice Thomas deemed the polygraph results as inadmissible in court, though the Federal Bureau of Investigation and Central Intelligence Agency still use the polygraph for their interview processes. Despite the fallibility of the polygraph, research examining other psychophysiological measures, such as electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI), has offered some meaningful insights into deceptive behavior.

Electroencephalogram (EEG). EEG is particularly useful in deception research because it provides insights into the real-time brain processes that occur during deceptive acts. One of the primary EEG techniques used in deception research is the analysis of event-related potentials (ERPs). ERPs are time-locked brain responses to a specific event, like a stimulus or an action (Luck, 2014). In deception studies, researchers often focus on the ERP components that are believed to be associated with attentional processes, such as the P3 and its subcomponents (P3a and P3b) and the medial-frontal negativity (e.g., Gibbson et al., 2018). The P3 is a positive deflection in the ERP that occurs approximately 300 milliseconds after the onset of a stimulus and is often more prominent when the stimulus is relevant or significant to the individual (Luck, 2014). The P3a is associated with the brain's automatic attentional process towards novel or unexpected stimuli (Halgren, 1988). It typically appears as a positive wave around 250-280 milliseconds after a stimulus over the frontal midline of the brain. The P3b is a later occurring component, typically appearing around 300-600 milliseconds after a stimulus over the parietal region (Halgren, 1988). The P3b is associated with the conscious allocation of attention to a stimulus, and its amplitude reflects the significance afforded the stimulus by the subject (Halgren, 1988). The medial-frontal negativity is linked to error processing and conflict monitoring (Van Noordt et al., 2016). It is observed in reaction to stimuli in tasks that require internal monitoring of actions, especially when the subject is highly engaged in the task.

Gibbons et al. (2018) used ERP techniques to analyze the cognitive markers of instructed deception. This study explored how deception influences specific cognitive processes by examining changes in participants' response times, attentional focus, and specific ERP components – namely, the medial-frontal negativity, P3a, and P3b. The experimental design involved participants drawing two random tickets, one representing an animal and the other a plant, from separate bowls containing five options each. The critical aspect of the task was that participants were instructed to intentionally misclassify these items, categorizing plants as animals and vice versa, effectively engaging in counterfactual behavior. The study revealed several key results. First, it was observed that when participants engaged in counterfactual behavior, both their reaction times and error rates increased (Gibbons et al., 2018). This finding is consistent with the notion that deception imposes a more significant cognitive load compared to truthful responses. More importantly, the study found that all three investigated ERP components exhibited increased amplitude when participants responded to stimuli that required deception. The increased P3a amplitude was interpreted as the act of lying requiring heightened attentional resources (Gibbons et al., 2018). The medial-frontal negativity effect indicated that the brain was actively engaged in monitoring and adjusting the deceptive responses. Finally, the enhanced P3b component was thought to reflect the increased cognitive demand of processing and executing the deceptive act. These findings led to the conclusion that presenting stimuli necessitating deception triggers an initial automatic orientation of attention, followed by conflict monitoring adjustment, and culminates in the conscious processing and decision-making required for successful deception (Gibbons et al., 2018).

Other studies involving the P3 component without dividing it into its subcomponents have provided additional insights into the cognitive processes underlying deception. When individuals are presented with stimuli related to their deceptive act, the P3 is larger, indicating increased cognitive processing (Farwell & Donchin, 1991; Rosenfeld et al., 1991). In one study, subjects were presented with items related to a mock crime they had committed, and the results showed a significantly larger P3 in response to crime-related stimuli compared to irrelevant stimuli (Rosenfeld et al., 1991). In another study utilizing the guilty knowledge test, Farwell and Donchin (1991) found that subjects exhibited larger P3 responses to known stimuli, which could be interpreted as signs of recognition (stimulus significance) and cognitive processing associated with deception.

Functional Magnetic Resonance Imaging (fMRI). Studies utilizing fMRI have advanced understanding of the neural correlates of deception. Yin and Weber (2019) made a notable contribution to this field by employing fMRI to study spontaneous deception, identifying several brain regions that are intricately involved in this process. Their research revealed decreased activity in the ventromedial prefrontal cortex, the right inferior frontal gyrus, the left dorsolateral prefrontal cortex, and the left caudate during acts of spontaneous deception (Yin & Weber, 2019). Each of these brain regions plays an interpretable role in the cognitive processes associated with lying. The ventromedial prefrontal cortex, linked to the emotional regulation of episodic and semantic memory (Gage & Baars, 2018), should be important for liars who need to regulate emotions and retain the memory of their fabrications. The right inferior frontal gyrus, involved in inhibitory control (Hampshire et al., 2010), could aid in suppressing truthful information during the act of lying. The left dorsolateral prefrontal cortex, associated with language processing (Hertrich et al., 2021), and the left caudate, which also plays a role in language, especially in multilingual individuals (Driscoll et al., 2022), should both be involved in the formulation and articulation of deceptive statements. These findings show that deception engages multiple cognitive systems, particularly those related to emotional regulation, inhibitory control, and language processing.

Recognizing the variability and inconsistency in neuroimaging findings is crucial, as grasping these differences enables researchers to interpret results more accurately and develop a deeper, more coherent understanding of the brain’s deception processing mechanisms. As noted by Spence and Kaylor-Hughes (2008), while it is commonly believed that deceptive behavior heavily relies on prefrontal executive systems, the specific neural correlates identified can differ between studies. This inconsistency might be attributed to various factors, including differences in experimental designs, the type of deception being studied (e.g., spontaneous vs. rehearsed lies), and individual differences in cognitive processing.

Furthermore, Jiang et al. (2017) employed fMRI to examine the neural response to perceived believability of statements. Participants listened to statements that were spoken confidently, unconfidently, or prosodically unmarked (i.e., neutral). Participants rated statements spoken confidently and prosodically unmarked as more believable than statements spoken unconfidently. Jiang et al. observed increased frontal activity when participants listened to confident statements, increased temporal activity when participants listened to unconfident statements, and increased medial temporo-occipital and cerebellum activity when listening to prosodically unmarked statements. This study's emphasis on the listener's perspective and neural response to the believability of information highlights an important shift toward understanding how individuals process and judge the credibility of information that they receive.

Eye-Tracking. Eye-tracking technology has been increasingly employed in deception detection research. This technology assesses eye movements and pupil dilation, changes that often accompany deceptive responses due to the cognitive load associated with lying (Webb et al., 2009). Studies have shown that gaze aversion, pupil dilation, and changes in blink rate can be indicative of deceptive behavior (Pak & Zhou, 2013; Proudfoot et al., 2016; Wang et al., 2010). For example, pupil dilation increases with the extent of deception, and blink rates decrease during the act of lying (Chen & Epps, 2014; Ledger, 2013). However, research focusing on the receiver's visual processing in deception detection remains limited. Schimmel (2021) found that the time spent viewing different facial regions did not predict deception detection accuracy. While eye-tracking informs visual attention patterns and cognitive load, its direct application in text-based environments is limited.

Problem and Purpose

Deception in Digital Interactions

This dissertation focuses on deception in online environments, where the prevalence of text-based communication and massive amounts of misinformation make understanding how people make deceptiveness judgements important to understand so that we can help people to become better at recognizing lies. This is pivotal because it empowers people to enhance their proficiency in discerning falsehoods, equipping them with the necessary skills to navigate the complexities of digital deception more effectively. In digital contexts, stripped of non-verbal cues, communication relies solely on written words, making readers more susceptible to deception. This susceptibility is compounded by a general overestimation of one's ability to distinguish truth from lies in text (Hancock et al., 2007). The study of deception detection in specific online areas, such as online dating, social media, and cybersecurity, poses unique challenges and research opportunities, as each domain has its own dynamics affecting how deception is perpetrated and recognized.

Online Dating. The intersection of deception detection and online dating has been a prominent area of research. Studies show that individuals often strategically tailor their online dating profiles, usually exaggerating positive traits and downplaying negative ones (Drouin et al., 2016; Hall et al., 2010; Hancock et al., 2007; Toma et al., 2008). Despite common misrepresentations, users frequently distance themselves from accepting such deceptive practices (Ludwig et al., 2016; Toma & Hancock, 2012). Deceptive communicators tend to use achievement-oriented language (i.e., hero and earn) and argumentative wording (i.e., cause, know, ought) to improve perception, carefully structuring messages to evade detection (Ludwig et al., 2016; Toma & Hancock, 2012). Interestingly, those who deceive often suspect deception in others, affecting their judgment of a potential partner's trustworthiness and the likely success of future face-to-face meetings (Lo et al., 2013; Markowitz & Hancock, 2018; Sharabi & Caughlin, 2019).

Technological advancements have spawned sophisticated algorithms for detecting deception in online dating, capable of scrutinizing large datasets for inconsistencies in profiles and communication patterns (Tong et al., 2016; Zhou et al., 2004). A prime example is the Linguistic Inquiry and Word Count software (LIWC; Pennebaker et al., 2015), which analyzes language in profiles and messages to identify deception patterns. LIWC detects specific words (i.e., content words such as emotional terms) and sentence structures (i.e., prepositions, conjunctions, and auxiliary verbs) linked to deceptive communication (Newman et al., 2003; Toma & Hancock, 2012). Despite these advances, such technologies are not widely accessible for user-level deception detection. This highlights the importance of understanding individual perceptions of deceptive text, particularly as digital communication increasingly supplants face-to-face interactions (Szmigiera, 2022; Vogels, 2020), because recognizing how people interpret and react to deceit in digital formats is key to effectively identifying and mitigating the impact of misinformation.

Social Media. Deception detection on social media is crucial due to widespread misinformation and the challenges of discerning truth in digital interactions. Researchers are focusing on deceptive behavior identification, misinformation spread, and detection method development. Social media, a common platform for misinformation spread for various motives, including political and personal gain, is challenging to regulate once misinformation goes viral (Sanchis-Gomar et al., 2020; Vosoughi et al., 2018). While scientific efforts to detect deception on social media involve machine learning algorithms for analyzing content and patterns (Conroy et al., 2015) and tools like LIWC for assessing content authenticity, individual ability to discern truth from lies and trust media is important. In a study examining the effects of political affiliation and analytical thinking on the ability to identify truths from lies on 60 varying websites found that democrats' with increased analytical thinking skills reported decreased trust in websites outside of mainstream news sources (Pennycook & Rand, 2019). On the other hand, Republicans across the board reported greater trust in hyper-partisan and fake news websites (Pennycook & Rand, 2019). The significant societal impact of social media misinformation (Lazer et al., 2018) emphasizes the need for effective detection and educational strategies to enhance critical evaluation and responsible user behavior.

Cybersecurity. Cybersecurity is the practice of defending systems, networks, and programs from digital attacks, which often target sensitive data, extort money, or disrupt business processes (*What Is Cybersecurity?*, n.d.). Deception and misinformation are central in cyber-attacks and defense strategies (Almeshekah & Spafford, 2016; Avery et al., 2017). Attackers use tactics like phishing, where deceptive emails lure users into divulging sensitive information, and social engineering, exploiting human vulnerabilities to bypass security protocols. These practices can result in significant data breaches, financial loss, and reduced user trust (Anderson & Rainie, 2023). Misinformation spread via cybersecurity breaches can exacerbate these issues (Hadnagy, 2011). Deception detection in cybersecurity involves spotting abnormal activities indicative of threats, such as unusual network traffic, phishing emails, and deviant user behavior (Avery et al., 2017; Button, 2014). User training and awareness are vital for enhancing skills in recognizing and responding to threats (Meadow et al., 2015). However, keeping pace with evolving attack methods remains a significant challenge (Workman, 2008).

Online vs. In-Person Deception

There has been limited research on how people detect text-based deception online. One example examined how machine learning models could help humans identify online deception in contexts such as scam emails and misinformation campaigns. Lai and Tan (2019) compared human performance in detecting deception with varying levels of machine-learning assistance. They utilized a dataset created by Ott et al. (2012), which contained 800 deceptive reviews of 20 hotels in Chicago. They collected a sample of 800 genuine reviews of the same hotels using Trip Advisor. Eighty percent of the reviews were used as training data to develop the machine-learning model which learned words and linguistic patterns that were most predictive of deception, and then the remaining 20% was used to test the model. There were six levels of machine-learning assistance. The first level was the control, meaning the participants received no guidance from the machine-learning model. The second level was feature-based explanations. In this condition, the machine-learning model highlighted the top ten words that were predictive of deceptive reviews. The third level was also feature-based, but in this condition, the top ten words were highlighted using a heat map, whereby the words with the highest predictive power were darker than the words with the lowest predictive power. The fourth level contained relevant examples (one example of each genuine and deceptive review) from the training data. In the fifth level, participants were given the examples from the fourth model and the model highlighted the predictive words. In the sixth model, both examples and the heat-map highlighted words were provided. They found that human performance in detecting deceptive reviews was improved with machine-learning assistance, with greater success at the highest level of assistance.

Another study examining text-based deception online directly compared face-to-face and computer-mediated interactions; 76 participants were recruited to interact in person or via instant messaging (Eskritt et al., 2021). Participants read a vignette where a student had the opportunity to cheat on an exam. Participants were instructed to discuss whether the student should have cheated. Some participants were instructed to lie during the discussion by telling their partner the opposite of what they thought the student should have done (i.e., tell their partner they believe the student should have cheated when they believe the student should not have cheated). Eskritt et al. (2021) reported that deception detection accuracy stayed the same irrespective of the type of communication. Therefore, people seem to be equally as bad at detecting accuracy in computer-mediated interactions as during face-to-face interactions. However, little is known about what cues people use in these situations.

Study Aim and Significance

The proposed research aims to enhance the understanding of the perception of deception in online, text-based interactions, a domain increasingly relevant due to the proliferation of social media, mobile-app dating, online gaming, and immersive virtual environments like the Metaverse. This shift in interaction modes underscores the necessity to comprehend the dynamics of deception in digital communication. Specifically, this project investigates how individuals perceive and decide on deception, focusing on the role of linguistic cues such as mistakes and unusual language. It aims to fill a knowledge gap in how these cues contribute to judging deceit in text-based interactions. The research comprises three studies: the first two delve into behavioral data regarding deception perception, investigating the influence of language irregularities on deception judgments. The third study extends to the neural correlates of language comprehension in deceptive contexts, employing ERPs to observe brain activity when processing unexpected or disfluent language.

This multi-faceted approach seeks to uncover both the behavioral and electrophysiological aspects of the perception of deception. By doing so, the project not only contributes to the theoretical understanding of language comprehension and its reaction to deceptive cues but also has practical implications for online communication. It addresses the pressing need to develop effective strategies for managing deception in digital contexts, particularly in an era where digital interactions are ubiquitous and the risk of online misinformation is high. Overall, this research represents a significant step forward in understanding human communication in the digital age, with potential benefits for various online platforms and their users.

Chapter II – Focused Literature Review

Many types of deception exist, such as bald-faced lies (BFLs), misleading literal truths (MLTs), and misinformation. The field of deception research is weighted most toward BFLs and the cues associated with deception detection (Sporer & Schwandt, 2006; Suchotzki et al., 2017b; Vrij & Lochun, 1997). BFLs refer to outright falsehoods, where the communicator knows the information is completely false. BFLs can be contrasted with MLTs and misinformation. MLTs include providing incomplete or misleading information yet are technically true in that they state a fact. Misinformation is incorrect or misleading information, but it is not always presented with the intent to deceive. BFLs and MLTs are always deliberate, whereas misinformation is not always deliberate. Thus, there are many ways that people can mislead each other, and expanding research to include MLTs and misinformation could provide a broader understanding of deception. Adopting a more comprehensive approach to studying deception could uncover fresh perspectives on the mechanisms of deception, the ways people interpret and respond to various forms of deception, and the development of effective strategies to counter the impact of deceptive information in an era characterized by extensive digital communication and abundant information.

The equivalence of various forms of falsehoods remains a contentious subject regarding the philosophy of deception. Meibauer (2016) argues that not all BFLs constitute a lie in the traditional sense, particularly in scenarios where the primary motivation is not to deceive. Meibauer (2016) provides the example, "I only lied for fear of being harmed" (p. 366), suggesting that in such instances, the motivation behind lying is self-preservation rather than outright deception. Meibauer claims that such reasoning for lying intends to avoid harm rather than directly deceive. Accordingly, in such cases, people should not hold the deceiver as accountable for their lie as they would otherwise. In contrast to Meibauer's perspective, a set of studies investigated the public's perception of BFLs and found that on average, 95% of participants feel that deceptive intention exists in all BFLs (Arico & Fallis, 2013; Meibauer, 2018; Rutschmann & Wiegmann, 2017). Additionally, Weissman and Terkourafi (2019) explored the perception of MLTs and found that participants typically do not count MLTs as lies, even though there is an intention to mislead. These findings shed some light on how individuals perceive deception, emphasizing that the veracity of the words holds more significance than the intent behind them. The current research aimed to build upon the groundwork laid by Weissman and Terkourafi (2019). It sought to explore and quantify the relative perception of deceptiveness associated with BFLs and MLTs, particularly in varied contexts such as criminal acts and accidents.

The second focal point of this research delves into how linguistic inaccuracies or unconventional word choices influence perception of deception. A substantial body of research identifies speech errors as critical markers of deceptive behavior (Curtis & Hart, 2015; De Waele & Claeys, 2017; Levine, 2018; Sporer & Schwandt, 2006; Wright Whelan et al., 2014). Sporer and Schwandt's (2006) meta-analysis scrutinized nine verbal cues linked to detecting deception. They found that voice pitch and response latency were positively associated with deception. Additionally, they noted that deceptive messages were shorter in duration and contained more speech errors compared to their truthful counterparts. Similarly, Wright Whelan et al. (2014) analyzed video footage from 32 public appeals for help with missing or murdered relatives. Of these, 16 were subsequently proven to be deceptive due to overwhelming scientific (e.g., DNA) and/or direct (e.g. CCTV) evidence. Deceptive appeal videos contained a higher frequency of speech errors compared to truthful appeal videos. Additionally, deceptive appeal videos contained a notable scarcity of hopeful sentiments and positive emotional expressions toward the relative in question.

To extend the research on speech production cues and their association with deception, De Waele and Claeys (2017) undertook a comprehensive analysis of 160 crisis-related videos, spanning events from 1977 to 2015. The content of these videos ranged from the Watergate scandal to the attack on the Radisson Blu Hotel in Mali. Over three-quarters of the videos involved crisis communication in organizations (e.g., business and government), and the remaining quarter involved personal crises (e.g., politicians and public figures). De Waele and Claeyes concentrated on identifying verbal cues in both truthful and dishonest statements within these videos. They found that dishonest statements contained more speech errors and speech hesitations than honest statements. Additionally, they found that speech errors and hesitation were predictive of decreased perceived believability, meaning they were judged more deceptive. Thus, voice pitch, speech hesitations, and speech errors are linked to deceptive behavior and deceptiveness ratings. Notably, the bulk of existing research has predominately focused on in-person interactions or audio/visual content analysis. As a result, there is a significant gap in understanding the cues associated with deception detection when considering the increase in preference for online interactions (Shabahang et al., 2022). This research aimed to bridge this gap by investigating how speech errors influence the perception of deception in text-only formats.

The question of how language fluency impacts perception of deception in text-only communication is a relatively unexplored area of inquiry in deception research. A few exceptions have employed computational methods to dissect syntax, semantics, and lexical elements in order to reveal language patterns indicative of deception (Arciuli et al., 2010; Hancock et al., 2007; Meibauer, 2018; Vrij, 2008). Liars use more generalizing terms (e.g., always, never, everyone, no one) than truth tellers, and liars refer to themselves less often than do individuals telling the truth (Hancock et al., 2007; Vrij, 2008). In their narratives, liars also refrain from using emotional words (e.g., never, hurt, ugly) and motion words (e.g. walk, move, go; Hancock et al., 2007; Toma & Hancock, 2012). This research underscores the potential for analyzing language choices in online, text-based interactions to understand and detect deception.

Shifting the focus to neurological aspects of deception and deception detection, it is noteworthy that there are specific electrophysiological signatures of brain activity associated with language processing. These signatures are sensitive to various linguistic elements, including grammatical errors and language fluency, across both oral and written forms of communication. One of the most extensively researched event-related potential (ERP) components related to language is the N400 (Kutas & Hillyard, 1980; Luck, 2014). The N400 is a negative deflection in the ERP peaking approximately 400 ms after the eliciting stimulus, and it is largest over central and parietal electrode sites. This voltage deflection is observed in response to violations of semantic expectancy, indicating a disruption in the anticipated meaning or context of the sentence or phrase (Luck, 2014). Another ERP component associated with language processing is the P600. The P600 is a positive deflection occurring approximately 600 ms after the eliciting stimuli (Osterhout & Holcomb, 1995; Luck, 2014). The P600 is primarily associated with syntactic violations, such as grammatical errors and garden-path sentences(i.e., sentences structured to cause confusion, for example, *The old man the boat*).

The potential sensitivity of the N400 and P600 brain responses to the perception of deception is an area that remains largely unexplored. Though there has been notable work examining ERPs related to the act of attempting to deceive, work investigating the perception of deception is rare, and typically not focused on making deceptiveness judgments. For example, Weimer et al. (2019) examined N400 when participants evaluated statements that were either socially amicable or not (not deceptive, but mildly hostile), crossed with semantic congruity. Statements were either semantically congruent (e.g., “You ask the waitress for a glass of water.”), semantically incongruent (“You ask the waitress for a glass of shoes.”), socially amicable (e.g., “You ask someone to coffee and that person says yes.”) or socially unamicable (e.g., “You ask someone to coffee and that person says no.”). N400 amplitude was significantly larger for statements that were semantically incongruent than for statements that were semantically congruent. There was no significant difference between socially amicable and unamicable N400 amplitudes. More relevant to the current work, Rigoulot et al. (2014) examined ERPs elicited by blunt truths versus white lies. In this work white lies were considered more socially appropriate than blunt truths, despite the deception. They found no significant effect on N400 amplitude.

Finally, two studies have observed larger N400s in response to false-affirmative statements compared to true-affirmative statements (He et al., 2022; Nieuwland & Kuperberg, 2008). Critically, in these studies the statements were not evaluated in the context of deception, but rather just in the context of accurate versus inaccurate facts. Nieuwland and Kuperberg (2008) examined the N400 elicited by affirmative vs negated sentences crossed with accuracy. They found a larger N400 to inaccurate-affirmative statements (e.g., "With proper equipment, scuba diving is very dangerous") and inaccurate-negated (e.g., "With proper equipment, scuba diving isn't very safe") compared to accurate-affirmative (e.g., "With proper equipment, scuba diving is very safe") and accurate-negated statements (e.g., "With proper equipment, scuba diving isn't very dangerous"). Similarly, He et al. (2022) examined the N400 elicited by disfluent statements. They specifically looked at how this response interacted with the nature of the statements – negative vs affirmative – and their accuracy – true vs false. By subtracting the ERPs elicited by disfluent statements from those elicited by fluent statements, they isolated the impact of fluency on brain responses. The results revealed a robust N400 response but did not show a significant P600 response. Notably, the difference-wave N400 did not exhibit a statistical difference between accurate and inaccurate statements. However, the N400 was larger for inaccurate-affirmative statements (e.g., "a trout is a vehicle") compared to accurate-affirmative statements (e.g., "a trout is a fish"), with the smallest N400 observed for fluent affirmative sentences (e.g., "the woman reads a newspaper"). Although the primary focus of these two studies was not deception per se, their findings suggest that the N400 may be sensitive to processing inaccurate statements. If further research corroborates these findings, it could lead to a deeper understanding of the neural correlates of deception and its detection.

Aside from the above studies, all the other ERP research that I could find focuses on exploring the sensitivity of the N400 to the act of deceiving or telling the truth. For example, in an investigation of 296 sentences, assessed for emotional content and categorized into accurate or inaccurate statements with varying affective values, participants responded as quickly and accurately as possible, indicating ‘yes’ or ‘no’ with finger presses based on the instruction to lie or tell the truth. Participants demonstrated a higher error rate when instructed to lie, particularly with emotionally charged accurate statements and neutral inaccurate statements, suggesting the cognitive load of deception varies with the emotional context of the statement (Proverbio et al., 2013). The study further revealed that the N400 was larger during instructed lies compared with instructed truths. In another study examining the N400 during instructed deception, Meek et al. (2013) utilized slides to depict a crime scenario followed by a written narrative that was read aloud. Participants were then instructed to respond truthfully or deceptively to 100 test items about the crime and narrative. Participants displayed longer response times when instructed to lie than when instructed to tell the truth. Neurophysiological findings revealed that deceptive responses were associated with larger N400 amplitude than truth telling. Furthermore, the N400 was more negative over the left hemisphere when being deceptive and more negative over the right hemisphere when being truthful.

Another ERP component that may be relevant to deception detection is the reward positivity. The reward positivity is characterized by a positive deflection observed over the frontal midline in reaction to rewarding outcomes. This phenomenon has been source-localized to the medial prefrontal cortex (Miltner et al., 1997). Zhu et al. collected EEG and behavioral data from 45 individuals. The participants engaged in a sender-receiver task. All participants were the senders and were shown three letters (A-C) at the beginning of the task. Each letter had a corresponding monetary payoff displayed. Next, one of the three letters would appear on the screen and the participant would choose one of the three letters to send to the receiver and earn the payoff associated with the letter on the first screen. Therefore, participants could lie in order to receive a higher payout (see Appendix A for task layout). They assessed the reward positivity ERP component for deceptive and honest trials. They found that the reward positivity was larger for more deceptive responses than honest responses. They suggest that the observed increase in the amplitude of the reward positivity during spontaneous deception could indicate a perception of greater reward, possibly linked to the successful execution of a deceitful act. This implies that deception can be motivated by a simulation of the potential reward. The results of this study suggest the neural processes associated with reward processing are also engaged when choosing to deceive.

Building on the intriguing findings from previous research on the neural correlates of deception and the linguistic cues associated with deceit, this work shifted focus towards understanding how individuals perceive deception. This investigation specifically examined the interplay between mistakes in communication (i.e., syntax errors), ambiguous language (i.e., semantic fluency), and the level of deception (i.e., BFL vs. MLT vs. Control Truth statements; CT). This study was designed as a series of three experiments, each aiming to test these interactions and their impact on the perception of deception. To facilitate this, I crafted sets of short stories, with each story culminating in a scenario where the main character(s) faced the opportunity to engage in deceptive behavior. Participants rated how deceptive they perceived the statements. A key hypothesis driving this research was that both the level of deception and the presence of language errors would significantly influence the ratings of deceptiveness assigned by participants.

Chapter III – Experiment 1

Experiment 1 Methodology

Experiment 1 investigated the interplay between linguistic errors (correct syntax vs. incorrect syntax) and different categories of deception (BFL vs. MLT vs. CT). The statements used in this study were originally crafted for use in an ERP experiment. However, due to the constraints imposed by the COVID-19 pandemic, the experiment was modified to an online format focusing on behavioral data collection. I hypothesized the following:

1a) Based on the findings of Arico and Fallis (2013), Meibauer (2018), and Rutschmann and Wiegmann (2017), I hypothesized that individuals would rate BFLs as more deceptive than MLT and CT.

1b) Informed by research indicating that speech errors are reliable cues for deception detection (Sporer & Schwandt, 2006), I hypothesize that individuals would rate statements with incorrect syntax as more deceptive than statements with correct syntax.

1c) However, considering Meibauer's (2016) claim that some BFLs may not be perceived as deceptive, I hypothesized that individuals would rate BFLs with incorrect syntax as less deceptive than BFLs with correct syntax because mistakes may cue individuals to believe there was not a direct intention to deceive.

Experiment 1 Participants

Eighty-five individuals (34 women) between the ages of 20 and 69 (*M* = 39.4, *SD* = 11.9) participated in this study. The initial plan was to analyze the data using an analysis of variance (ANOVA). However, this approach was later revised in favor of a multi-level model. Thus, I calculated the appropriate sample size using G*Power 3 (Faul et al., 2007), targeting a medium effect size of 0.35 and a power of 0.8 for a repeated measure, between factors ANOVA. I recruited participants through Amazon's Mechanical Turk (M-Turk; Seattle, WA). Participants received $8 after completing the survey. The Utah State University IRB approved this study. I provided participants with a letter of information to read and agree to before completing the survey. Participants did not provide any identifying information.

Experiment 1 Materials

Experiment 1 Vignettes. I created 30 short vignettes between 50 and 125 words for this study. These vignettes were entirely fictional and designed to outline one to three scenarios in which the main character(s) might employ deception to evade blame (Appendix B).

Experiment 1 Statements. I developed 264 statements, categorized into six groups: BFLs with correct syntax, BFLs with incorrect syntax, MLTs with correct syntax, MLTs with incorrect syntax, CTs with correct syntax, and CTs with incorrect syntax. This resulted in a range of 6 to 18 statements per vignette. Each statement adhered to a consistent linguistic structure: direct subject □ action verb □ subject complement. The action verb was varied to create correct- and incorrect-syntax trials, while the subject complement was altered according to the type of lie (Table 1; Appendix B).

Table 1

Sample Statement for Experiment 1

	Direct subject	Action Verb (Syntax Error)	Subject Complement (Sentence Type)
BFL Correct	The plate	was shattered	by the children
BFL Incorrect	The plate	was shatter	by the children
MLT Correct	The plate	was shattered	by someone
MLT Incorrect	The plate	was shatter	by someone
CT Correct	The plate	was shattered	by me
CT Incorrect	The plate	was shatter	by me

Note. This table demonstrates a sample statement from each category (Bald-Faced Lie; BFL vs Misleading Literal Truth; MLT vs Control Truth; CT, and correct vs incorrect syntax) for the following scenario: “George and Rhonda are married. George decided to clean the house, do the laundry, and change the oil in the car to help his wife. George accidentally broke Rhonda’s fine China while dusting. He washed the whites with the reds and turned Rhonda’s favorite dress pink. He also mixed up the oil types and put partially synthetic in the car, which requires full synthetic. Now the truck won’t run. When Rhonda gets home, George tells her the following:”

Experiment 1 Procedure

I created the survey using Qualtrics (Qualtrics, Provo, UT). Each vignette was presented on a new page, followed by all the statements corresponding to the vignette. I randomized the statement order for each participant using the software on Qualtrics. Participants followed the prompts on M-Turk. They began by reading the information letter (Appendix C) and agreeing to participate. Next, participants read the vignettes and all corresponding statements. They rated the statements on a Likert scale of 1-7, where one was not deceptive at all and seven was the most deceptive. I included a validity check, whereby participants needed to mark a specific answer to filter out any participants who were not paying attention. The survey took approximately one hour to complete.

Experiment 1 Statistical Analysis

I analyzed the data using Multilevel Modeling (MLM), also known as Hierarchical Linear Modeling (HLM) or Mixed Effects Regression. MLM allows for the appropriate analysis of data that exists on more than one level (Hox et al., 2017). I conducted all data analyses using R version 4.3.2 (R Core Team, 2023) and utilized both the lme4 (Bates et al., 2015) and performance (Lüdecke et al., 2021) packages. I investigated the effects of the independent variables – type of lie (BFL vs MLT vs CT) and syntax (correct vs incorrect) – on the perception of deception (i.e., the dependent variable of deception rating) while controlling for the covariates of age and gender. The MLM included three levels. Level one (micro-units) was comprised of the statements and nested within the vignettes (level two/meso-units). All vignettes were read by every participant (level three/macro-units). I used the same approach for the model to examine the effects of the independent variables (level one).

Experiment 1 Model Fit

I utilized a bottom-up approach for building the final MLM. This approach involved fitting a series of models by building from a series of null models (no independent variables or covariates). Although Wald-like t-tests for parameter estimates utilizing Satterthwaite degrees of freedom are displayed in the table of results, I used likelihood ratio tests (LRT; Bates & Chambers, 1992) to judge statistical significance during model building. Satterthwaite degrees of freedom adjusts the degrees of freedom in a proportional manner to enhance the precision of p-value estimates (Satterthwaite, 1946; West et al., 2014). LRTs are statistical comparisons between two models: one that serves as a baseline and an alternative model that includes additional parameters (Harwell, 1997; Hox et al., 2017). The LRT evaluates whether the inclusion of these extra parameters significantly improves model fit, based on the ratio of the likelihoods of the two models. This significance is assessed using a chi-square distribution, where the degrees of freedom (df) is equal to the difference in the number of parameters between the two models (Raudenbush & Bryk, 2002). Upon determining the best fit model, I conducted follow-up analyses. Estimated Marginal Means (EMM) pairwise tests were employed to compare the means of groups within the independent variables and covariates. These tests help elucidate specific differences between groups, and the results are expressed in terms of Standardize Mean Differences (SMD; Brysbaert & Stevens, 2018). Additionally, simple slopes analyses were performed to interpret interaction effects for continuous variables (Hox et al., 2017).

First, I fit the null models (intercept only, no predictors) to include fixed and random intercepts for participant differences only, participant per vignette difference, and vignettes nested under participants. I fit all null models via both Maximum Likelihood and Restricted Maximum Likelihood to investigate fixed effects, as well as random intercepts and slopes. I computed the intra-class correlations (ICCs) for all null models and performed an LRT to compare the null models. Following the analysis, I concluded that only random effects for participants would be included in subsequent models. Thus, while data pertains to a hierarchy of three-levels (person, vignette, statement) a two-level structural model is appropriate due to the vignette accounting for negligible variance.

To build the remaining models, I first examined the main effects of each independent variable. Then, I examined any interaction effects of the independent variable. Subsequent models included controlling for the main effects of the covariates, examining cross-level interactions between independent variables and covariates, and exploring a four-way interaction between the two independent variables and two covariates. Before I built each subsequent model, models with the best fit were selected using LRTs. The R code used for model specification and data analysis can be found in Appendix J.

Experiment 1 Results

Table 2 reports the descriptive statistics for each condition. The model comparisons established that the model examining the cross-level interaction between the type of lie and the two covariates was the best-fit model for the data, $\chi^2(9) = 332.53$, $p < .001$ (see Table 3).

Table 2

Aggregated Deception Ratings Across All Six Categories of Experiment 1, M (SD)

	Bald-Faced Lies (BFL)	Misleading Literal Truths (MLT)	Control Truths (CT)
Correct Syntax	5.75 (1.00)	4.57 (0.96)	2.69 (1.52)
Incorrect Syntax	5.69 (0.95)	4.56 (0.95)	2.85 (1.61)

Table 3

Experiment 1: Parameter Estimates for the Final 2-Level Random-Intercepts Multilevel Model for Deception Ratings for Experiment 1, Adjusting for Covariate Moderation

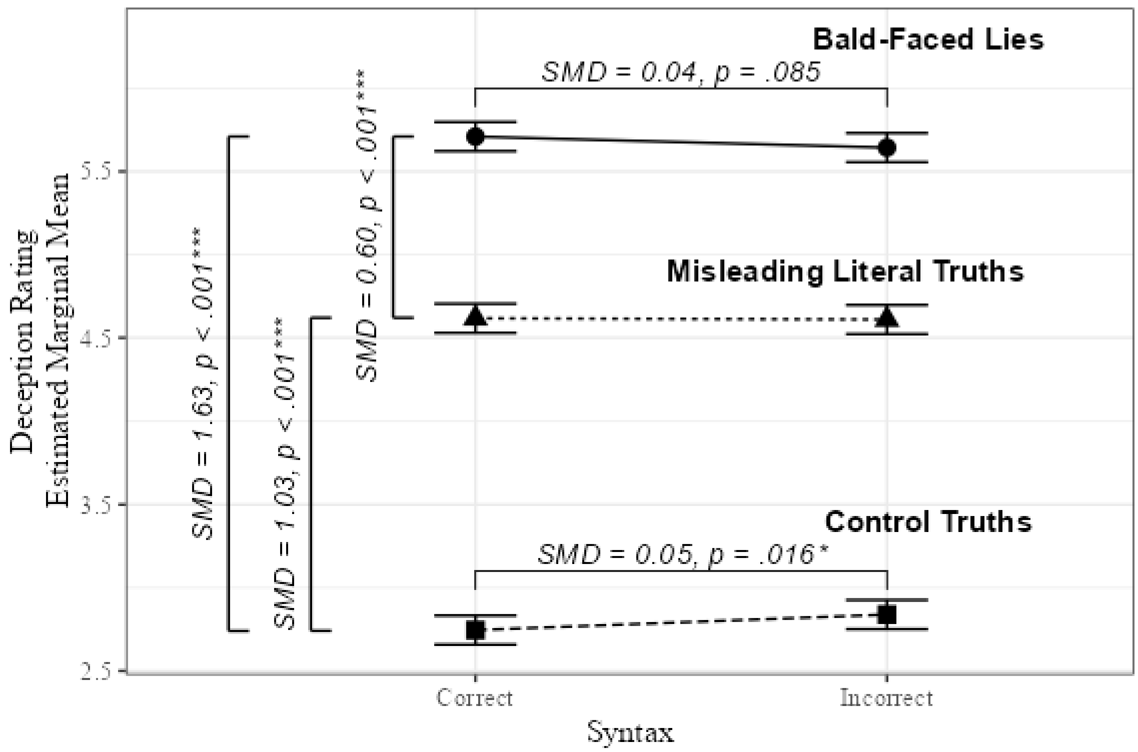
	b	**SE**	***t-value***	***p-value***
FIXED EFFECTS				
Intercept	5.2	0.40	12.87	< .001
Main Effects				
Statement Type (*reference = Bald-Faced Lies)*				
Misleading Literal Truths	-0.61	0.13	-4.59	< .001
Control Truths	-2.12	0.13	-15.87	< .001
Syntax *Correct vs. Incorrect*	-0.01	0.04	-1.72	.085
Age	0.01	0.01	1.22	.226
Gender *Man vs. Woman*	-0.10	0.06	-0.17	.869
Interactions				
Statement Type * Syntax				
Misleading Literal Truths	0.06	0.05	1.08	.280
Control Truths	0.16	0.05	2.93	.003
Age * Gender	0.00	0.01	0.26	.796
Statement Type * Age				
Misleading Literal Truths	-0.01	0.00	-3.46	< .001
CT	-0.02	0.00	-6.10	< .001
Statement Type * Gender				
Misleading Literal Truths	0.60	0.19	3.10	.002
Control Truths	1.22	0.19	6.26	< .001
Statement Type * Gender * Age				
Misleading Literal Truths	-0.02	0.00	-3.59	< .001
Control Truths	-0.03	0.00	-7.13	< .001
RANDOM EFFECTS	**Var**	**SD**		
Between-Subjects (Intercepts)	0.57	0.75		
Within-Subjects(Residual)	2.77	1.67		

Note. Significance of fixed effects are based on Wald-like t-test utilizing Satterthwaite's method of degrees of freedom. Model fit to 22,3333 statements on 85 participants.

As suggested by the descriptive statistics, the final model supported the initial hypothesis (1a). The Satterthwaite method indicated a significant main effect of the type of lie (BFL vs MLT and BFL vs CT) on deception rating, $p < .001$ and $p < .001$ respectively, indicating that people found MLTs as less deceptive than BFLs, and CTs to be substantially less deceptive than BFLs. Contrary to my predictions made in hypothesis 1b, there was not a significant main effect of syntax, $p = .085$. This indicates that syntax type did not have a significant impact on the rating of deception. However, consistent with hypothesis 1c, the final model revealed a significant interaction comparing BFLs with CTs and syntax correctness, $p = .003$, indicating that syntactic errors impacted deception ratings differently depending on the type of statement. Specifically, pairwise tests revealed that participants perceived CTs with correct syntax as less deceptive than those with incorrect syntax, $p = .016$, $SMD = 0.04$, and while not significant, the pattern between means hinted at an effect where BFLs with correct syntax were rated as more deceptive than those with incorrect syntax, $p = .085$, $SMD = 0.04$, as illustrated in Figure 1.

Figure 1

Estimated Marginal Means (±SEM) for the Multilevel Model (MLM) For The Interaction Of Statement Type and Syntax Error



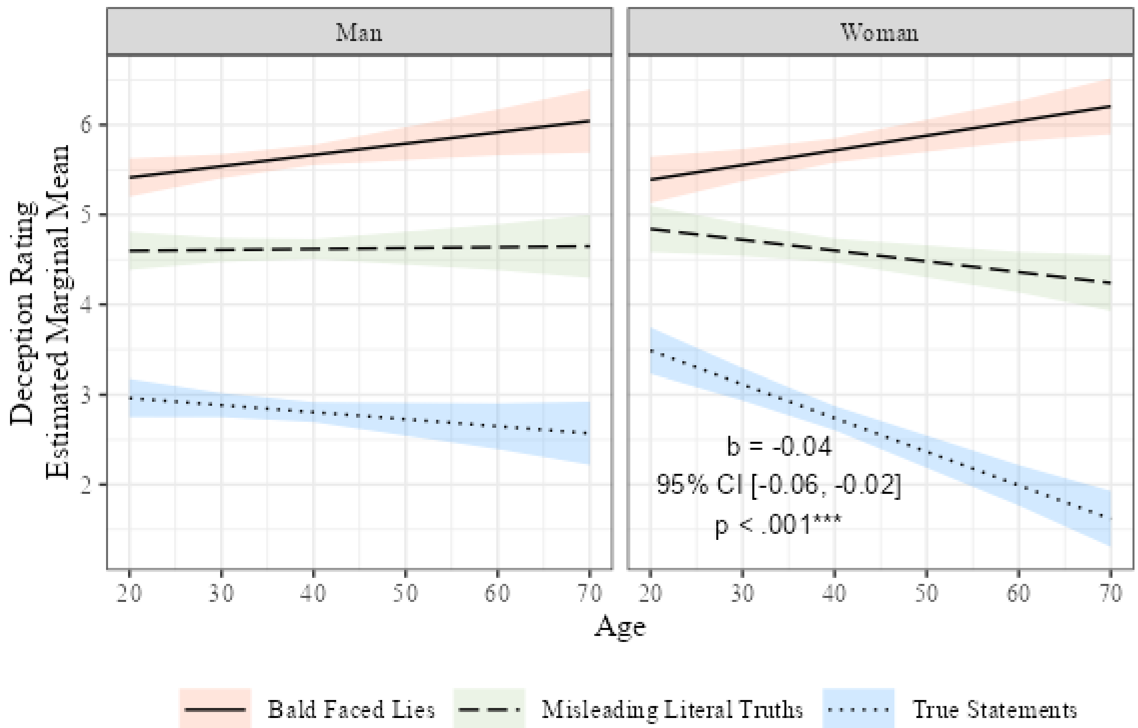
Note. This figure illustrates the estimated marginal means of deception ratings for Bald-Faced Lies, Misleading Literal Truths, and Control Truths across conditions with correct and incorrect syntax errors, and includes significant differences denoted by brackets with Standardized Mean Differences (SMD) and p-values for each pairwise comparison without correction for multiple compairisions.

* p < .05. *** p < .001.

The addition of the cross-level interaction in the final model revealed a noteworthy interaction effect. There was a significant 3-way interaction between the type of lie (BFLs vs MLTs and BLFs vs CTs), gender, and age, $p < .001$ and $p < .001$ respectively. These results imply that as women age, they perceive lies as less deceptive compared to women or men of any age (Figure 2). The interaction suggests that gender and age do not operate independently in shaping the perception of lies.

Figure 2

Simple Slopes (b) with a 95% Confidence Interval for MLM for the Interaction of Age, Gender, and Sentence Type



Note. This figure presents the interaction effects between statement type and age on deception ratings, with separate panels for men and women. The significant simple slope is denoted by a slope coefficient (b). The 95% confidence interval for this slope and its associated p-value are provided.

*** $p < 0.001$

Experiment 1 Discussion

The results of this study provide a nuanced understanding of how individual differences, types of lies, and syntactical correctness interact to shape perception of deception. As indicated by the ICC, a substantial amount of the variance in deceptive ratings can be attributed to individual differences. This suggests that individual perceptions of deception are highly subjective and indicates that individual variability should be taken into account in designing deception detection research studies.

While I did not examine variations in the underlying intentions of the deceiver, the significant differences between the types of lies aligns with the findings of Arico and Fallis (2013), Meibauer (2018), and Rutschmann and Wiegmann (2017). Specifically, these studies similarly identify a distinction in how different kinds of lies are perceived, indicating that the nature or category of a lie influences its judgement by others. In my study, MLTs were perceived as more deceptive than CTs, which works against the position that MLTs are inherently viewed as non-deceptive (see Weissman & Terkourafi, 2019).

Out of alignment with findings by Sporer and Schwandt (2006), who suggested that speech errors are reliable cues for deception detection, my study showed that people are not influenced by speech errors in a straightforward manner. In my study design, the focus was on determining whether people perceive speech errors as indicative of deception by examining their impact on deception ratings. The lack of a significant main effect of syntax error alone challenges the assumption that syntactical errors are generally perceived as cues of deception and underscores the complexity of the perception of deception in text-based communication.

The interaction of syntax with type of lie indicates the syntactic errors can make BFLs seem less deceptive but can make CTs seem more deceptive. When a lie is overt, the presence of correct syntax might contribute to the perception of the statement being more calculated or deliberately crafted. This could lead observers to perceive a higher level of intentionality and deceit. Conversely, in truthful statements, correct syntax might reinforce a sense of honesty or transparency, suggesting that when a statement is true, the correct use of language can aid in its perceived veracity, reducing the suspicion of deceit.

Chapter IV – Experiment 2

Experiment 2 Methodology

Experiment 2 replicated and extended Experiment 1 in five distinct ways. First, I introduced a semantic fluency manipulation. This manipulation involved varying the semantic congruity of word choices within statements. While some word choices were semantically correct and contextually expected (e.g., "I didn't wash the load that turned your dress pink."), others were unusually general and not expected contextually, despite remaining semantically accurate (e.g., " I didn't wash the load that turned your apparel pink."). To succinctly describe this manipulation, I adopted the terms "fluent" and "disfluent" because a critical aspect of this semantic manipulation was to maintain the truth condition across levels of semantic congruity. This means that words deemed incongruent or disfluent had to be true in the context of the statement. This approach is supported by the literature on conceptual fluency, were fluency is often associated with the ease or difficulty with which information is processed (Whittlesea, 1993). Second, each participant only rated one statement per vignette instead of all corresponding statements. Third, I categorized the vignettes into crimes versus accidents. This manipulation was intended to investigate if ratings of deceptiveness were influenced by the situational context. It also controlled for any potentially confounding effects by allowing me to distribute crimes and accidents equally in each level of lie, syntactic error, and fluency condition. Fourth, I opted for more natural language. Unlike Experiment 1, designed for an ERP study and following a rigid linguistic pattern, I used colloquial language in Experiment 2. Finally, I removed the MLT statements, as there was no significant difference in deception ratings between MLTs that had correct syntax versus MLTs that had incorrect syntax in Experiment 1. I hypothesized the following:

2a) In line with the findings from Experiment 1, I hypothesized that participants would perceive BFLs with syntax errors and semantic disfluency as less deceptive than BFLs that were syntactically correct and semantically fluent.

2b) Consistent with the outcomes of Experiment 1, I hypothesized that participants would judge CTs with syntax errors and semantic disfluency as more deceptive compared to CTs with correct syntax and semantic fluency.

2c) O'Connell and Whelan (1996) report survey data showing that people consider violent crimes as more serious than any other type of crime (i.e. financial crimes, theft, property damage). I anticipated that crimes in general would be considered more serious than accidents, and that participants would rate the crime vignettes as more deceptive than the accident vignettes.

Experiment 2 Participants

I recruited 147 individuals through M-Turk. To ensure the validity of the responses, I included two checks, starting with a captcha at the beginning of the survey and ending the survey with asking them to type "human" as a response. Using G*Power (Faul et al., 2007), I calculated the required sample size to detect a medium effect size of 0.35 with a power of 0.8. This calculation was done before I decided to change the planned analysis method. Out of the initial pool, 31 individuals did not meet the inclusion criteria for correct task completion. First, they had to complete at least half of the survey to be included. Second, they needed to demonstrate an understanding of the difference between BFL and CT statements. Specifically, for error-free statements, BFLs should be rated significantly higher, and CTs significantly lower, on the deception scale. I set a threshold of a minimum of 4-point difference in their ratings for inclusion in the analysis. That is, any participant who did not consistently rate fluent, syntactically correct CTs lower on deception than fluent, syntactically correct BFLs was not showing a basic understanding or adherence to the task and their data was removed before analysis. Participants were compensated $2 upon completing the survey. The Utah State University IRB approved this study. I provided participants with a statement of information to read and agree to before completing the survey. I used a letter of information instead of traditional informed consent forms according to my approved IRB protocol to ensure no identifying information was disclosed.

Experiment 2 Materials

Experiment 2 Vignettes. I modified 28 vignettes from Experiment 1 and created four new ones, resulting in 32 short stories. Each vignette, entirely fictional, ranged from 25 to 50 words and outlined a single instance where the main character could use deception (Appendix D). I divided these vignettes into two categories: crime and accident. To validate these categories, I conducted a pilot study with 34 participants. Following In's (2017) recommendation, a pilot study sample size should be between 28 and 60 participants. In this pilot study, 100% of participants consistently identified the crime vignettes as crimes and the accident vignettes as accidents, confirming the effectiveness of the categorization.

Experiment 2 Statements. To assess the effect of lie type (BFL vs. CT), syntax error (correct vs. incorrect), and semantic fluency (fluent vs. disfluent), I crafted eight statements for each of the 32 vignettes, resulting in 256 statements. These statements were deliberately unstructured and employed a colloquial language style, tailored to the context of each vignette. To manipulate the syntax and lie type, I varied the action verb in each statement. Similarly, for semantic fluency, I altered the direct object (Table 4; Appendix D).

Table 4

Example Statement for Experiment 2

	Subject	Action Verb (Syntax Error)	Direct Object (Semantic Fluency)
BFL Correct/Fluent	I	didn't steal	the figurine.
BFL Incorrect/Fluent	I	didn't stealing	the figurine.
BFL Correct/ Disfluent	I	didn't steal	the object.
BFL Incorrect/Disfluent	I	didn't stealing	the object.
CT Correct/Fluent	I	stole	the figurine.
CT Incorrect/Fluent	I	stealing	the figurine.
CT Correct/ Disfluent	I	stole	the object.
CT Incorrect/Disfluent	I	stealing	the object.

Note. This table demonstrates a sample statement from each category (Bald-Faced Lie; BFL vs Control Truth; CT, correct vs incorrect syntax, and fluent vs disfluent semantics) for the following scenario: "Kristi went to a rare art silent auction. Kristi found a beautiful, expensive-looking figurine at a rare art silent auction. When no one was looking, she stole the figurine and stashed it in her bag. When bags were checked at the end of the night, the security guard asked if she stole the figurine. She replied:"

Experiment 2 Procedure

I deployed the survey using Qualtrics (Qualtrics, Provo, UT). In the survey, each vignette was presented on a new page, followed by only one of the eight statements for that vignette. I randomized the statement for each participant using the software on

Qualtrics. Participants saw four statements per condition throughout the 32 vignettes. Participants followed the prompts on M-Turk. They had the opportunity to read and agree to the letter of information (Appendix E). Next, they read the vignettes and rated the corresponding statement. They rated each statement on a Likert scale of 1-7, where one was not deceptive at all and seven was the most deceptive. No identifying information was collected, and the survey took approximately 15 minutes to complete.

Experiment 2 Statistical Analysis

I analyzed the data for Experiment 2 similarly to Experiment 1, with three exceptions. First, I added two independent variables: type of vignette (crime vs accident) and semantic fluency (fluent vs disfluent). Second, there were only two types of lies (BFL vs CT) instead of three (MLT). Finally, gender and age were not collected in this study. I investigated the effects of the independent variable – type of lie, syntax error, semantic fluency, and type of vignette – on the perception of deception. The MLM included three levels. Level one (micro-units) was comprised of the statements and nested within the vignettes (level two/meso-units). All vignettes were read by every participant (level three/macro-units). I used the same approach for the model to examine the effects of the independent variables. Three independent variables were applied at level one: type of lie (BFL vs CT), syntax error (correct vs incorrect) and semantic fluency (fluent vs disfluent). One independent variable was applied at level two: type of vignette (crime vs accident).

Experiment 2 Model Fit

Similar to Experiment 1, I fit null models to include fixed and random intercepts for participant differences only, participant per vignette difference, and vignettes nested under participants via both Maximum Likelihood and Restricted Maximum Likelihood. I again concluded that only random effects for participants would be included in subsequent models. Participant differences accounted for 10.3% of the variance (ICC_{null} = .103). To build the remaining models, the main effects of each of level one's independent variables were then examined. Next a three-way interaction was fit between these variables. After, models controlled for independent variables at level two and any cross-level interactions. Finally, a four-way interaction model was fit between all four independent variables. Before I built each subsequent model, I selected the models with the best fit using LRTs. The R code used for model specification and data analysis can be found in Appendix J.

Experiment 2 Results

Table 5 reports the descriptive statistics for each condition. The model comparisons established that the model examining the three-way interaction between the three independent variables at level one was the best fit model for the data, $\chi^2(6) = 102.55$, $p < .001$ (see Table 6).

Table 5

Aggregated Deception Rating Across All Eight Categories Of Experiment 2, M (SD)

	Bald-Faced Lies (BFL)	**Control Truths (CT)**
Correct/Fluent	5.79 (0.89)	2.20 (1.19)
Incorrect/Fluent	5.40 (1.17)	3.10 (1.82)
Correct/Disfluent	5.62 (1.13)	3.11 (1.83)
Incorrect/Disfluent	5.45 (1.13)	3.01 (1.94)

Table 6

Experiment 2: Parameter Estimates for the Final 2-Level Random Intercepts Multilevel Model for Deception Ratings

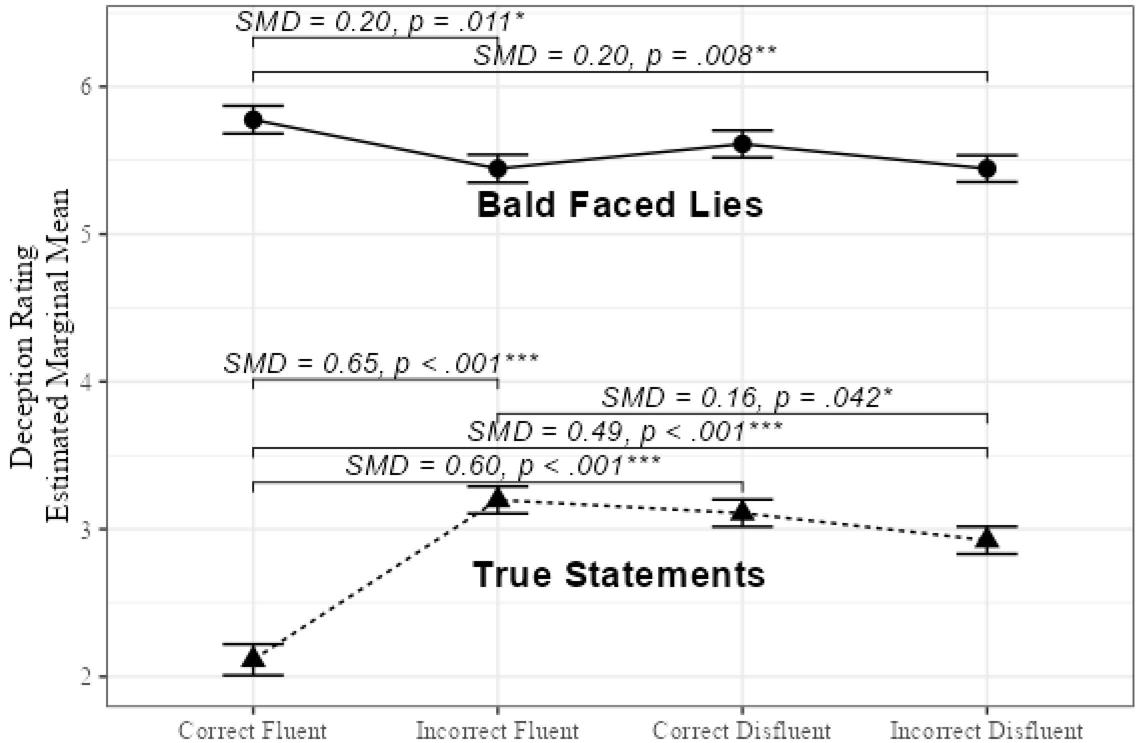
	B	**SE**	***t-value***	***p-value***
FIXED EFFECTS				
Intercept	5.61	0.09	61.23	< .001
Main Effects				
Statement Type – *Bald-Faced Lie vs Control Truth*	-2.50	0.10	-24.30	< .001
Syntax – *Correct vs. Incorrect*	-0.17	0.10	-1.65	.099
Semantics – *Fluent vs Disfluent*	0.16	0.10	1.56	.118
Interactions				
Statement Type * Syntax	-0.02	0.15	-0.12	.909
Statement Type * Semantics	-1.16	0.16	-7.41	< .001
Syntax * Semantics	-0.16	0.15	-1.11	.267
Statement Type * Syntax * Semantics	1.43	0.22	6.66	< .001
RANDOM EFFECTS	**Var**	**SD**		
Between-Subjects (Intercept)	0.37	0.60		
Within-Subjects (Residual)	2.39	1.55		

Note. B = Significance of fixed effects are based on Wald-like t-test utilizing Satterthwaite’s method of degrees of freedom. Model fit to 3,491 statements on 116 participants.

As suggested by the descriptive statistics, the final model supported hypotheses 2a and 2b. The Satterthwaite method indicated a significant interaction between the type of lie, syntax error, and semantic fluency, $t(3413.37) = -6.56$, $p < .001$. I conducted follow-up pairwise comparisons and found that participants perceived BFLs with correct syntax and fluent semantics as more deceptive than BFLs with incorrect syntax and disfluent semantics, $p = .008$, *SMD* = 0.2. Interestingly, a significant difference was also observed between how participants perceived BFLs with correct syntax and fluent semantics as more deceptive than BFLs with incorrect syntax but fluent semantics, $p = .011$, *SMD* = 0.2. This significant effect aligns with the trend observed in Experiment 1 (see Chapter 3). In addition, participants perceived CTs with correct syntax and fluent semantics as less deceptive than CTs with incorrect syntax and disfluent semantics, $p < .001$, *SMD* = 0.49. Furthermore, participants perceived CTs with correct syntax and fluent semantics as less deceptive than CTs with incorrect syntax but fluent semantics, $p < .001$, *SMD* = 0.65. Participants also perceived CTs with correct syntax and fluent semantics and less deceptive than CTs with correct syntax but disfluent semantics $p < .001$, *SMD* = 0.6. However, participants perceived CTs with incorrect syntax but fluent semantics as slightly more deceptive than CTs with incorrect syntax and disfluent semantics, $p = .042$, *SMD* = 0.16 (Figure 3). The final hypothesis (2c) was not supported by the final model or other models. There was no main effect of type of vignette, $t(3414.7) = -0.72$, $p = .473$, and no four-way interaction, $t(3409.57) = 0.23$, $p =.823$.

Figure 3

Estimated Marginal Means (±SEM) for the Multilevel Model (MLM) for the Interaction of Statement Type, Syntax (Correct vs Incorrect), and Semantic Fluency (Fluent vs Disfluent)



Note. This figure illustrates the effects of syntax error (Correct vs Incorrect) and semantic fluency (Fluent vs Disfluent) on deception ratings for Bald-Faced Lies and Control Truths. Significant differences are highlighted with brackets, alongside Standardize Mean Differences (SMD) and p-values.

* p < .05. ** p < .01. *** p < .001

Experiment 2 Discussion

Similar to Experiment 1, the ICC revealed that a substantial amount of the variance in deceptiveness ratings can be attributed to individual differences alone. This further supports that individual perceptions of deception are highly subjective, and it underscores the importance of considering individual variability in deception detection research. The final model's significant three-way interaction suggests that correct grammar and fluent word choices can enhance the perceived deceptiveness of overtly false statements. In overtly false statements, such as BFLs, individuals may find linguistic errors as more ambiguous, thus influencing the perceived level of intentionality. That being said, the significant difference in perception of linguistically accurate BFLs and BFLs with incorrect syntax alone and lack of significant difference between the aforementioned and BFLs with disfluent semantics alone, suggest that the grammatical structure of the statement might have a greater impact on the perception of intentionality and deceit.

However, it is important to note that the opposite is true for CTs. These findings echo and reinforce the results observed in Experiment 1, adding additional support to the conclusion that linguistic inaccuracies and disfluency increase the suspicion of deceptiveness in truthful statements. Furthermore, the significant difference between CTs with incorrect syntax but fluent semantics and CTs with both syntactic errors and semantic disfluency, and the lack of significant difference between CTs with incorrect syntax alone and CTs with disfluent semantics alone further suggests that grammatical errors might influence the suspiciousness of deception more so than unusual word choices.

Since no significant main effects or interaction effects of the type of vignette were observed, results indicate that perceived deception is not influenced by the severity of the situation. This finding might prompt a reevaluation of how context is considered in deception detection.

Chapter V – Experiment 3

Experiment 3 Methodology

Experiment 3 replicated and expanded Experiment 2 in three ways. First, I collected EEG data. Second, I made substantial changes to the vignettes and statements, including doubling the amount of vignettes and statements. More specifically, I altered the statements to have a structure conducive to time-locking the EEG data to the instance of each syntactic, semantic, and truth manipulation, while controlling for variability in length and complexity of the other words in the statements. Third, participants rated only two of the eight possible statements per vignette to minimize boredom and or disengagement that could come from reading the same vignette over and over. I developed four hypotheses for this study:

3a) In line with Experiments 1 and 2, I hypothesized that participants would rate BFLs with syntax errors and semantic disfluency as less deceptive than BFLs with correct syntax and fluent semantics.

3b) Similar to Experiments 1 and 2, I hypothesized that participants would rate CTs with syntax errors and semantic disfluency as more deceptive than CTs with correct syntax and fluent semantics.

3c) I hypothesized that the syntax errors would amplify the P600, and the semantic errors would amplify the N400 (Kutas & Hillyard, 1980; Luck, 2014; Osterhout & Holcomb, 1992).

3d) I hypothesized that the amplification of the P600 and N400 would be predictive of deception ratings. Specifically, statements with larger P600s and

N400s would be associated with higher ratings of deceptiveness than statements with smaller P600s and N400s.

3e) Finally, I predicted that comparing the ERPs between BFLs and CTs would reveal a component that marked the difference in processing truths and lies. I hypothesized that this component would resemble the N400 or the P600, given that the N400 and P600 at a general level mark inconsistent and/or unexpected language. I expected that this heretofore undiscovered component would be predictive of the deceptiveness ratings.

Experiment 3 Participants

I recruited 18 individuals (13 women, *M* = 19.94, *SD* = 2.41) to participate in Experiment 3. I determined a sample size of 16 would be sufficient based on previous ERP literature and a sample size calculator (Faul et al., 2007), which estimated the sample size needed for a within-group design containing 128 trials. I recruited two extra participants to account for potential subject exclusion and bad data. All 18 individuals who participated were included in the analysis. All participants were recruited through Utah State University's online portal and received 3 SONA credits for their participation. Participants were fluent in English. The Utah State University IRB approved this experiment, and all participants gave informed consent.

Experiment 3 Materials

Experiment 3 Vignettes. I modified the 32 vignettes from Experiment 2 to make them shorter and to minimize any chance of misunderstanding. Additionally, I changed lengthy keywords to shorter words and longer names to single-syllable names to minimize differences in word length and complexity as these factors could influence the

EEG, increasing noise in the data. Those 32 vignettes were then duplicated and modified. While maintaining a similar thematic structure, the situations in each vignette were diversified by changing specific nouns and verbs. This approach allowed for 64 unique vignettes that each presented distinct circumstances, creating various situations for analysis (Appendix F).

Experiment 3 Statements. Like the vignettes, I duplicated and then edited the corresponding statements to align with each vignette's context. Then, I modified all statements (512 in total) to adhere to the specific linguistic style used in Experiment 1: direct subject → action verb →, subject complement (Appendix F). This linguistic style allows each statement's ERP triggers to be time-locked to the onset of each stimulus. I manipulated the direct subject to vary semantic fluency, the action verb to vary syntactic correctness, and the subject complement to vary if the statement was a truth or a lie (Table 7).

Table 7

Example Statement for Experiment 2

	Direct subject (Semantic Fluency)	Action Verb (Syntax Error)	Subject Complement (Statement Type)
BFL Correct/Fluent	The dress	was stained	by John.
BFL Incorrect/Fluent	The dress	was staining	by John.
BFL Correct/Disfluent	The apparel	was stained	by John.
BFL Incorrect/Disfluent	The apparel	was staining	by John.
CT Correct/Fluent	The dress	was stained	by me.
CT Incorrect/Fluent	The dress	was staining	by me.
CT Correct/Disfluent	The apparel	was stained	by me.
CT Incorrect/Disfluent	The apparel	was staining	by me.

Note. This table demonstrates a sample statement from each category (Bald-Faced Lie; BFL vs Control Truth; CT, correct vs incorrect syntax, and fluent vs disfluent semantics) for the following scenario: "George and Rhonda are married with a teenage boy named John. George washed Rhonda's white dress with his red t-shirt. The t-shirt turned the dress pink. When Rhonda got home, George tells her:"

Experiment 3 Procedure

Individuals signed up to participate using the SONA system. SONA is an online platform utilized for efficiently managing research participant recruitment. . After signing up, they received directions to the neuromodulation lab in the Edith Bowen building, room 244. When participants arrived, they read and agreed to the informed consent (Appendix G) and completed a quick demographics questionnaire (Appendix H). While they filled out the questionnaire, I prepared the EEG for data acquisition (see *EEG Acquisition* below). I then guided participants to the EEG data collection room (244B) and had them sit comfortably in front of the computer screen. The participants placed their chin on a chinrest and forehead against a bar to keep their viewing distance from the screen constant (21.5 inches). I adjusted the height of the chinrest for each participant's comfort. Participants then completed the task (see *Deception Rating Task* below). The task took approximately 30 minutes, and the whole procedure took approximately 2 hours, including the questionnaires, EEG set-up, task, and clean-up. Clean-up involved removing the EEG cap and providing the participant shampoo and conditioner to wash the EEG gel out of their hair. After they cleaned the gel off their head, I provided a debriefing form and allowed them to ask additional questions about the task (see Appendix I).

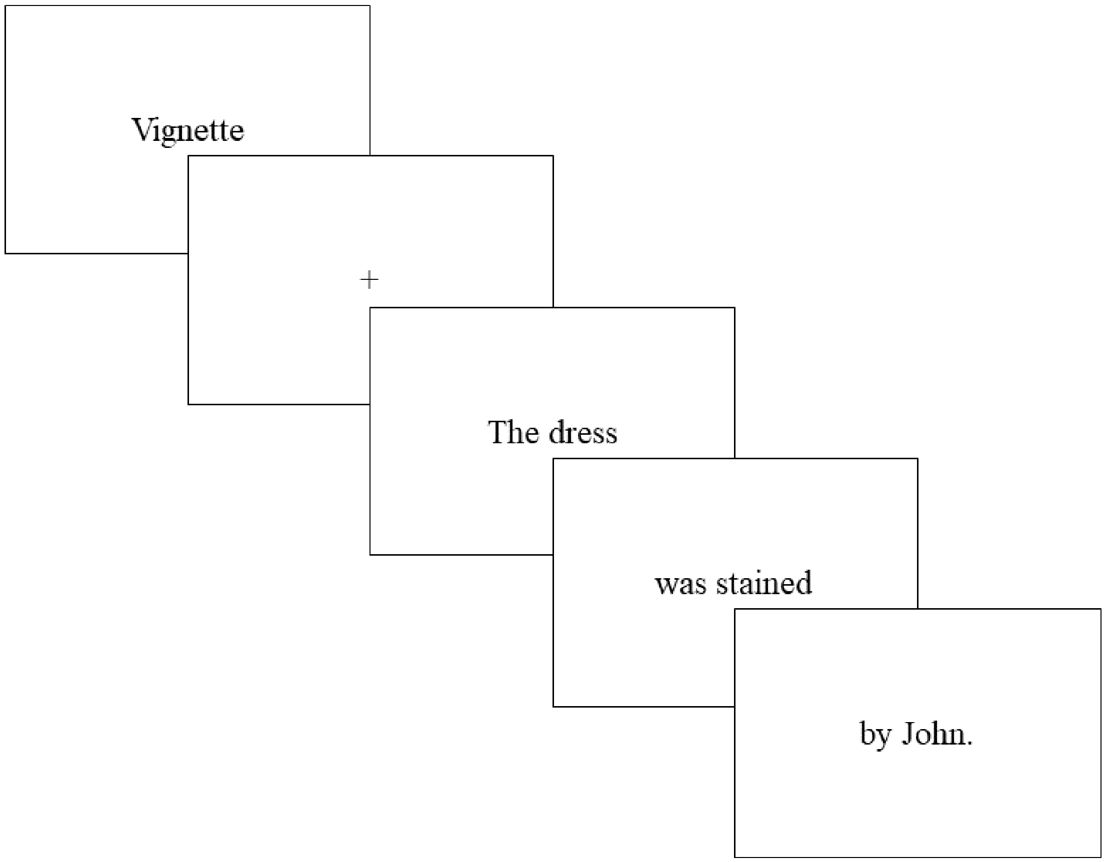
Deception Rating Task. The task was programmed using E-Prime software (Psychology Software Tools, Pittsburgh, PA), and MATLAB version R2017b (The Mathworks Inc., Natick, MA) was used to implement the counterbalancing and randomization of the selection and order of the vignettes and statements. Participants first read the instruction screen, which stated:

> "*Read the situation and rate the following statements on how deceptive they are on a scale of 1-7, where 1 is not deceptive at all and 7 is the most deceptive. If you notice any grammatical errors, assume that they are intentional and that it is exactly what the character in the vignette said. Press any key to continue*"

Participants then read one vignette in its entirety on one screen, followed by one corresponding statement that was presented in a phrase-by-phrase manner, each appearing for 1200 milliseconds, with no blank intervals between phrases (see Figure 4). Each phrase contained a set of two or three words. The first phrase contained the first two words of the statement and marked the semantic fluency condition. The second phrase contained the next two or three words and marked the syntax correctness condition. Most phrases had two words; however, a few sentences contained a third word to complete the phrasal verb. The last phrase contained the final two words of the statement and marked the type of sentence condition. Research on the P600 ERP time frame ranges from 600 to 1000 milliseconds (Frisch et al., 2002; Osterhout & Holcomb, 1992), and research on the N400 ERP time frame ranges from 300 to 500 milliseconds (Dambacher & Kliegl, 2007; Kutas & Federmeier, 2011; Lee et al., 2012). Thus, 1200 milliseconds gave the participants ample time to read each phrase and for the corresponding ERP to run its course before the onset of the next words or response screen. After reading the statement, participants rated its perceived deceptiveness on a scale of 1-7, where 1 was not deceptive at all, and 7 was the most deceptive it could be. This response was recorded by the participant pressing a number on the keyboard before them. Each vignette was presented to the participants twice but in a pseudorandomized sequence, appearing once in the first half of the experiment, and once more in the last half. The statement selection was also constrained such that participants were always exposed to perfectly contrasting statements for each vignette. For example, if a participant initially read a statement with correct syntax, disfluent semantics, and deceptive content, the second time they were exposed to the same vignette, the statement would feature incorrect syntax, fluent semantics, and truthful content.

Figure 4

Task layout for Deception Rating Task



Note. This figure depicts the task setup, starting with the presentation of the vignette, which participants could read at their own pace before proceeding to the next slide by pressing any key. Following the vignette, a fixation cross appeared for 1200 ms, succeeded by three statement fragments, each presented for 1200 ms and coded with a trigger to capture the ERP responses associated with each fragment. After viewing the statement fragments, participants were prompted to rate the perceived deceptiveness of the statement.

EEG Acquisition. The EEG was continuously recorded during the task using an acti64 Champ System (BrainVision, Morrisville, NC) from 64 electrodes, arranged according to the 10/20 system, and referenced to Fz. Data was sampled at 500 Hz and low-pass filtered with a 140 Hz cutoff and a resolution of .049 µV. Impedance levels were monitored throughout the experiment and maintained at less than 15 KOhms.

EEG Preprocessing. Raw EEG data was preprocessed using BrainVision Analyzer 2.0 (Brain Products GmbH, München, Germany). The raw EEG data underwent band-pass filtering using Infinite Impulse Response (IIR) Butterworth filters. A low-pass filter at 30 Hz and a high-pass filter at 0.1 Hz was applied to eliminate low-frequency drifts and high-frequency noise, effectively isolating the frequency range relevant to ERP analysis. The EEG data were re-referenced to the average of all electrodes to yield scalp distributions uninfluenced by reference location (Dien, 2017).

Next, artifacts in the EEG caused by eye movements were removed using the ocular-artifact correction method developed by Gratton et al. (1983). This correction approach involves the utilization of channels near the eyes to gauge the effect of eye-movements on the EEG. Eye movements engender a distinctive and discernible pattern within EEG data, manifesting as symmetrical voltage deflections in opposing directions across electrodes situated on opposite sides of the eyes (Gratton et al., 1983). By exploiting the symmetrical nature of these voltage deflections, it becomes possible to gauge how voltage deflections across the scalp were affected by specific eye movements. The Horizontal Electrooculogram (HEOG) was measured at F7 referenced to F8 and the Vertical Electrooculogram (VEOG) was measured at Fp1 referenced to the common reference.

Following ocular correction, I further refined the artifact rejection protocol to eliminate segments tainted by muscle activity, large amplitude fluctuations, or other nonbrain-related artifacts. EEG segments with voltage values exceeding 100µV or dropping below -100µV and/or those showing rapid voltage changes greater than 35µV per millisecond were marked as contaminated by artifacts using an algorithm provided in the BrainVision software. I then reviewed marked segments to decide whether to exclude the associate trial, or if the artifact could be eliminated by removing data from a single electrode and replacing it with estimated activity interpolated from surrounding electrodes. During the EEG data collection and ERP analysis, one participant's data exhibited irregularities with a single electrode (POz), showing substantial noise and consistent, large voltage deflections. Data from this electrode was replaced with interpolation during the artifact rejection procedure using a procedure provided with the BrainVision software.

ERP Analysis. The preprocessed EEG data were segmented into epochs around the event of interest (i.e., critical stimulus), spanning from -200 ms to 1000 ms relative to its onset. These epochs were used to compute the average ERP waveforms. Baseline correction was then applied, adjusting each segment by the average activity during the 200 ms pre-stimulus period. The baseline correction is used to mitigate the gradual shifts in the EEG signal, which can arise from factors such as electrode movement or changes in skin impedance, ensuring that voltage differences in the ERPs between conditions reflect only true event-related changes.

Electrodes and time windows selected for analyses of each ERP component were selected based on previous N400 and P600 studies and informed by visual inspection of the grand average waveforms. Grand average waveforms were calculated in BrainVision for each experiment condition by averaging the segments for each condition and participant and then averaging across participants. I created difference waves to isolate the difference in the ERP due to each manipulation. The N400 was isolated by subtracting the average of the fluent condition from the average of the disfluent condition. The P600 was isolated by subtracting the average wave of the incorrect condition from the correct condition. The ERP component associated with the type of statement was isolated by subtracting the BFLs from the CTs. The electrodes for each component were selected based on visual inspection of the topology of the difference waves. The N400 component for the semantic fluency conditions was quantified as the average across the electrode sites C1, C2, C4, CP1, CP2, CP4, CPz, Cz, P1, P2, P4, and Pz in the latency range of 300-400 ms (Dambacher & Kliegl, 2007; Kutas & Federmeier, 2011; Lee et al., 2012). The P600 component for the syntactic error conditions was quantified as the average across the electrode sites Pz, POz, P1, P2, PO3, and PO4, and the latency range 500-700 ms (Gouvea et al., 2010; Hagoort & Brown, 2000; Molinaro et al., 2011). ERP analysis for the CT vs BFL conditions was exploratory, and based only on visual inspection of wave distribution across the scalp. This ERP was quantified as the average across the electrode sites C2, C4, Cz, FC2, FC4, and FCz and the latency range of 300-400 ms.

Experiment 3 Statistical Analysis

I analyzed the data for Experiment 3 similarly to Experiments 1 and 2. For the behavioral data, I investigated the effects of the independent variables – the type of lie (BFL vs CT), syntax error (correct vs incorrect), and semantic fluency (fluent vs disfluent) – on the perception of deception while controlling for the covariates of age, gender, and race. For the ERP data, I investigated the effects of the independent variables on the ERP amplitudes for each condition. For the exploratory analysis of the impact of the ERP data on the behavioral data, I investigated the effects of the independent variables, ERP amplitudes, and covariates on the perception of deception. The MLMs included three levels. Level one comprised the statements and were nested with the vignettes (level two). All vignettes were read by every participant (level three). The three manipulated independent variables were applied at level one, as well as the ERP amplitudes. The covariates were applied at level three.

Experiment 3 Model Fit

Three (behavioral, ERP, exploratory) analyses were conducted in the following manner. First, null models included the fixed and random intercepts for participant differences only, participant per vignette differences, and vignettes nested under participant via both Maximum Likelihood and Restricted Maximum Likelihood. Similar to Experiments 1 and 2, I conclude that only random effects for participants would be included in subsequent models. Participant differences account for 3.6% of the variance (ICC_{null} = 0.036). To build the remaining models, the main effects of each independent variable were examined. Then, models were fit examine any interactions between these variables. Subsequent models controlled for the covariates' main effects and examined cross-level interactions. Before each subsequent model was built, models with the best fit were selected using both LRTs and ensuring significant higher-level interactions. If a model’s higher-level interaction was not significant, lower-level interactions were examined and included in subsequent models if significant. When examining the effects of the independent variables on each ERP amplitude, only one model was fit per ERP component. When examining the exploratory effects of each ERP component on the perception of deception, each model was built from the final model of the behavioral data. For these models, the ERP amplitude values were controlled for by condition on the perception of deception. The R code used for model specification and data analysis can be found in Appendix J.

Experiment 3 Results

Behavioral Data

Table 8 reports the descriptive statistics for each condition. The model comparisons established that the model examining the main effect of semantic fluency while controlling for the interaction effect of the type of sentence and syntactic error cross-interacted with gender was the best-fit model for the data (see Table 9), because when fitting additional complexity, the model did not improve fit, $\chi^2(3) = 3.59$, $p = .309$.

Table 8

Aggregated Deception Ratings Across All Eight Categories of Experiment 3, M (SD)

	Bald-Faced Lies (BFL)	**Control Truths (CT)**
Correct/Fluent	5.72 (1.43)	1.58 (0.49
Incorrect/Fluent	5.95 (0.95)	2.43 (1.39)
Correct/Disfluent	6.06 (0.96)	2.16 (1.06)
Incorrect/Disfluent	6.18 (0.74)	2.81 (1.46)

Table 9

Experiment 3 Behavioral Data: Parameter Estimates for the Final 2-Level Random Intercepts Model for Deception Ratings, Adjusting for Covariate Moderation

	b	**SE**	***t-value***	***p-value***
FIXED EFFECTS				
Intercept	6.44	0.26	24.96	< .001
Main Effects				
Semantics – *Fluent vs. Disfluent*	0.38	0.06	6.03	< .001
Statement Type – *Bald-Faced Lie vs. Control Truth*	-5.22	0.14	-38.47	< .001
Syntax – *Correct vs. Incorrect*	-0.31	0.14	-2.25	.025
Gender – *Man vs. Woman*	-1.03	0.30	-3.43	.003
Interactions				
Statement Type * Syntax	0.57	0.13	4.52	< .001
Statement Type * Gender	1.67	0.14	11.82	< .001
Syntax * Gender	0.67	0.14	4.72	< .001
RANDOM EFFECTS	**Var.**	**SD**		
Between-Subjects (Intercept)	0.27	0.52		
Within-Subjects (Residual)	2.31	1.52		

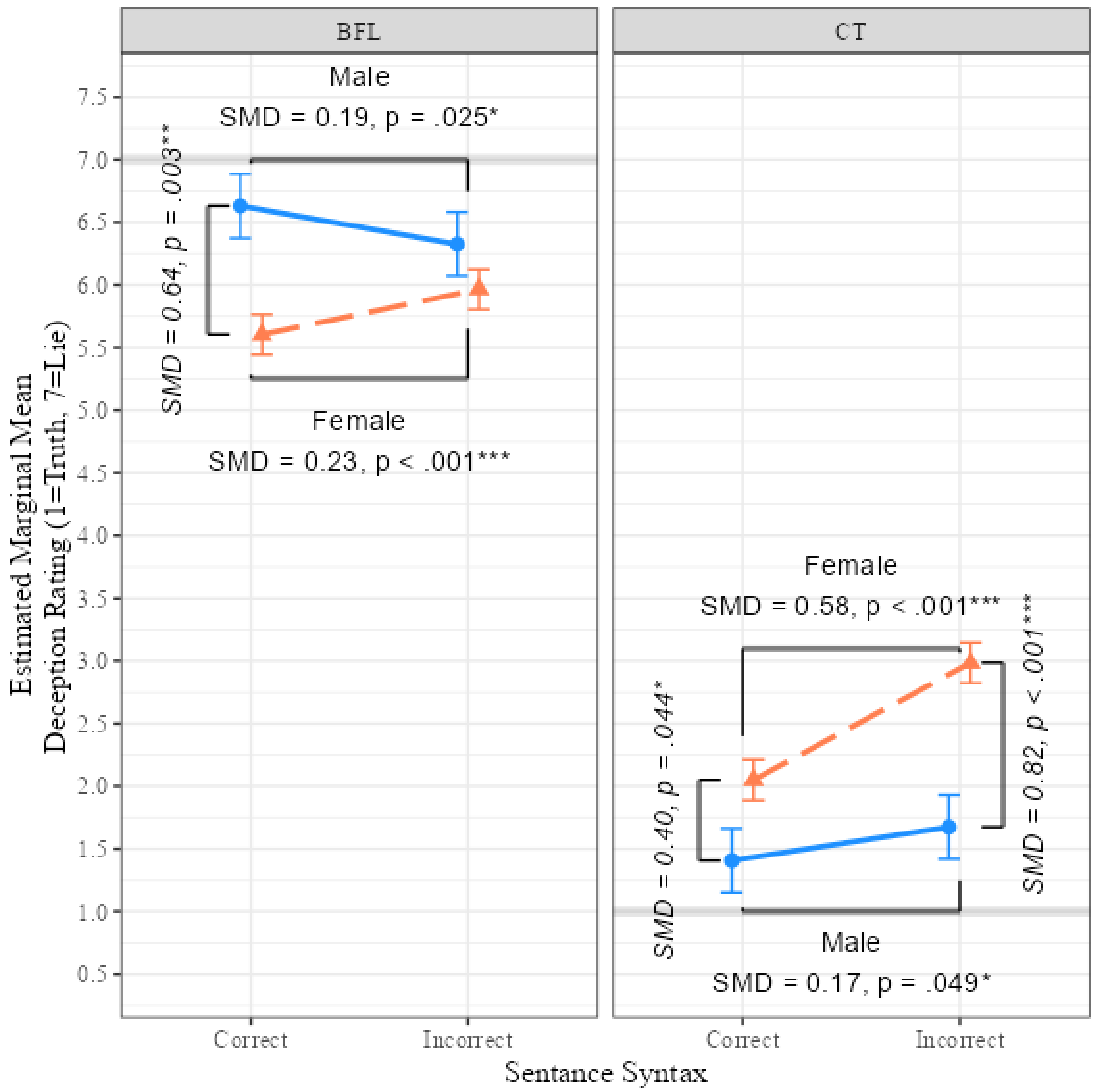
Note. Significance of fixed effects are based on Wald-like t-test utilizing Satterthwaite's method of degrees of freedom. Model fit to 2,304 statements on 18 participants.

The final model did not support hypothesis 3a but partially supported 3b. The Satterthwaite method indicated a significant main effect of semantic fluency $p < .001$, indicating that statements with semantic disfluency were rated more deceptive than statements with semantic fluency. However, there were no significant interactions between semantic fluency, syntax correctness, and the type of lie told. There was a significant interaction between syntax correctness and the type of lie told, $p < .001$. I conducted follow-up pairwise comparisons and found that while participants rated BFLs with incorrect syntax as more deceptive than BFLs with correct syntax, the difference was not significant, *SMD* = -0.02, $p = .762$. This observation does not align with the results observed in Experiments 1 or 2 because in Experiments 1 and 2, BFLs with incorrect syntax were rated as less deceptive than BFLs with correct syntax. Nonetheless, in line with Experiments 1 and 2, participants rated CTs with correct syntax less deceptive than CTs with incorrect syntax, *SMD* = -0.37, $p < .001$.

The addition of cross-level interactions in the final model revealed two noteworthy effects. Significant interactions existed between the type of lie told and gender, $p < .001$, and gender and syntactic correctness $p < .001$. Men rated lies as more deceptive than women, and men rated truths as less deceptive than women. Women rated statements with incorrect syntax as significantly more deceptive than statements with correct syntax. All significant pairwise interactions can be seen in Figure 5. These results reveal that women rate statements more moderately regardless of if they are the truth or a lie, whereas men rate statements closer to the ceiling and floor based on if they are the truth or a lie. Furthermore, men are less influenced by syntactic correctness, whereas women's perception of deception is highly influenced by syntactic correctness.

Figure 5

Estimated Marginal Means (±SEM) for the Multilevel Model (MLM) for the Interaction of Statement Type, Syntax Error, and Gender



Note. This figure illustrates the influence of syntax error on deception ratings collapsed across statement type and participant gender. Each panel represents one sentence type, within which two lines denote the deception ratings by gender: orange for women and blue for men. Significant differences are indicated with brackets, accompanied by Standardize Mean Differences (SMD) and p-values.

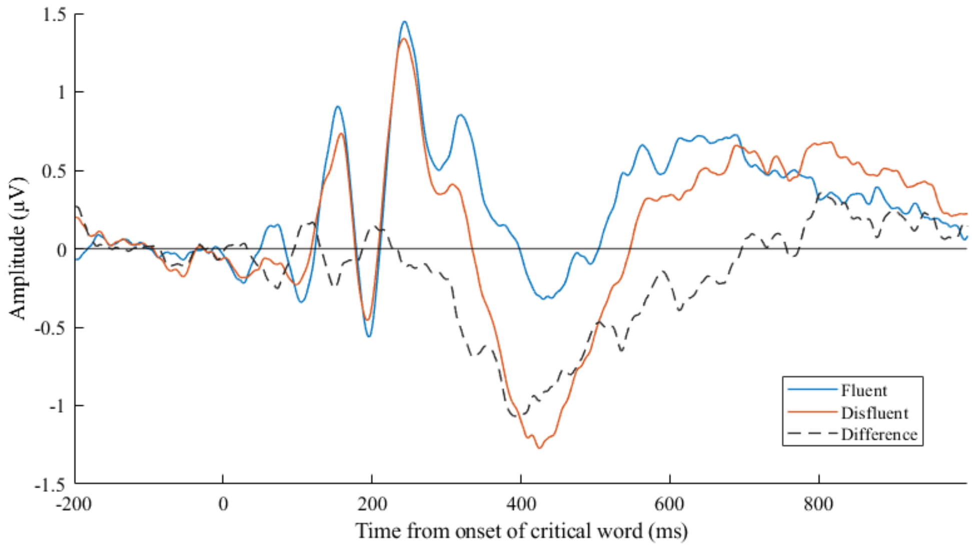
* $p < .05$. ** $p < .01$. *** $p < .001$

Electrophysiological Data

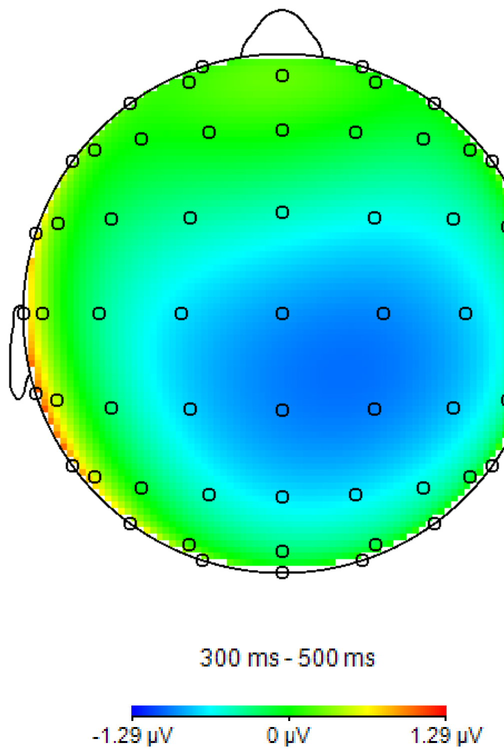
Stimulus Locked N400 Amplitude: Semantic Fluency. Figure 6 shows the grand average ERPs time-locked to the visual onset of the critical words for semantic fluency. Relative to the semantically fluent counterparts, semantically disfluent critical words elicited a larger negative deflection that emerged in the grand average at about 315 ms, peaked at 425 ms, lasted for about 215 ms, and reached its maximum over the central, central-parietal, and parietal scalp sites. These characteristics are representative of a standard N400 effect (Kutas & Federmeier, 2011). Using the mean amplitude, the MLM model revealed a significant difference between the N400 amplitude in the semantically fluent and semantically disfluent conditions, $t(2286) = -4.22$, $p < .001$. This not only supports hypothesis 3c, but also serves as a successful manipulation check, confirming that my experimental methods were sufficiently robust to reveal this well-established, expected effect. This outcome validates the effectiveness of the design in manipulating semantic fluency and underscores the reliability of the findings.

Figure 6 A-B

Grand Average ERP Waveforms and Topographical Scalp Map Time-Locked to the Onset of the Fluency Manipulation



Panel A. Grand-averaged ERPs for the conditions of semantically fluent (blue solid line), semantically disfluent (orange solid line), and the difference wave (black dashed line) separately.

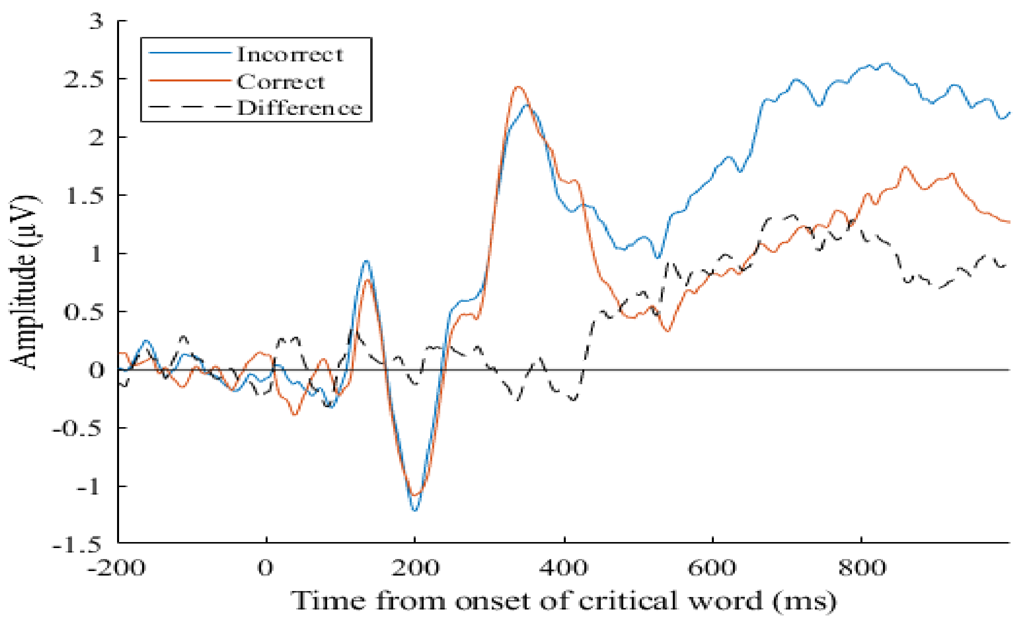


Panel B. Topographical map of the voltage amplitudes for N400 in the 300-500 ms. The topology is broadly dispersed over parietal sites, as is typical for the N400.

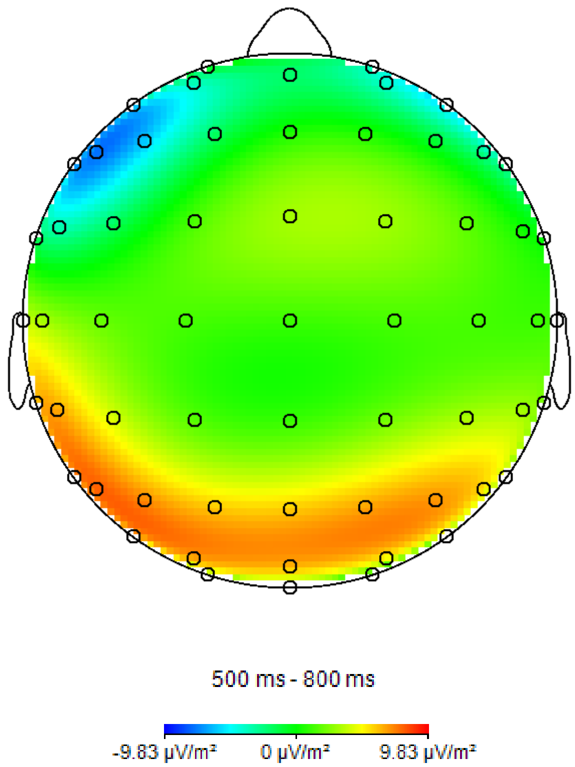
Stimulus Locked P600 Amplitude: Syntax Error. Figure 7 shows the grand average ERPs time-locked to the visual onset of the critical words for syntactic errors. Relative to the syntactically correct counterparts, syntactically incorrect critical words elicited a larger positive deflection that emerged in the grand averages about 525 ms after the visual onset, peaked at 700 ms, lasted for about 450 ms, and reached its maximum over parietal and occipital scalp sites. The timing is typical of a standard P600 effect, and the topology is slightly more posterior than typical, but still within a range often observed (Kaan et al., 2000; Osterhout & Holcomb, 1992). Using the mean amplitude, the MLM model revealed a significant difference between the P600 amplitude in the syntactically correct and syntactically incorrect conditions, $t(2286) = 4.28$, $p < .001$. This supports hypothesis 3c and again serves as a successful manipulation check. The presence of a significant difference between syntactic correctness validates the effectiveness of the design and highlights the reliability of the findings.

Figure 7 A-B

Grand Average ERP Waveforms and Topographical Scalp Map Time-Locked to the Onset of Syntax Error



Panel A. Grand-averaged ERPs for the conditions of incorrect syntax (blue solid line), correct syntax (orange solid line), and the difference wave (black dashed line) separately.

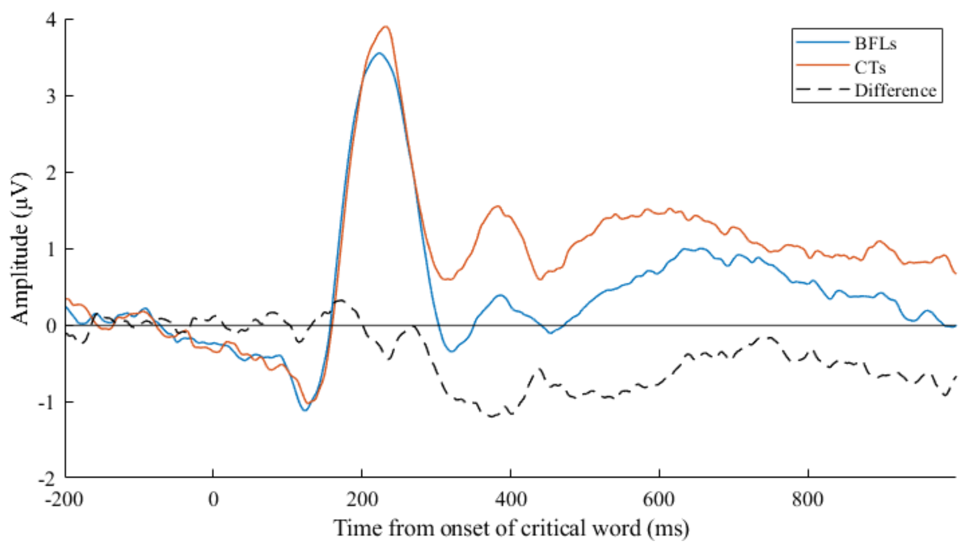


Panel B. Topographical map of the voltage amplitudes for P600 in the 500-800 ms. The topology is dispersed over occipital sites with slight lateralization to the left.

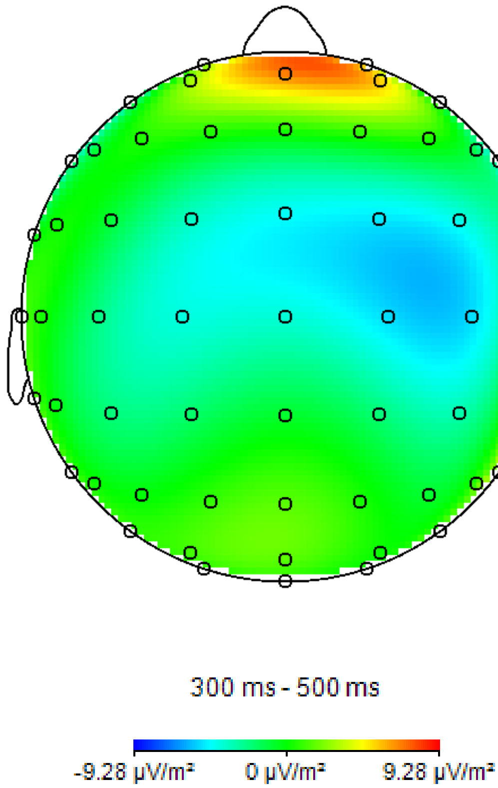
Exploratory Stimulus Locked Amplitude: Sentence Type. Figure 8 shows the grand average ERPs time-locked to the visual onset of the critical word, distinguishing if the sentence was a truth or a lie. Relative to the truthful statements, lie statements elicited a larger negative deflection that emerged in the grand averages about 300 ms after the visual onset, peaked at 385 ms, lasted for about 100 ms, and reached its maximum over central and frontal-central scalp sites. Based on these characteristics, I concluded that the type of sentence elicited amplitude component similar to a N400 in time range, but with a smaller and more rostral scalp distribution. I refer to this ERP as the Semantic Veracity Processing 400 (SVP400). Using the mean amplitude, the MLM model revealed a significant difference between this SVP400 amplitude in the truth and lie conditions, $t(2286) = 5.05$, $p < .001$. This partially supports hypothesis 3e.

Figure 8 A-B

Grand Average ERP Waveforms and Topographical Scalp Map Time-Locked to the Onset of Statement Type



Panel A. Grand-averaged ERPs for the conditions of BFLs (blue solid line), CTs (orange solid line), and the difference wave (black dashed line) separately.



Panel B. Topographical map of the voltage amplitudes for SVP400 in the 300-500 ms. The topology is dispersed over frontal parietal sites with lateralization to the right.

Interaction of Electrophysiological and Behavioral Data

To explore the effects of the electrophysiological markers on the behavioral data, I incorporated the ERPs as independent variables on the perception of deception. The model comparisons established that the final behavioral model fit with the main effect of the N400 amplitude time-locked to the semantic condition and interaction of the exploratory ERP amplitude with the type of sentence was the best-fit model, $\chi^2(13) = 7.25$, $p = .007$ (see Table 10).

Table 10

Experiment 3 Integration of ERP and Behavioral Data: Parameter Estimates for the Final 2-Level Random Intercepts Multilevel Model for Deception, Adjusting for Covariate Moderation

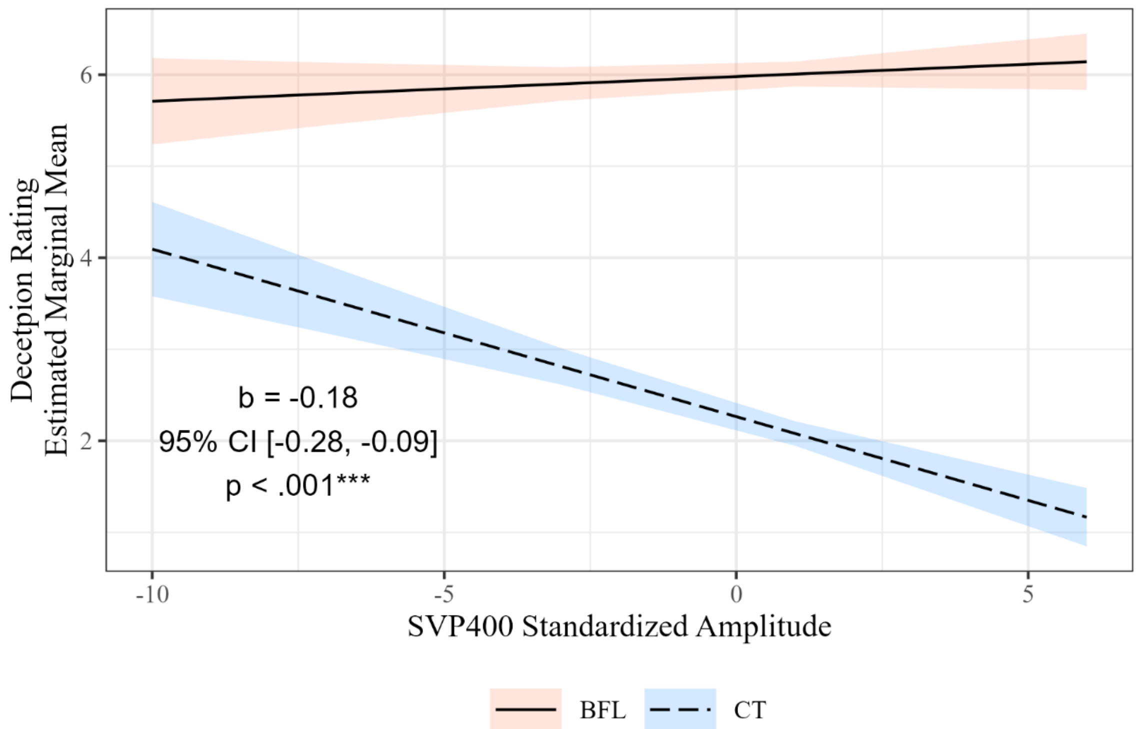
	b	**SE**	***t-value***	***p-value***
FIXED EFFECTS				
Intercept	6.46	0.25	25.85	< .001
Main Effects				
Semantics – *Fluent vs. Disfluent*	0.35	0.06	5.59	< .001
Statement Type – *Bald-Faced Lie vs. Control Truth*	-5.16	0.14	-37.86	< .001
Syntax – *Correct vs. Incorrect*	-0.30	0.14	-2.25	.025
Gender – *Man vs. Woman*	-1.04	0.30	-3.58	.002
Standardized N400 Amplitude	-0.09	0.03	-2.68	.008
Standardized SVP400 Amplitude	0.03	0.05	0.59	.557
Interactions				
Statement Type * Syntax	0.54	0.13	4.24	< .001
Statement Type * Gender	1.63	0.14	11.51	< .001
Syntax * Gender	0.66	0.14	4.71	< .001
Statement Type * SVP400	-0.21	0.06	-3.25	.001
RANDOM EFFECTS	**Var.**	**SD**		
Between-Subjects (Intercept)	0.25	0.50		
Within-Subjects (Residual)	2.29	1.51		

Note. Significance of fixed effects are based on Wald-like t-test utilizing Satterthwaite's method of degrees of freedom. Model fit to 2,304 statements on 18 participants.

The data did not support hypothesis 3d, but did support hypothesis 3e. The amplification of the P600 interacting with the syntactic condition and N400 interacting with the semantic condition did not influence the deception ratings, $p = .395$ and $p = .809$ respectively. However, the N400 amplitude did have a main effect on the ratings of deception p = .007. As the N400 amplitude increased, the deception rating decreased. Exploratory analysis of the SVP400 revealed a significant interaction, p = .001. This ERP component appears to be related to the perception of deception; that is, the amplitude of this component is predictive of how extreme participants rate the deceptive statement. When the component amplitude is more positive, the participants rate truths as less deceptive and lies as more deceptive. Conversely, when the amplitude is more negative, the ratings are less extreme (Figure 9). Importantly, the interaction between the SVP400 and behavioral measure of the deception rating underscore the validity of this ERP component in discerning lies from truths. This finding supports the interpretation that the SVP400 is a genuine marker of deception, rather than a mere spurious difference, reinforcing its significance in understanding the neural mechanisms underlying deception detection.

Figure 9

Simple Slopes (b) With A 95% Confidence Interval for MLM For Interaction of Age, Gender, and Sentence Type



Note. This figure displays the relationship between the standardized amplitude of the SVP400 component and deception ratings. The analysis highlights a significant simple slope, marked on the graph, characterized by a coefficient (b). The 95% confidence interval and corresponding p-value are provided.

Experiment 3 Discussion

Unlike Experiments 1 and 2, the ICC revealed that only a small amount of the variance in deceptiveness ratings were attributed to individual differences alone. This difference between experiments could be due to having a substantially smaller sample size in experiment 3. Additionally, participants in Experiment 3 were all college students and younger in age, whereas, participants in Experiments 1 and 2 were collected from the general population, and the age range in Experiment 1 was close to 50 years.

While the behavioral model's significant main effect of semantic fluency and two-way interaction between sentence type and syntax correctness supports the claim that grammar and word choice influence the perception of deception, the findings do not completely replicate those found in Experiments 1 and 2. Although there was not a significant interaction between semantic fluency, syntax, and sentence type, the results still support that word choice does affect the perception of deception to some degree. The significant interaction between syntax and sentence type partially replicated the findings in Experiments 1 and 2. All three experiments support the claim that when the statement is true, mistakes in language increase the perceived deceptiveness of that statement. It is unclear how these mistakes influence the perceived deceptiveness of overtly false statements overall. Nonetheless, the significant interaction between syntax correctness and the type of lie, especially the differing perceptions based on gender, highlights the complexity of deception perception.

The results of the EEG findings, particularly regarding the N400 and P600 components, are critical for several reasons that reinforce the robustness and validity of my research methodology and findings. The adequacy of the sample size is underscored by the significant effects observed in the N400 and P600 amplitudes. These effects were observed in our sample of 18, providing a high level of confidence in the reliability and generalizability of the findings. Observing the expected N400 and P600 effects indicates that participants were engaged and adhered to the task, that my experimental design was effective, that the data collected was of high quality, and processing of that data was done correctly.

These results have led to the discovery of a novel ERP component associate with veracity judgments, which I refer to as the SVP400. This component was characterized by distinct electrophysiological responses when participants were exposed to deceptive versus truthful statements. Specifically, the SVP400 demonstrated a clear pattern of amplitude variation in response to participants' judgements of deception. For BFLs and CTs, as participants perceived statements as more deceptive, there was a significant increase in the SVP400 amplitude, indicating a stronger electrophysiological response to perceived deception. When participants judged statements as truthful, the SVP400 amplitude was comparatively lower, suggesting a diminished response to perceived truthfulness. This amplitude variation correlates with the degree of perceived deceptiveness, providing a quantifiable link between the electrophysiological activity and the participants' subjective assessment of truthfulness and deception.

This distinct electrophysiological pattern observed, akin to a modified N400 response but with a smaller and more rostral scalp distribution, suggests a unique cognitive process activated during the perception of deceptive and truthful judgements. This dual sensitivity suggests that the pattern may serve as a neural marker for the cognitive evaluation of veracity, highlighting its role in discerning the authenticity of information irrespective of its deceptive or truthful nature. This finding enriches understanding of the neural correlates of deception by indicating that the brain processes deceptive and truthful statements differently, within 400 ms of exposure. The discovery of the SVP400 component highlights it's the brain's capability to rapidly analyze language for consistency and truthfulness. This parallels the N400's involvement in semantic processing and suggests a specialized system may be at work within the first 400 ms of processing language, specifically tuned to evaluate the veracity of statements. The identification of the SVP400 opens new avenues for research into the cognitive and neuroscientific underpinnings of deception. It presents a novel tool for investigating how different populations process deceptive information. Furthermore, it offers a unique perspective on the role of context in deception detection, potentially leading to breakthroughs in understanding how situational factors influence the ability to discern truths from lies. The implications of this component extend beyond theoretical models, offering practical applications in forensic and clinical settings, where accurate detection of deception has profound consequences.

Chapter VI – General Conclusions

In my research project, I significantly advanced the field of deception detection in online text-based communication. My systematic exploration focused on how individuals interpret and decide on deceptive content, particularly emphasizing the role of linguistic irregularities and anomalies. The experiments I conducted probed both the behavioral dynamics underpinning deception judgments and the electrophysiological responses to incorrect or disfluent language. Consistent patterns emerged across the studies, highlighting the importance of language in assessing truthfulness and deceit in digital contexts. The implication of these findings are significant for academia and fields such as cybersecurity, forensic linguistics, and online content moderation. These studies set a foundation for future research and potential advancements in deception detection technology.

Discussion of Results

Subjectivity in Deception Perception

The findings from all three experiments have highlighted the significant role of individual subjectivity in the perception of deception. Across the three experiments, the data consistently demonstrated that individual differences significantly influence how deception is perceived and judged. The methodological differences between experiments, such as variations in sample size, participant selection criteria, and measures to ensure participant engagement and authenticity (e.g., “bot”-catching tactics), may also explain some of the variability in my findings. For instance, Experiments 1 and 2 involved more diverse sample populations, thus the variance in deception ratings attributable to individual differences was substantial. While Experiment 2 had a larger sample size, participants only saw one of the corresponding statements per vignette; therefore, the number of ratings of the perception of deception was substantially less in Experiment 2. Nonetheless, these findings, derived from a more diverse sample population than experiment 3, suggest that individual backgrounds and cognitive predispositions are key factors in shaping perceptions of deception. Experiment 3, which involved a more homogeneous group of participants, largely composed of traditional-aged college students, provided a contrasting yet reinforcing perspective. Despite the reduced extent of individual variability in this younger, more uniform demographic, the persistence of differences in deception perception indicated intrinsic cognitive diversity even within similar groups. This outcome implies that individual differences are a consistent factor in deception perception, regardless of demographic homogeneity. The implications of these findings suggest that approaches to detecting deception must account for the diverse ways in which individuals interpret information. The recognition of the variability in how individuals judge deception is pivotal for devising training methods aimed at enhancing deception detection skills. Acknowledging these differences is essential to develop programs that are not only effective but also adaptable to diverse interpreters. Moreover, these finding necessitate a careful consideration of ethical implications, particularly in how training for improved detection might be implemented without infringing on privacy rights or enabling misuse. It is crucial to explore how we can address the inherent variability in deception judgments to equip individuals with the tools they need to more accurately discern truth from deceit, because such an approach ensures that training is grounded in the realistic complexities of human perception and judgement, while also being mindful of the ethical landscape surrounding these efforts.

Syntax and Semantic Influences

The findings from these experiments indicate that linguistic anomalies, such as grammatical inaccuracies and semantic disfluencies, contribute to how individuals perceive and evaluate deception. This was quantitatively evidenced by significant differences in deception ratings based on the presence or absence of these linguistic features in varying levels of deceptive statements. For instance, syntactic errors were found to affect perceptions of deception differently in BFLs compared to CTs, particularly in Experiments 1 and 2, where syntactic errors were perceived as less deceptive in BFLs and more deceptive in CTs. The observation that syntactic errors increase deceptiveness ratings for truths but decreases them for lies invites speculation on the mechanisms that might be interrupting people's truth-bias. One plausible explanation, within the framework of the Truth-Default Theory (Levine, 2014), is that mistakes and disfluency may serve as disruptive cues that trigger skepticism, leading to a reevaluation of truthfulness of statements. In contrast, the cognitive reevaluation for BFLs could lead to a reduction in the perception of deception for a couple of reasons. First, they may attribute such anomalies to nervousness, mitigating the perception of intentional deception. Second, people might expect lies to be more polished and coherent, and thus errors do not match the expected profile of a carefully constructed lie.

The studies extended beyond behavioral data to analyze electrophysiological responses to linguistic anomalies, thus providing a deeper insight into the cognitive processes involved in responding to deceptive language. Specifically, the analysis of the ERP amplitudes, helped to reveal differences in brain activity when processing deceptive versus truthful statements. These differential responses support previous research to the brain's sensitivity to linguistic inconsistencies and anomalies (e.g., Kaan et al., 2000; Kutas & Federmeier, 2011; Osterhout & Holcomb, 1992) and suggests additional cognitive processing associated with discerning deception. These findings have significant implications for the field of deception detection, particularly in online environments. They suggest that linguistic cues influence how people perceive the level of deception in statements, underscoring that the impact of these cues on deception is context-dependent. Understanding these dynamics is essential for developing more sophisticated and accurate tools for deception detection in digital communication contexts.

The differential impact of syntactic errors and semantic disfluencies observed across the experiments can partly be attributed to methodological distinctions, including the presentation format of deceptive statements and the strategies to maintain participant engagement. For example, in Experiment one, the inclusion of all corresponding statements to each vignette may have decreased participant engagement and increased fatigue. In contrast, in Experiment 2, the reduction of the number of statements seen and the inclusion of periodic checks may have heightened participant attentiveness to linguistic details, thereby amplifying the perceived deception in statements with syntax errors.

Gender and Age Differences

This research provided some insights into the influence of gender and age on the perception of deception. This was elucidated through a systematic analysis of how these factors interplay with linguistic cues in shaping deception judgments. Notably, Experiments 1 and 3 provided key insights into gender-specific differences in deception perception. Women rated CTs as more deceptive than men and BFLs as less deceptive than men. Furthermore, women rated statements with incorrect syntax as more deceptive than correct syntax, whereas there was no significant difference in men. These findings highlight that men and women not only perceive deception differently regardless of linguistic cues, but that they process and interpret linguistic cues differently when assessing the truthfulness of a statement. Such gender-related variations in perception were evident in the differential responses to syntax errors and their impact on perceived deception. Additionally, Experiment 1 revealed that younger women were more likely to rate CTs as more deceptive than older women, which could suggest that younger women may be more suspicious of deception online or older women may have a greater truth-bias than younger women. These insights into gender differences are crucial for developing more effective and inclusive deception detection strategies because they point to the importance of tailoring deception detection tools and methodologies to account for demographic variability. Thus, there is an opportunity to explore the impact of demographics more deeply and to further investigate the neuroscientific underpinnings of deception perception.

Electrophysiological Insights

The integration of EEG data in my research provided novel neuroscientific insights into the mechanisms of language comprehension in the context of deception. The demonstration of the semantic veracity difference was a novel finding. This new component represents a unique electrophysiological response to deceptive versus truthful statements, suggesting a specialized neural response to deception. The distinctive topology coupled with the similar timing and polarity to the previously studied N400 suggest a related process to detecting semantic disfluency that may engage more frontal regions of the brain. Nonetheless, it is crucial to acknowledge that previous studies have observed significant differences in the N400 in deceptive contexts (He et al., 2022; Meek et al., 2013; Nieuwland & Kuperberg, 2008; Proverbio et al., 2013). Importantly, these studies did not delve into the realm of perceived deception but rather explored the N400 in statements where participants were prompted to lie. Moreover, while other prior research noted increased N400 amplitude for inaccurate statements (He et al., 2022; Nieuwland & Kuperberg, 2008), such statements were not inherently deceptive but merely factually incorrect. This distinction underscores the unique contribution of my research in isolating the truth-lie dichotomy in terms of veracity through the novel SVP400 signal. Integrating the behavioral findings with the ERP results uncovered the compelling interaction between the electrophysiological responses and participants' deception ratings, notably that as the amplitude of the SVP400 became more negative, participants rated CTs as more deceptive. This finding, highlighting a direct correlation between neural activity and subjective perceptions of deception, offers a nuanced understanding of how brain responses to linguistic cues are intricately linked to the cognitive processes involved in evaluating the veracity of statements.

These findings have important implications for our understanding of the cognitive underpinnings of deception detection. They provide empirical evidence that the brain responds differently when making decisions about the level of deceit in deceptive and truthful statements, which could lead to the development of more sophisticated technology for understanding the process of identifying deception. For example, by integrating these findings into training programs for professionals involved in forensic analysis, security screenings, and hiring practices, we could enhance their ability to interpret and critically evaluate linguistic cues in statements. This approach would not directly increase the accuracy of technologies like lie detectors, but rather improve the subjective judgments and decision-making processes by bringing awareness of the biases associated with deception detection.

Limitations and Future Studies

While advancing the field of deception in online text-based communication, this project encountered several limitations across its three experimental phases. Due to the restrictions imposed by the COVID-19 pandemic, Experiment 1 was conducted online rather than utilizing ERP and EEG technology. This mode of delivery meant that the statements presented to participants were not based on colloquial language structure, potentially affecting the naturalness and ecological validity of the deceptive contexts. Additionally, participants were required to read all statements for each vignette, elongating the survey duration, possibly inducing fatigue or disengagement and potentially prompting participants to rank order statement ratings, affecting the authenticity of their reactions to the deceptive statements. Acknowledging these concerns, subsequent experiments sought to mitigate these limitations. Experiment 2 introduced modifications by reducing the number of statements per vignette to one and employing more naturalistic language. These modifications aimed to diminish response set bias and increase ecological validity. However, I did not collect demographic information about the participants, restricting the ability to analyze the demographic factors, a key consideration in understanding and applying these findings across more diverse populations.

Experiment 3 further mitigated limitations and had some limitations of its own. First, Experiment 3 aimed to capture the electrophysiological responses, and therefore the sentence structure was similar to Experiment 1. Thus, it shared the limitation of non-colloquial presentation. Additionally, participants read each vignette twice and rated two of the possible statements per vignette. While this may have increased fatigue or disengagement, this approach allowed for the appropriate manipulation and analysis of the difference waves for the ERPs. Moreover, the participant pool was relatively homogenous. This lack of diversity limits the generalizability of the findings to broader populations. Furthermore, across all three experiments, the participants were from English-speaking, Westernized American cultural backgrounds, raising questions about the applicability of the results to other cultures and languages. For example, while most culture perceive white lies as polite, some cultures such as in Germany, blunt truths are perceived as more appropriate than white lies (Giles et al., 2019).

The inherent design of these experiments, where participants were always objectively aware of the veracity of the statements, may have still influenced their perception of lies and truths. Qualitative questionnaires could help researchers understand participants' perspectives. Furthermore, preliminary findings hint at the possibility that the cognitive processing of lies versus truths might not evoke the same kind of incongruity reaction typically associated with the N400 response, suggesting a distinct neurocognitive mechanism at play. This observation opens avenues for further research to explore the subtleties distinguishing lies from truths. For example, the next study could adapt the sentences to mimic the stimuli used in (Nye, 2017) and contextual vignettes. In a contextual vignette, the scenario would lead up to the main character choosing to engage in a deceptive task; however, the final sentence of the vignette would be the corresponding statement. The statement would have a pre-critical region, which would be the subject and verb. The statement would have a post-critical region, which would solidify if the statement were true or false. The critical region would be manipulated to be true, implausible, or a violation.

Implications for Future Research

Combining behavioral data with electrophysiological correlates helps lay a foundation for future investigations in the field of deception detection. These findings have important implications for both the academic community and practical applications in various fields. Academically, this research expands the understanding of linguistic and cognitive processes involved in deception detection. It highlights the need for multi-dimensional approaches that consider individual differences, linguistic nuances, and neuroscientific insights. Future research can build upon these findings to explore more specific aspects of deception, such as cultural influence on language processing and the development of age-specific deception detection models.

In practical terms, the implications of this research are helpful for fields like cybersecurity, law enforcement, and online content moderation. These results can inform the development of more sophisticated programs that improve individuals' ability to interpret and respond to deception by fostering a deeper understanding of the factors and biases influencing deception judgments. For example, developing training modules that enhance awareness of how syntax errors and semantic anomalies influence deception judgments can be instrumental for professionals in fields like online fraud prevention. By educating these professionals on user-specific factors and the nuanced ways in which linguistic cues shape perceptions of deception, we can improve their ability to critically assess and response to potential fraud and misinformation online.

Furthermore, future efforts could focus on leveraging our understanding of how people perceive deception. This could involve identifying the cognitive and neuroscientific markers associated with the accurate detection of deception, thereby informing training programs designed to improve the accuracy of human judgement. Before translating these insights into practical interventions for improving lie detection, intermediate research steps are essential. These steps should focus on rigorous validation of the identified neurocognitive components and behavioral patterns associated with deception and its perception. Experimental studies could be designed to systematically test the efficacy of these components in varying contexts and populations, thus establishing their reliability and validity in real-world scenarios. Additionally, interdisciplinary research involving scientists in respective fields and practitioners could explore how these neurocognitive makers and behavioral indicators can be integrated into training programs.

Simulated environments and role-playing scenarios could be utilized to refine these interventions, allowing for the adjustment of training modules based on feedback and performance outcomes. This iterative process ensures that the interventions are both theoretically grounded and practically effective. Such training programs, grounded in a deep understanding of the cognitive and neurological underpinnings of the perception of deception, could be revolutionary in settings where high-stakes deception detection is critical, such as in legal investigations or security screenings.

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APPENDICES

Appendix A. Task layout described in Zhu et al. (2019)

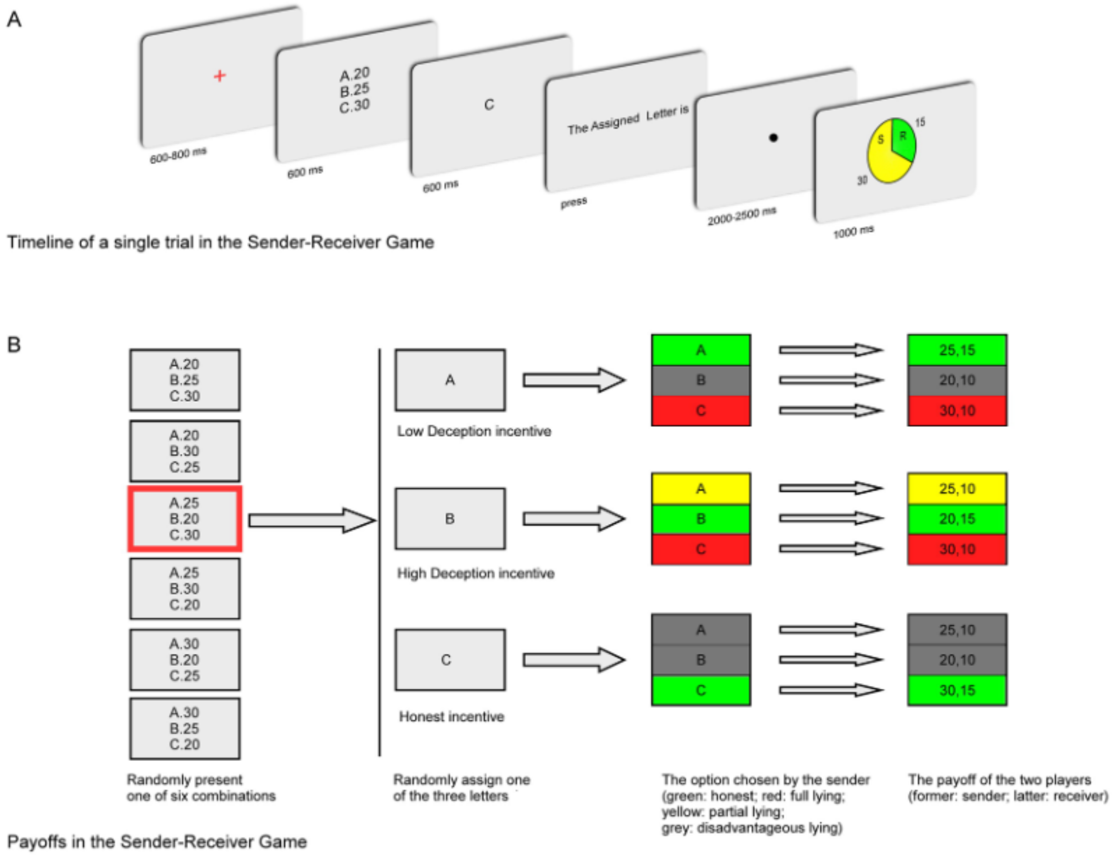

Figure 1. Overview of the task and trial structure. (**A**) At the beginning of each trial, three letters (i.e., **A**–**C**) with different payoffs (i.e., 20, 25, and 30) were presented. After one of these letters appeared randomly, the sender chose an option to send a message about this letter to the receiver and earned the payoff associated with his/her chosen option. (**B**) According to the associated payoff for the assigned letter, there were three conditions, i.e., HI, LDI and HDI. Then, the sender's actions were divided into four categories, i.e., honest, full lying, partial lying and disadvantageous lying, depicted by green, red, yellow and gray, respectively. The sender's payoff depended only on his/her chosen option, and the receiver's payoff was dependent on whether the sender sent the true message.

Appendix B. Vignettes and Statements used in Experiment 1.

(1-18) George and Rhonda are married. George decided to clean the house, do the laundry, and change the oil in the car to help his wife. George accidentally broke Rhonda's fine China while dusting. He washed the whites with the reds and turned Rhonda's favorite dress pink. He also mixed up the oil types and put partially synthetic in the car, which requires full synthetic. Now the truck won't run. When Rhonda gets home, George tells her the following:

Bald-Face Lies

The plate was shattered by the children.
The plate was shatter by the children.
The dress was stained red by the children.
The dress was staining red by the children.
The truck was damaged by the children.
The truck was damages by the children.

Literal Truths

The plate was shattered by someone.
The plate was shatter by someone.
The dress was stained red by someone
The dress was staining red by someone.
The truck was damage by someone.
The truck was damages by someone.

Control Truths

The plate was shattered by me
The plate was shatter by me
The dress was stained red by me
The dress was staining red by me
The truck was damaged by me.
The truck was damages by me.

(19-24) William was on his way to the store. He wasn't sure what all he needed to buy, so he texted his roommate Josh. As he was texting, he ran a swerved and hit a parked car. William did not want to be charged with reckless driving and have his insurance increase, so when the police arrived, he told them:

Bald-faced Lies

The car was hit by Albert.
The car was hitting by Albert.

Literal Truths

The car was hit by someone.
The car was hitting by someone.

Control Truth

The car was hit by Josh.
The car was hitting by Josh.

(25-36) Lauren wants to surprise her fiancé for her birthday and asks her roommate, Steph, for help because both Lauren and her fiancé work long hours. Lauren informed Steph that her fiancé's favorite cake is red velvet. Lauren also asks Steph to wrap the gift she got. When Lauren and her fiancé return home. Lauren tells her fiancé:

Bald-faced lies

The cake was baked by me.

The cake was bakes by me.

The present was wrapped by me.

The present was wrap by me.

Literal Truths

The cake was baked by someone.

The cake was bakes by someone.

The present was wrapped by someone.

The present was warp by someone.

Control Truths

The cake was baked by Steph.

The cake was bakes by Steph.

The present was wrapped by Steph.

The present was wrap by Steph.

(37-42) Sean and his friend, Albert, are avid skiers and are excited that the ski resorts got a lot of fresh snow. Albert is waiting for his new skis to arrive, so Sean lets Albert borrow his. Albert decides to go down a slope with fresh powder. As he descends the hill, he miscalculates and falls. The fall ends up breaking Sean's skis. Albert returns how home and tells Sean:

Bald-faced lie

Your skis were broken by a stranger.

Your skis were breaking by a stranger.

Literal Truths

Your skis were broke by someone.

Your skis were breaking by someone.

Control Truths

Your skis were broken by me

Your skis were breaking by me.

(43-54) Aashish just bought a new iPad. He was so excited to have the chance to use it, but he had to go to work first. He left his iPad on the counter. While he was at work, his roommate saw the new iPad on the counter. His roommate needed extra money to pay rent, so he stole the iPad to sell. When Aashish returned from work, he received a notification saying the remainder of rent was paid. He also noticed that his iPad was missing. His roommate said:

Bald-faced lie

The iPad was stolen by a burglar.

The iPad was steals by a burglar.

The rent was paid by selling my Xbox

The rent was pay by selling my Xbox.

Literal Truths

The iPad was stolen by someone.

The iPad was steals by someone.

The rent was paid by someone.

The rent was pay by someone.

Control Truths

The iPad was stolen by me
The iPad was steals by me.
The rent was paid by selling your iPad.
The rent was pay by selling your iPad.

(55-66) Pete is an aspiring singer and songwriter. He shows some of his work to his girlfriend, Kristi. Kristi knows her friend writes a lot of poetry, so she takes her friend's work to help Pete write better songs. Pete uploads a video of him singing one of Kristi's friend's songs, and it gets a lot of attention. Kristi's friend recognizes it's her poem and accuses him of stealing it. Pete tells her:

Bald-faced lie
The song was written by Kristi.
The song was writing by Kristi.
The poetry was taken by your boyfriend.
The poetry was take by your boyfriend.

Literal Truths
The song was written by someone.
The song was writing by someone.
The poetry was taken by someone.
The poetry was take by someone.

Control Truths
The song was written by you.
The song was writing by you.
The poetry was taken by Kristi.
The poetry was take by Kristi.

(67-72) Anita decided to attend a rally for the upcoming presidential election with her friend Georgie. Georgie is big into politics and tends to get enraged by many of the debates. The rally attendees began to get aggressive, and several fights broke out. Georgie was so mad because of one of the opposite party's comments, so she took out her lighter and lit the attendee's flag on fire. The cops rush in to find out what happened. Anita tells them:

Bald-faced lie
The flag was burned by the attendee.
The flag was burns by the attendee.

Literal Truths
The flag burned by someone.
The flag burns by someone.

Control Truths
The flag was burned by Georgie.
The flag was burns by Georgie.

(73-78) Bryce just finished his first semester at college, and his parents got him a ticket to fly home for the holidays. Upon arrival, Bryce discovered that his luggage was not at the baggage claim. The airline investigated the matter and discovered that an employee mismarked the bag and it was sent to a different airport. The airline told Bryce:

Bald-faced lie
The luggage was lost because of you.

The luggage was losing because of you.

Literal Truths

The luggage was lost because of someone.

The luggage was losing because of someone.

Control Truths

The luggage was lost because of our employee.

The luggage was losing because of our employee.

(79-84) Jenna works for a large corporate company. Although she knows she is not supposed to, she uses the same password for all her computers, emails, and sites. She also uses the same password for personal and professional use. She responded to a phishing email, and her personal and professional information was compromised. This led to a breach in the company as well. Her boss traced the break to her and questioned her. She said:

Bald-faced lie

The computer was hacked because of Janet.

The computer was hack because of Janet.

Literal Truths

The computer was hacked because of someone.

The computer was hack because of someone.

Control Truths

The computer was hacked because of me.

The computer was hack because of me.

(85-90) Jacqueline had always been a pyromaniac. She played with the campfire, made tiny fires in her house, burned paper over the sink, really anything she could burn, she would. One day, Jacqueline was out behind her neighbor's old barn. She would light a piece of hay and let it burn out. She grabbed a pieced and lit them, but they burned her hand, so she dropped them. The whole barn was engulfed in flames. The neighbor saw her out there earlier and asked her what happened. Jacqueline told him:

Bald-faced lie

The fire was started by lightening.

The fire was starts by lightening.

Literal Truths

The fire started by someone.

The fire starts by someone.

Control Truths

The fire was started by me.

The fire was starts by me.

(91-102) Justin was Wilson's partner in crime. They worked out of Wilson's trailer, making blue meth. They underestimated their production supply and began to sell outside their usual territory. The rival sellers started to get angry and accosted a customer and a suspected seller. They asked the customer where they got their product. The customer and seller told the gang leader:

Bald-faced lie

The drugs were sold by your boys.

The drugs were selling by your boys.

The blue meth was cooked by the Mexican cartel.
The blue meth was cooks by the Mexican cartel.
Literal Truths
The drugs were sold by someone.
The drugs were selling by someone.
The blue meth was cooked by someone.
The blue meth was cooks by someone.
Control Truths
The drugs were sold by the seller.
The drugs were selling by the seller.
The blue meth was cooked by Justin and Wilson.
The blue meth was cooks by Justin and Wilson.

(103-114) Audrey is currently living at her friend Carly's house while her house is being remodeled. Carly does not allow shoes in the house, but Audrey wears them anyway when Carly is not home. Carly already left for work, and Audrey was getting ready to go. As Audrey was leaving the house, she realized she forgot her phone. She ran to grab her phone and left a trail of dirt from her shoes. She was so flustered that when she left, she forgot to lock the door. Carly arrived home before Audrey, and found the front door unlocked and a trail of dirty footprints. Carly asked Audrey what happened when she got home. Audrey said

Bald-faced lie
The door was left unlocked by a burglar.
The door was left unlocking by a burglar.
The shoes were worn by your husband.
The shoes were wear by your husband.
Literal Truths
The door was unlocked by someone.
The door was unlocking by someone.
The shoes were worn by someone.
The shoes were wear by someone.
Control Truths
The door was left unlocked by me.
The door was left unlocking by me.
The shoes were worn by me.
The shoes were wear by me.

(115-120) Gary liked to think of himself as a handyman. One day, Gary's mom called him up to ask him to fix her washer. Gary happily drove down to his mother's house to help her out. He discovered that the washing machine was missing a key piece and had several loose bolts. Gary sent his mother to the store with a description of the missing piece. While she was gone, Gary continued his work, but he forgot to shut off the water. As he was working, he hit the house and faucets. Water rushed out and quickly flooded the laundry room and the rest of the basement. When Gary's mom got home, Gary told her

Bald-faced lie
The house flooded because of you.
The house floods because of you.

Literal Truths

The house flooded because of someone.

The house floods because of someone.

Control Truths

The house flooded because of me.

The house flooding because of me.

(121-126) Steven was leaving the store. As he was backing up, he wasn't paying close attention to the cart return next to his truck. He turned too quickly and hit the passenger door on the cart return, causing significant damage to the truck. When he got home he told his wife:

Bald-faced lie

The truck door was dented because of a stranger.

The truck door was dent because of a stranger.

Literal Truths

The truck door was dented because of an accident.

The truck door was dent because of an accident.

Control Truths

The truck door was dented because of me.

The truck door was dent because of me.

(127-138) Karen has terrible road rage. While Karen was heading to work, a man passed her on a residential road. At the next light, the Karen rear-ended him. Karen was so enraged, so she got out of the car and hit the man's car window with her purse. The impact cracked the window. When the cops arrived on the scene, they asked the witness what happened. The witness said:

Bald-faced lie

Karen ran into the car because she was speeding.

Karen runs into the car because she was speeding.

The window was cracked by the man.

The windows cracking by the man.

Literal Truths

Karen ran into the car because someone was speeding.

Karen runs into the car because someone was speeding.

The window was cracked by someone.

The window was cracking by someone.

Control Truths

Karen ran into the car because the man was speeding.

Karen runs into the car because the man was speeding.

The window was cracked by Karen.

The window was cracking by Karen.

(139-150) Alex was a maintenance man at the local hospital. He was asked to fix the lighting in the lab. Alex mixed up the wires and cut the wire that ran the lab equipment, not the lighting. Several expensive tests were voided due to the error. Alex became so angry at himself that he threw his open water bottle. The water spilled all over the lab's computers, damaging the. Alex did not want to have to pay for the tests to be rerun or the computers, so he said:

Bald-faced lie

The wire was cut by a nurse.
The wire was cuts by a nurse.
The water was spilled by accident.
The water was spill by accident.

Literal Truths

The wire was cut by someone.
The wire was cuts by someone.
The water spilled by someone.
The water spill by someone.

Control Truths

The wire was cut by me.
The wire was cuts by me.
The water was spilled on purpose.
The water was spill on purpose.

(151-156) Miguel was running for class president, and his friend, Miri, was helping with his campaign. Miguel and some of the other students wanted to win so badly, so Miri decided to rig the election so Miguel would win by default. After Miguel was elected, some of the other students overheard Miri talking about how she fixed the election. A student, Joey, reported what he heard to the principal. Miguel told the principal:

Bald-faced lie

The poll was tampered with by Joey.
The poll was tampering with by Joey.

Literal Truths

The poll was tampered with by someone.
The poll was tampering with by someone.

Control Truths

The poll was tampered with by Miri.
The poll was tampering with by Miri.

(157-168) Christian was an employee at a local bank. Christian and his friend, Saul, were both struggling with money, so they decided to rob the bank where Christian worked. Saul entered the building when Christian was working and demanded money. The week prior, Christian disabled the bank's emergency buttons. Christian quickly grabbed a bag and filled it with cash. He handed the bag to Saul. However, a customer called 911, and police arrived shortly after Saul left the premise. They found that the button was disabled, and they asked Christian what happened. Christian said

Bald-faced lie

The button was disabled by another employee.
The button was disables by another employee.
The bank was robbed by a stranger.
The bank was rob by a stranger.

Literal Truths

The button was disabled by someone.
The button was disables by someone.
The bank was robbed by someone.

The bank was rob by someone.

Control Truths

The button was disabled by me.

The button was disables by me.

The bank was robbed by me and Saul.

The bank was rob by me and Saul.

(169-180) Drew and his wife, Sara, needed to pay off a lot of debt. They decided to kidnap the mayor's son for ransom. The mayor paid the ransom to get his son back. Sara dropped off his son at a remote location and Drew picked up the money. The police questioned Sara and Drew. During the interrogation, Sara told the cops:

Bald-faced lie

The ransom was collected by our neighbor.

The mayor was collecting by our neighbor.

The child was kidnapped by my sister.

The child was kidnaps by my sister.

Literal Truths

The ransom was collected by someone.

The ransom was collecting by someone.

The child was kidnapped by someone.

The child was kidnaps by someone.

Control Truths

The ransom was collected by Drew.

The ransom was collecting by Drew.

The child was kidnapped by me.

The child was kidnaps by me.

(181-186) It was Alexa's birthday, and her friends threw her a party. Alexa's best friend bought her a limited edition aged whiskey worth over $150. While at the party, Alexa's boyfriend was dancing and not paying attention. He knocked over the bottle and it broke and spilled all over the floor. Several people heard the noise and went to check it out. Alexa's boyfriend told her:

Bald-Faced Lie

The bottle was shattered by the cat

The bottle was shatter by the cat

Literal Truths

The bottle was shattered by someone

The bottle was shatter by someone

Control Truths

The bottle was shattered by me

The bottle was shatter by me

(187-192) Oscar went to stay at his sister's house for the weekend. While he was there, his sister needed his help to set up the new projector she and her husband, Jim, just bought. His sister ran upstairs while Oscar and Jim started to set up all the materials. Oscar dropped the projector, and the lightbulb cracked. When his sister came back downstairs, Oscar said:

Bald-faced lie

The projector was damaged by your dog.

The projector was damages by your dog.

Literal Truths

The projector was damaged by someone.

The projector was damages by someone.

Control Truths

The projector was damaged by me.

The projector was damages by me.

(193-198) Preston borrowed his brother's car to go pick up the party platter for their father's retirement party. On the way, Preston hit some black ice and hit the median, scratching the front bumper. When Preston returned, he told his brother:

Bald-faced lies

The car was scratched by your wife.

The car was scratching by your wife.

Literal Truths

The car was scratched by someone.

The car was scratching by someone.

Control Truths

The car was scratched by me.

The car was scratching by me.

(199-204) Elizabeth and her friend, April, are avid snowboarders and are excited about the season. April is waiting for her snowboard to be refinished, so Elizabeth lets April borrow hers. April decides to go down a slope with fresh powder. As she descends the hill, she miscalculates a jump. The jump ends up fracturing Elizabeth's snowboard. April returns how home and tells Elizabeth:

Bald-faced lie

Your snowboard was fractured by a stranger.

Your snowboard was fractures by a stranger.

Literal Truths

Your snowboard was fractured by someone.

Your snowboard was fractures by someone.

Control Truths

Your snowboard was fractured by me

Your snowboard was fractures by me.

(205-210) Rose was leaving her friend's house late one night. As she was backing up, she was listening to a message on her phone. She didn't notice her friend's roommate's boyfriend's van was parked on the street partially covering the driveway. Rose hit the van and nicked the back wheel well. Rose left without saying anything and the next day her friend asked if she knew what happened. Rose said:

Bald-faced lie

The van was nicked because of a stranger.

The van was nick because of a stranger.

Literal Truths

The van was nicked because of an accident.

The van was nick because of an accident.

Control Truths

The van was nicked because of me.

The van was nick because of me.

(211-216) Joseph had a lot of medical bills that he needed to pay off. He was also the tax rep for a large company. While doing the large company's taxes, he noticed they had an extra thousand-dollar return. Rather than giving it to the company, Joseph kept it for himself and told the company.

Bald-faced lie

The money was embezzled by the IRS

The money was embezzling by the IRS

Literal Truths

The money was embezzled by someone

The money was embezzling by someone

Control Truths

The money was embezzled by me.

The money was embezzling by me.

(217-222) Sandy was running for mayor, and her friend, Mandy, was helping with her campaign. Mandy and some of the other politicians didn't want Sandy to win, so Mandy decided to help the opponent's campaign by transferring funds to the other electors. Sandy became suspicious and asked Mandy. Mandy said:

Bald-faced lie

The campaign was sabotaged by voters.

The campaign was sabotages by voters.

Literal Truths

The campaign was sabotaged by someone.

The campaign was sabotages by someone.

Control Truths

The campaign was sabotaged by me.

The campaign was sabotages by me.

(223-228) Jordan was the manager of an apartment complex in a snowy area. One Saturday, it snowed three inches, but Jordan did not want to go out and shovel for the residents. Later that day, he received a call from a resident who slipped, fell, and broke her leg since the sidewalks had not been properly cleared. The resident's lawyer asked why the snow wasn't shoveled, and the manager said:

Bald-faced lie

The snow was left because of the residents.

The snow was leave because of the residents.

Literal Truth

The snow was left because of someone.

The snow was leave because of someone.

Control Truth

The snow was left because of me.

The snow was leave because of me.

(229-234) Austin and Dipen are students at a large university. They live in the dorms. Although they know they are not supposed to, they download programs and games onto the school's computers. Austin downloaded a game that contained a virus. The virus allowed hackers to leak thousands of school records. The school tracked the downloaded virus to him and questioned him. He said:

Bald-faced lie

The virus was installed because of Dipen.

The virus was installing because of Dipen.

Literal Truths

The virus was installed because of hackers.

The virus was installing because of hackers.

Control Truths

The virus was installed because of me.

The virus was installing because of me.

(235-246) Nicole and Rayne were masters at sleight-of-hand. Nicole would distract as Rayne pick-pocketed watches, wallets, and anything valuable off strangers. After the stranger would leave, Rayne would pass the stollen goods off to Nicole, who would then travel to different shops to pawn the items. One day, they pick-pocketed a police officer. Rayne handed to products over to Nicole who quickly left. The cop returned and arrested Rayne. Rayne told the detectives:

Bald-faced lie

The goods were pocketed by Nicole.

The goods were pocket by Nicole.

The items were pawned by me.

The items were pawns by me.

Literal Truths

The goods were pocketed by someone.

The goods were pocket by someone.

The items were pawned by someone.

The items were pawns by someone.

Control Truths

The goods were pocketed by me.

The goods were pocket by me.

The items were pawned by Nicole.

The items were pawns by Nicole.

(247-264) Greg and Rosalinda are getting ready. Greg decided to clean their house before the wedding and honeymoon. Greg accidentally broke Rosalinda's expensive hummingbird trinket. While cleaning up, he knocked over a box that had her wedding dress and a bottle of paint. The paint spilled all over the dress. He ran to get help, slipped, and fell into the wedding flowers that Rosalinda's cousin brought by early. When Rosalinda walks in, Greg tells her the following:

Bald-Face Lies

The hummingbird was shattered by your mom.

The hummingbird was shatter by your mom.

The paint was spilled by the flower girl.

The paint was spilling by the flower girl.

The flowers were smashed by the children.

The flowers were smashes by the children.

Literal Truths

The hummingbird was shattered by someone.

The hummingbird was shatter by someone.

The paint was spilled by someone
The paint was spilling by someone.
The flowers were smashed by someone.
The flowers were smashes by someone.

Control Truths

The hummingbird was shattered by me
The hummingbird was shatter by me
The paint was spilled by me
The paint was spilling by me
The flowers were smashed by me.
The flowers were smashes by me.

Appendix C. Letter of Information presented to participants before they agreed to participate in Experiment 1.

The power of language: Perspective differences in deceptive statements

Introduction

You are invited to participate in a research study conducted by Stephanie Crank, a graduate student in the Psychology Department at Utah State University. The purpose of this research is to investigate the interaction of language and the perception of deception. Your participation is entirely voluntary.

As described in more detail below, we will ask you to read several vignettes that are followed by statements that may or may not be deceptive and report on how dishonest you feel the statements to be. Someone like you might be interested in participating because of the increase in media that may or may not be deceptive. Because there are some risks, such as eye strain due to the length of the survey, you may not wish to participate. It is important for you to know that you can stop your participation at any time. More information about all aspects of this study is provided below.

This form includes detailed information on the research to help you decide whether to participate. Please read it carefully and ask any questions you have before you agree to participate.

Procedures

Your participation will involve reading thirty total vignettes followed by 6-18 statements each. The vignettes range in length and detail, with a minimum of 40 words and a maximum of 115 words. The statements will be displayed one at a time followed by a rating questions. Each vignette and corresponding statements will take about 2 minutes to complete. Your total participation in the project is expected to be one hour. If you agree to participate, the researchers will also collect your age and gender identification. We anticipate that 80 people will participate in this research study.

Risks

The risks of participating in this study are minimal and not expected to be greater than experienced in daily life. Some of the questions or statements may cause some individuals to feel uncomfortable, and everyone has the right to omit answers to any questions.

If you have a bad research-related experience or are injured in any way during your participation, please contact the principal investigator of this study right away. You can reach Dr. Chris Warren at chris.warren@usu.edu.

Benefits

Although you will not directly benefit from this study, it has been designed to learn more about deception.

Anonymity

The researchers will make every effort to ensure that the information you provide as part of this study remains anonymous. No identifying information will collected during the course of this study.

We will collect survey data using computer-based data acquisition programs. This data will be securely stored in a restricted-access folder on Box.com, an encrypted, cloud-based storage system. Survey data will be kept for three years after the study is complete, and then it will be destroyed.

Voluntary Participation & Withdrawal

Your participation in this research is entirely voluntary. If you agree to participate now and change your mind while taking the survey, you may exit the browser and your survey will be discarded.

Compensation

You will be compensated $8 through M-Turk's system for your participation.

Study Findings

If you wish to learn the findings of this study, please contact the student researcher at stephanie.crank@aggiemail.usu.edu or the PI at chris.warren@usu.edu.

IRB Review

The Institutional Review Board (IRB) for the protection of human research participants at Utah State University has reviewed and approved this study. If you have questions about the research study itself, please contact the Principal Investigator stephanie.crank@aggiemail.usu.edu. If you have questions about your rights or would simply like to speak with someone other than the research team about questions or concerns, please contact the IRB Director at (435) 797-0567 or irb@usu.edu.

Christopher Warren, Ph.D.	Stephanie D Crank
Principal Investigator	Student Investigator
(435) 797-5704; chris.warren@usu.edu	stephanie.crank@aggiemail.usu.edu

Informed Consent

By checking "I agree to participate in this study and do not have or have answered all questions." you agree to participate in this study. You indicate that you understand the risks and benefits of participation, and that you know what you will be asked to do. You also agree that you have asked any questions you might have, and are clear on how to stop your participation in the study if you choose to do so.

Appendix D. Vignettes and Statements used in Experiment 2.

(1-8: Accident1) George and Rhonda are recently married. George washed Rhonda's wedding dress with his red undergarments. The red undergarments turned the dress pink. When Rhonda got home, George tells her the following:

I didn't wash the load that turned your dress pink.
I didn't washes the load that turned your dress pink.
I didn't wash the load that turned your apparel pink.
I didn't washes the load that turned your apparel pink.
I washed the load that turned your dress pink.
I washes the load that turned your dress pink.
I washed the load that turned your apparel pink.
I washes the load that turned your apparel pink.

(9-16: Crime1) William was texting and driving. He swerved and hit a parked car. When the police arrived, he told them:

I wasn't texting when I hit the car.
I wasn't texts when I hit the car.
I wasn't texting when I hit the automobile.
I wasn't texts when I hit the automobile.
I was texting when I hit the car.
I was texts when I hit the car.
I was texting when I hit the automobile.
I was texts when I hit automobile.

(17-24: Accident2) Lauren surprised her fiancé for his birthday with the help of her roommate, Steph. Steph baked a cake. When Lauren and her fiancé returned home, Lauren told him:

I baked the cake.
I bakes the cake.
I baked the dessert.
I bakes the dessert.
Steph baked the cake.
Steph bakes the cake.
Steph baked the dessert.
Steph bakes the dessert.

(25-32: Accident3) Albert borrowed Sean's skis. Albert fell and broke Sean's skis. Albert returns home and tells Sean:

I didn't break your skis.
I didn't breaking your skis.
I didn't break your snow gear.
I didn't breaking your snow gear.
I broke your skis.
I breaking your skis.
I broke your snow gear.
I breaking your snow gear.

(33-40: Crime2) Kristi went to a rare art silent auction. Kristi found a beautiful, expensive-looking figurine at a rare art silent auction. When no one was looking, she stole the figurine and stashed it in her bag. When bags were checked at the end of the night, the security guard asked if she stole the figurine. She replied:

I didn't steal the figurine.
I didn't stealing the figurine.
I didn't steal the object.
I didn't stealing the object.
I stole the figurine.
I stealing the figurine.
I stole the object.
I stealing the object.

(41-48: Crime3) Georgie and Anita attended a rally. At the rally, Georgie lit a flag on fire. The cops asked Anita what happened. Anita tells them:

Georgie didn't burn the flag.
Georgie didn't burns the flag.
Georgie didn't burn the pennant.
Georgie didn't burns the pennant.
Georgie burned the flag.
Georgie burns the flag.
Georgie burned the pennant.
Georgie burns the pennant.

(49-56: Accident4) Bryce flew home for the holidays. His luggage was not at baggage claims. The airline discovered his luggage had been lost in transit. The airline told Bryce:

We didn't lose your luggage.
We didn't losing your luggage.
We didn't lose your stuff.
We didn't losing your stuff.
We lost your luggage.
We losing your luggage.
We lost your stuff.
We losing your stuff.

(57-64: Accident5) Jenna uses the same password for all her computers, emails, and sites. She responded to a phishing email at work. This led to a breach in the company. Her boss asked what happened, and she said:

It's not my fault the computer was hacked.
It's not my fault the computer was hack.
It's not my fault the machine was hacked.
It's not my fault the machine was hack.
It's my fault the computer was hacked.
It's my fault the computer was hack.
It's my fault the machine was hacked.
It's my fault the machine was hack.

(65-72: Crime4) Jacqueline was playing with matches behind an old barn. She tried to catch one of the hay bales on fire. As it was burning, the sprinklers came on and stopped the flames from spreading. The neighbor later asked what happened, and Jacqueline told him:

I didn't start the fire.

I didn’t starts the fire.
I didn’t start the combustion .
I didn’t starts the combustion.
I started the fire.
I starts the fire.
I started the combustion.
I starts the combustion.

(73-80: Crime5) Wilson was a drug dealer. Wilson was taken into custody by the police. When the police asked Wilson about drugs, Wilson told them:

I don’t know who sells drugs.
I don’t know who selled the drugs.
I don’t know who sells contraband.
I don’t know who selled contraband.
I sell drugs.
I selled drugs.
I sell contraband.
I selled contraband.

(81-88: Accident6) Audrey and Carly are roommates. Audrey forgot her phone as she was leaving for work. She ran back inside and tracked dirt through the house, staining the carpet. Carly asked Audrey what happened when she got home. Audrey said:

I didn’t wear my dirty shoes in the house.
I didn’t wore my dirty shoes in the house.
I didn’t wear my dirty footgear in the house.
I didn’t wore my dirty footgear in the house.
I wore my dirty shoes in the house.
I wear my dirty shoes in the house.
I wore my dirty footgear in the house.
I wear my dirty footgear in the house.

(89-96: Accident7) Gary went to his mom’s house to fix her washing machine. Gary forgot to shut off the main water, and flooded his moms house. When his mom got home, Gary told her:

I didn’t flood the house.
I didn’t floods the house.
I didn’t flood the building.
I didn’t floods the building.
I flooded the house.
I floods the house.
I flooded the building.
I floods the building.

(97-104: Accident8) Steven was leaving the store and accidently turned too soon out of the parking spot. He hit the cart return on the passenger side, denting the car door. When he got home, he told his wife:

I didn’t dent the truck door.
I didn’t dented the truck door.
I didn’t dent the truck entrance.
I didn’t dented the truck entrance.

I dented the truck door.
I dent the truck door.
I dented the truck entrance.
I dent the truck entrance.

(105-112: Crime6) Karen was cut off on the highway. She got angry and purposefully rear-ended the car at a stoplight. When the cops arrived, they asked Karen what happened. She said:

I accidentally hit the car.
I accidentally hitting the car.
I accidentally hit the vehicle.
I accidentally hitting the vehicle.
I purposefully hit the car.
I purposefully hitting the car.
I purposefully hit the vehicle.
I purposefully hitting the vehicle.

(113-120: Accident9) Alex was an electrician at a local hospital. Alex was fixing the lighting in the Radiology department. Alex cut the wire to the X-ray machine instead of the overhead lights. The X-ray machine was ruined. Alex told the hospital:

I didn't cut the wires.
I didn't cuts the wires.
I didn't cut the cords.
I didn't cuts the cords.
I cut the wires.
I cuts the wires.
I cut the cords.
I cuts the cords.

(121-128: Crime7) Miguel was running for mayor. Miguel rigged the election to ensure he would win. A fellow candidate suspected Miguel of rigging it and reported it to the governor. Miguel told the governor:

I didn't tamper with the votes.
I didn't tampering with the votes.
I didn't tamper with the responses.
I didn't tampering with the responses.
I tampered with the votes.
I tampering with the votes.
I tampered with the responses.
I tampering with the responses.

(129-136: Crime8) Christian and Saul worked at a bank. They decided to systematically rob the bank while working. They would each slip a 5, 10, or 20 under their sleeve during some transactions with customers. A co-worker noticed what they were doing and reported them to the police. They told the police:

I don't know who robbed the bank.
I don't know who rob the bank.
I don't know who robbed the institution.
I don't know who rob the institution.
Saul and I robbed the bank.

Saul and I rob the bank.
Saul and I robbed the institution.
Saul and I rob the institution.

(137-144: Accident10) Alexa was given a limited-edition aged whiskey for her birthday. Alexa's boyfriend was dancing and knocked over the bottle, breaking it. Alexa's boyfriend told her:

I didn't break the bottle.
I didn't breaking the bottle.
I didn't break the container.
I didn't breaking the container.
I broke the bottle.
I breaking the bottle.
I broke the container.
I breaking the container.

(145-152: Accident11) Oscar went to his sister's house to help set up her new projector. While she was upstairs, Oscar dropped the projector, and the lightbulb cracked. When his sister came back downstairs, Oscar said:

I didn't damage your projector.
I didn't damages your projector.
I didn't damage your apparatus.
I didn't damages your apparatus.
I damaged your projector.
I damages your projector.
I damaged your apparatus.
I damages your apparatus.

(153-160: Accident12) Preston borrowed his brother's car. There was black ice and Preston hit the median, scratching the front bumper. When Preston returned, he told his brother:

I didn't scratch the bumper.
I didn't scratching the bumper.
I didn't scratch the fender.
I didn't scratching the fender.
I scratched the bumper.
I scratching the bumper.
I scratched the fender.
I scratching the fender.

(161-168: Accident13) April borrowed Elizabeth's camera. She slipped down a hill and hit a rock. The rock cracks Elizabeth's camera lens. April returns and tells Elizabeth:

I didn't crack your camera.
I didn't cracked your camera.
I didn't crack your device.
I didn't cracked your device.
I fractured your camera.
I fracture your camera.
I fractured your device.
I fracture your device.

(169-176: Accident14) Rose was leaving her friend's house late one night. As she was backing up, she accidentally hit her friend's boyfriend's van. When she was asked what happened, she said:

I didn't hit the van.
I didn't hits the van.
I didn't hit the vehicle.
I didn't hits the vehicle.
I hit the van.
I hits the van.
I hit the vehicle.
I hits the vehicle.

(177-184: Crime9) Joseph is a tax rep for a large company. He noticed they had an extra thousand-dollar return. Joseph kept the money for himself, and when questioned, told the company:

I didn't embezzle the money.
I didn't embezzling the money.
I didn't embezzle the assets.
I didn't embezzling the assets.
I embezzled the money.
I embezzling the money.
I embezzled the assets.
I embezzling the assets.

(185-192: Crime10) Sandy was running for mayor, and her friend, Mandy, was helping with the campaign. Mandy transferred 10% of the funds to the other electors' campaigns. Sandy became suspicious and asked Mandy. Mandy said:

I didn't sabotage the campaign.
I didn't sabotages the campaign.
I didn't sabotage the competition .
I didn't sabotages the competition.
I sabotaged the campaign.
I sabotages the campaign.
I sabotaged the competition.
I sabotages the competition.

(193-200: Crime11) Jordan is a manager of an apartment complex, and it is his responsibility to shovel when it gets snowy. One day, he didn't shovel, and a resident slipped and broke her leg. When questioned by the resident's lawyer, Jordan said:

I did shovel the pavement.
I did shoveling the pavement.
I did shovel the surface.
I did shoveling the surface.
I didn't shovel the pavement.
I didn't shoveling the pavement.
I didn't shovel the surface.
I didn't shoveling the surface.

(201-208: Accident15) Dipen lives in the dorms. He downloaded a game that contained a virus on a school computer. The virus leaked thousands of school records. The school traced the virus and questioned Dipen. Dipen said:

I didn't install the virus.
I didn't installing the virus.
I didn't install the infection.
I didn't installing the infection.
I installed the virus.
I installing the virus.
I installed the infection.
I installing the infection.

(209-216: Crime12) Rayne and Nicole pick-pocketed watches, wallets, and rings off strangers in the city. They pick-pocketed a man in a suit. Rayne noticed the man was getting suspicious so she handed the goods to Nicole and Nicole slipped into the crowd. The man stopped Rayne and she told the him:

We didn't pocket the goods.
We didn't pocketed the goods.
We didn't pocket the possessions.
We didn't pocketed the possessions.
We pocketed the goods.
We pocket the goods.
We pocketed the possessions.
We pocket the possessions.

(217-224: Accident16) Greg and Rosalinda are cleaning their house. George accidentally broke Rosalinda's expensive hummingbird trinket. When Rosalinda walks in, Greg tells her the following:

I didn't damage the trinket.
I didn't damaging the trinket.
I didn't damage the decoration.
I didn't damaging the decoration.
I damaged the trinket.
I damaging the trinket.
I damaged the decoration.
I damaging the decoration.

(225-232: Crime13) Weston saw a nice necklace for sale at the supermarket. He was out of money, so he slipped the necklace into his pocket and rushed out of the store. When he got home, his roommate asked if he stole the necklace, as he knew Weston didn't have any money. Weston said:

I didn't steal the necklace.
I didn't steals the necklace.
I didn't steal the jewelry.
I didn't steals the jewelry.
I stole the necklace.
I steals the necklace.
I stole the jewelry.
I steals the jewelry.

(233-240: Crime14) Spencer lives in a city in Kansas near the Colorado border. Marijuana (weed) is legal in Colorado but illegal in Kansas. Spencer often drives to Colorado to pick weed to sell to his friends in Kansas. One of Spencer's friends rats him out to the cops and the cops pull him over as he crosses back over the Kansas boarder. They ask him if he bought any weed while in Colorado. Spencer tells them:

I didn’t buy any weed.
I didn't bought any weed.
I didn’t buy any drugs
I didn’t bought any drugs
I bought some weed.
I buy some weed.
I bought some drugs.
I buy some drugs.

(241-248: Crime15) Julie had a hug crush on Kedin. Kedin was already in a serious relationship with Dani. Julie made fake accounts and followed Dani on all social media platforms. Julie started to spam Dani with messages that called Dani names and threated Dani with violent acts. Dani reported the messages, but Julie continued. Finally, the cops got involved and interrogated Julie. Julie told them:

I didn’t make the fake accounts.
I didn’t making the fake accounts.
I didn’t make the fake identity.
I didn’t make the fake identity.
I made the fake accounts.
I making the fake accounts.
I made the fake identity.
I making the fake identity.

(249-256: Crime16) Devon and some friends decided to explore a dusty, old property just outside their hometown. They noticed the “no trespassing” sign but went to explore anyway. When the cops showed up, they asked Devon if they saw the “no trespassing” sign. He replied:

We didn’t see the warning sign.
We didn’t sees the warning sign.
We didn’t see the warning object.
We didn’t sees the warning object.
We saw the warning sign.
We sees the warning sign.
We saw the warning object.
We sees the warning object.

Appendix E. Letter of Information presented to participants before they agreed to participate in Experiment 2.

The power of language: Continued exploration of perception of deception

Introduction

You are invited to participate in a research study conducted by Stephanie Crank, a graduate student in the Psychology Department at Utah State University. You must be at least 18 years or older and reside in the US. The purpose of this research is to investigate the interaction of language and the perception of deception. Your participation is entirely voluntary.

As described in more detail below, we will ask you to read several vignettes that are followed by a statement that may or may not be deceptive and report on how dishonest you feel the statements to be. Someone like you might be interested in participating because of the increase in media that may or may not be deceptive. Because there are some risks, such as eye strain due to the length of the survey, you may not wish to participate. It is important for you to know that you can stop your participation at any time. More information about all aspects of this study is provided below.

This form includes detailed information on the research to help you decide whether to participate. Please read it carefully and ask any questions you have before you agree to participate.

Procedures

Your participation will involve reading thirty-two total vignettes followed by one statement. The vignettes range in length and detail, with a minimum of 25 words and a maximum of 60 words. The statement will be displayed and you will be asked to rate how deceptive you feel it is. Each vignette and corresponding statement will take about 0.5 minutes to complete. Your total participation in the project is expected to be 20 minutes. If you agree to participate, the researchers will also collect your age and gender identification. We anticipate that 130 people will participate in this research study.

Risks

The risks of participating in this study are minimal and not expected to be greater than experienced in daily life. Some of the questions or statements may cause some individuals to feel uncomfortable, and everyone has the right to omit answers to any questions.

If you have a bad research-related experience or are injured in any way during your participation, please contact the principal investigator of this study right away. You can reach Dr. Chris Warren at chris.warren@usu.edu.

Benefits

Although you will not directly benefit from this study, it has been designed to learn more about deception.

Anonymity

The researchers will make every effort to ensure that the information you provide as part of this study remains anonymous. No identifying information will be collected during the course of this study.

We will collect survey data using computer-based data acquisition programs. This data will be securely stored in a restricted-access folder on Box.com, an encrypted, cloud-based storage system. Survey data will be kept for three years after the study is complete, and then it will be destroyed.

Voluntary Participation & Withdrawal

Your participation in this research is entirely voluntary. If you agree to participate now and change your mind while taking the survey, you may exit the browser and your survey will be discarded.

Compensation

You will be compensated $1.50 through M-Turk's system for your participation.

Study Findings

If you wish to learn the findings of this study, please contact the student researcher at stephanie.crank@aggiemail.usu.edu or the PI at chris.warren@usu.edu.

IRB Review

The Institutional Review Board (IRB) for the protection of human research participants at Utah State University has reviewed and approved this study. If you have questions about the research study itself, please contact the Principal Investigator stephanie.crank@aggiemail.usu.edu. If you have questions about your rights or would simply like to speak with someone other than the research team about questions or concerns, please contact the IRB Director at (435) 797-0567 or irb@usu.edu.

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Informed Consent

By checking "I agree to participate in this study and do not have or have answered all questions." you agree to participate in this study. You indicate that you are older than the age of 18 and reside in the US. You indicate that you understand the risks and benefits of participation, and that you know what you will be asked to do. You also agree that you have asked any questions you might have and are clear on how to stop your participation in the study if you choose to do so.

Appendix F. Vignettes and Statements used in Experiment 3.

George and Rhonda are married with a teenage boy named John. George washed Rhonda's white dress with his red t-shirt. The t-shirt turned the dress pink. When Rhonda got home, George tells her:

The dress was stained by John.
The dress was staining by John.
The apparel was stained by John.
The apparel was staining by John.
The dress was stained by me.
The dress was staining by me.
The apparel was stained by me.
The apparel was staining by me.

William was texting and driving. He swerved and hit a parked car. Another driver, Anne, stopped to see if everything was alright. When the police arrived, William told them:

The car was hit by Anne.
The car was hits by Anne.
The automobile was hit by Anne.
The automobile was hits by Anne.
The car was hit by me.
The car was hits by me.
The automobile was hit by me.
The automobile was hits by me.

Lauren surprised her fiancé for his birthday with the help of her roommate, Steph. Steph baked a cake. When Lauren and her fiancé returned home, Lauren told him:

The cake was baked by me.
The cake was bake by me.
The dessert was baked by me.
The dessert was bake by me.
The cake was baked by Steph.
The cake was bake by Steph.
The dessert was baked by Steph.
The dessert was bake by Steph.

Albert borrowed Sean's skis to go to the resort with Trey. Albert fell and broke Sean's skis. When Albert returned home he told Sean:

Your skis were broken by Trey.
Your skis were break by Trey.
Your gear was broken by Trey.
Your gear was breaks by Trey.
Your skis were broken by me.
Your skis were break by me.
Your gear was broken by me.
Your gear was break by me.

Kristi and Kim went to a jewelry store. When nobody was looking, Kristi stole a necklace and put it in Kim's bag. When they were leaving, a security guard searched them, and found the necklace. Kristi said:

The necklace was stolen by Kim.
The necklace was stealing by Kim.
The adornment was stolen by Kim.
The adornment was stealing by Kim.
The necklace was stolen by me.
The necklace was stealing by me.
The adornment was stolen by me.
The adornment was stealing by me.

Anita and James attended a protest. At the protest, Anita lit a flag on fire. The police asked Anita what happened. Anita tells them:

The flag was burned by James.
The flag was burns by James.
The pennant was burned by James.
The pennant was burns by James.
The flag was burned by me.
The flag was burns by me.
The pennant was burned by me.
The pennant was burns by me.

Bryce and Joe borrowed Alan's universal charger to go on vacation. Bryce lost the charger between destinations. Bryce told Alan:

Your charger was lost by Joe.
Your charger was losing by Joe.
Your gadget was lost by Joe.
Your gadget was losing by Joe.
Your charger was lost by me.
Your charger was losing by me.
Your gadget was lost by me.
Your gadget was losing by me.

Jenna and Liz work at the same company and they frequently use the same laptop. Jenna dropped the laptop and it broke. Her boss asked what happened, and she said:

The computer was broken by Liz.
The computer was break by Liz.
The machine was broken by Liz.
The machine was break by Liz.
The computer was broken by me.
The computer was break by me.
The machine was broken by me.
The machine was break by me.

Jacqueline and Sam were playing with matches behind an old barn. Jacqueline lit a hay bale on fire, and it led to the barn burning down. When the police asked what happened, Jacqueline told them:

The fire was started by Sam.
The fire was starts by Sam.
The combustion was started by Sam.
The combustion was starts by Sam.
The fire was started by me.

The fire was starts by me.
The combustion was started by me.
The combustion was starts by me.

Wilson and Rob were roommates and Wilson was a drug dealer. The police searched their home and found drugs. Wilson said to the police:

The drugs are sold by Rob.
The drugs are selling by Rob.
The contraband is sold by Rob.
The contraband is selling by Rob.
The drugs are sold by me.
The drugs are selling by me.
The contraband is sold by me.
The contraband is selling by me.

Audrey, Carly, and Dan are roommates. One day, Audrey wore her shoes inside and left muddy footprints on the carpet. Carly asked Audrey what happened when she got home. Audrey said:

The shoes were worn by Dan.
The shoes were wear by Dan.
The footgear was worn by Dan.
The footgear was wear by Dan.
The shoes were worn by me.
The shoes were wear by me.
The footgear was worn by me.
The footgear was wear by me.

Gary and Kam went to their mom's house to fix her washing machine. Gary forgot to shut off the main water, and flooded his mom's house. When his mom got home, Gary told her:

The house was flooded by Kam.
The house was floods by Kam.
The building was flooded by Kam.
The building was floods by Kam.
The house was flooded by me.
The house was floods by me.
The building was flooded by me.
The building was floods by me.

Steven and his teenage son Greg were driving through a parking lot. Steven accidently hit a post, denting the car door. When he got home, he told his wife:

The door was dented by Greg.
The door was dent by Greg.
The entrance was dented by Greg.
The entrance was dent by Greg.
The door was dented by me.
The door was dent by me.
The entrance was dented by me.
The entrance was dent by me.

Karen was almost hit while someone was backing up in the parking lot. She got angry and purposefully pushed her cart into the car. When the police arrived, they asked Karen what happened. She said:

The car was hit on accident.
The car was hitting on accident.
The vehicle was hit on accident.
The vehicle was hitting on accident.
The car was hit on purpose.
The car was hitting on purpose.
The vehicle was hit on purpose.
The vehicle was hitting on purpose.

Alex and Joy were electricians at a local hospital. Alex was fixing the lighting in the Radiology department and cut the wire to the X-ray machine instead of the overhead lights. Alex told his boss:

The wires were cut by Joy.
The wires were cuts by Joy.
The cords were cut by Joy.
The cords were cuts by Joy.
The wires were cut by me.
The wires were cuts by me.
The cords were cut by me.
The cords were cuts by me.

Mav was helping Miguel run for mayor. Miguel thought he would lose, so he rigged the election. A fellow candidate suspected Miguel of rigging it and reported it to the governor. When questioned, Miguel told the governor:

The votes were tampered with by Mav.
The votes were tamper with by Mav.
The responses were tampered with by Mav.
The responses were tamper with by Mav.
The votes were tampered with by me.
The votes were tamper with by me.
The responses were tampered with by me.
The responses were tamper with by me.

Christian and Saul worked at a bank. Christian started slipping small bills into his sleeve during transactions. Saul noticed what Christian was doing and reported him to the police. Christian told the police:

The bank was robbed by Saul.
The bank was rob by Saul.
The institution was robbed by Saul.
The institution was rob by Saul.
The bank was robbed by me.
The bank was rob by me.
The institution was robbed by me.
The institution was rob by me.

Kate gave Alexa an expensive crystal vase for her birthday. Alexa's boyfriend was dancing at her birthday party, and he knocked over the bottle, breaking it. Alexa's boyfriend told her:

The vase was broken by Kate.
The vase was breaking by Kate.
The container was broken by Kate.
The container was breaking by Kate.
The vase was broken by me.
The vase was breaking by me.
The container was broken by me.
The container was breaking by me.

Oscar and Kim went to their sister's house to help set up her new projector. While she was upstairs Oscar dropped the projector, and the lightbulb cracked. When his sister came back downstairs, Oscar said:

The projector was damaged by Kim.
The projector was damages by Kim.
The apparatus was damaged by Kim.
The apparatus was damages by Kim.
The projector was damaged by me.
The projector was damages by me.
The apparatus was damaged by me.
The apparatus was damages by me.

Preston borrowed his brother's car to take his friend, Joe, to the store. There was black ice and Preston slid and hit the median, scratching the front bumper. When Preston returned, he told his brother:

The bumper was scratched by Joe.
The bumper was scratch by Joe.
The guard was scratched by Joe.
The guard was scratch by Joe.
The bumper was scratched by me.
The bumper was scratch by me.
The guard was scratched by me.
The guard was scratch by me.

April borrowed Elizabeth's camera to take pictures of Lynn. April slipped walking down a hill and dropped the camera, cracking the camera lens. April returned and told Elizabeth:

Your camera was cracked by Lynn.
Your camera was crack by Lynn.
Your device was cracked by Lynn.
Your device was crack by Lynn.
Your camera was cracked by me.
Your camera was crack by me.
Your device was cracked by me.
Your device was crack by me.

Rose and Cole were leaving their friend's house party late one night. As she was backing up, Rose accidentally hit her friend's motorcycle. When she was asked what happened, she said:

The motorcycle was hit by Cole.
The motorcycle was hits by Cole.
The transportation was hit by Cole.
The transportation was hits by Cole.
The motorcycle was hit by me.
The motorcycle was hits by me.
The transportation was hit by me.
The transportation was hits by me.

Joseph and Sam are tax reps. While helping a customer, Joseph noticed they had an extra thousand-dollar return. Joseph kept the money for himself, and when questioned, told his boss:

The money was embezzled by Sam.
The money was embezzling by Sam.
The assets were embezzled by Sam.
The assets were embezzling by Sam.
The money was embezzled by me.
The money was embezzling by me.
The assets were embezzled by me.
The assets were embezzling by me.

Sandy was running for mayor, and her friends, Mandy and Kate, were helping with the campaign. Mandy did not want Sandy to win and transferred 10% of her campaign funds to another candidate. Sandy became suspicious and asked Mandy about the missing money. Mandy said:

The campaign was sabotaged by Kate.
The campaign was sabotages by Kate.
The competition was sabotaged by Kate.
The competition was sabotages by Kate.
The campaign was sabotaged by me.
The campaign was sabotages by me.
The competition was sabotaged by me.
The competition was sabotages by me.

Jordan and Sue were hanging out by the train tracks. Jordan pulled out a can of spray paint and started to graffiti one of the trains. The police spotted the two leaving the tracks. The police questioned Jordan, and Jordan said:

The graffiti was painted by Sue.
The graffiti was painting by Sue.
The writing was painted by Sue.
The writing was painting by Sue.
The graffiti was painted by me.
The graffiti was painting by me.
The writing was painted by me.
The writing was painting by me.

Dipen lived in a student dormitory with Ash. Dipen downloaded a game that contained a virus onto a school computer. The school traced the virus to Dipen's dorm room. Dipen said:

The virus was installed by Ash.
The virus was installing by Ash.
The infection was installed by Ash.
The infection was installing by Ash.
The virus was installed by me.
The virus was installing by me.
The infection was installed by me.
The infection was installing by me.

Rayne and Jane went to Rayne's grandpa's house. Rayne noticed her grandpa's watch on the counter and pocketed it. Later, Rayne's grandpa asked her if she had seen his watch. Rayne said:

The watch was pocketed by Jane.
The watch was pocket by Jane.
The possession was pocketed by Jane.
The possession was pocket by Jane.
The watch was pocketed by me.
The watch was pocket by me.
The possession was pocketed by me.
The possession was pocket by me.

Greg, Rosalinda, and their son Dan were cleaning their house. Greg accidentally broke Rosalinda's expensive clay sculpture. When Rosalinda walked in, Greg told her the following:

The sculpture was damaged by Dan.
The sculpture was damages by Dan.
The decoration was damaged by Dan.
The decoration was damages by Dan.
The sculpture was damaged by me.
The sculpture was damages by me.
The decoration was damaged by me.
The decoration was damages by me.

While at the store with Nick, Weston saw a nice bracelet for sale. He slipped the necklace into his pocket and rushed out of the store. When he got home, his wife asked if he stole the bracelet. Weston said:

The bracelet was stolen by Nick.
The bracelet was steal by Nick.
The jewelry was stolen by Nick.
The jewelry was steal by Nick.
The bracelet was stolen by me.
The bracelet was steal by me.
The jewelry was stolen by me.
The jewelry was steal by me.

Spencer and his friend John met a girl on campus who turned them down. Upset by the rejection, Spencer started to stalk her. She reported him to Title 9. When questioned Spencer said.

The stalking was done by John.
The stalking was do by John.
The pursuing was done by John.
The pursuing was do by John.
The stalking was done by me.
The stalking was do by me.
The pursuing was done by me.
The pursuing was do by me.

Julie had a crush on Ken who was dating Dani. Julie made a fake social media account to spam Dani hateful messages. Dani reported the messages to the police. Julie told the police:

The account was made by Ken.
The account was making by Ken.
The identity was made by Ken.
The identity was making by Ken.
The account was made by me.
The account was making by me.
The identity was made by me.
The identity was making by me.

Devon and Ben decided to explore an abandoned house. They noticed the “no trespassing” sign. Ben decided not to go, but Devon went to explore anyway. When Devon got home, his parents asked if he went into the abandoned house. He replied:

The trespassing was done by Ben.
The trespassing was do by Ben.
The intrusion was done by Ben.
The intrusion was do by Ben.
The trespassing was done by me.
The trespassing was do by me.
The intrusion was done by me.
The intrusion was do by me.

Jerry and Riley are married with a teenage daughter named Jo. Jerry washed Riley’s yellow shirt with his red jacket. The jacket turned the shirt orange. When Riley got home, Jerry tells her:

The shirt was stained by Jo.
The shirt was staining by Jo.
The garment was stained by Jo.
The garment was staining by Jo.
The shirt was stained by me.
The shirt was staining by me.
The garment was stained by me.
The garment was staining by me.

Bill was on the phone while driving. He swerved and hit a parked motorcycle. Another driver, Ali, stopped to see if everything was alright. When the police arrived, Bill told them:

The motorcycle was hit by Ali.
The motorcycle was hits by Ali.
The chopper was hit by Ali.
The chopper was hits by Ali.
The motorcycle was hit by me.
The motorcycle was hits by me.
The chopper was hit by me.
The chopper was hits by me.

Lilly surprised her sister for his birthday with the help of her brother, Stew. Stew baked a pie. When Lilly’s sister returned home, Lilly told her:

The pie was baked by me.
The pie was bake by me.
The tart was baked by me.
The tart was bake by me.
The pie was baked by Stew.
The pie was bake by Stew.
The tart was baked by Stew.
The tart was bake by Stew.

Allan borrowed Steve’s sled to go to the hills with Tim. Allan hit a jump and broke Steve’s sled. When Alan returned home he told Steve:

Your sled was broken by Tim.
Your sled was break by Tim.
Your luge was broken by Tim.
Your luge was breaks by Tim.
Your sled was broken by me.
Your sled was break by me.
Your luge was broken by me.
Your luge was break by me.

Kate and Kyle went to a antique store. When nobody was looking, Kate stole a rare coin and put it in Kyle’s bag. When they were leaving, a security guard searched them, and found the coin. Kristi said:

The coin was stolen by Kyle.
The coin was stealing by Kyle.
The piece was stolen by Kyle.
The piece was stealing by Kyle.
The coin was stolen by me.
The coin was stealing by me.
The piece was stolen by me.
The piece was stealing by me.

Annie and Jay attended a rally. At the rally, Annie lit a banner on fire. The police asked Annie what happened. Annie tells them:

The banner was burned by Jay.
The banner was burns by Jay.

The streamer was burned by Jay.
The streamer was burns by Jay.
The banner was burned by me.
The banner was burns by me.
The streamer was burned by me.
The streamer was burns by me.

Bobby and Jill borrowed Adam's favorite book while going on a road trip. Bobby lost the book at hotel. Bobby told Adam:

Your book was lost by Jill.
Your book was losing by Jill.
Your text was lost by Jill.
Your text was losing by Jill.
Your book was lost by me.
Your book was losing by me.
Your text was lost by me.
Your text was losing by me.

Jackie and Lynn work at the same company and they frequently use the same iPad. Jackie dropped the iPad and it broke. His boss asked what happened, and he said:

The iPad was broken by Lynn.
The iPad was break by Lynn.
The device was broken by Lynn.
The device was break by Lynn.
The iPad was broken by me.
The iPad was break by me.
The device was broken by me.
The device was break by me.

Teenage friends, John and Kim, were playing behind an old shed. John brought a pack of cigarettes to smoke, but Kim refused. The owner of the shed caught the teenagers and noticed a cigarette butt on the ground. John told the owner:

The cigarette was smoked by Sam.
The cigarette was smokes by Sam.
The cubeb was smoked by Sam.
The cubeb was smokes by Sam.
The cigarette was smoked by me.
The cigarette was smokes by me.
The cubeb was smoked by me.
The cubeb was smokes by me.

Will and Ron were roommates and Will sold guns without background checks. The police searched their home and found the guns. Will said to the police:

The guns are sold by Ron.
The guns are selling by Ron.
The weapons are sold by Ron.
The weapons are selling by Ron.
The guns are sold by me.
The guns are selling by me.
The weapons are sold by me.

The weapons are selling by me.

Annie, Casey, and Don are roommates. One day, Annie wore her work boots inside and left oil stains on the carpet. Casey asked Annie what happened when she got home. Annie said:

The boots were worn by Don.
The boots were wear by Don.
The mukluks were worn by Don.
The mukluks were wear by Don.
The boots were worn by me.
The boots were wear by me.
The mukluks were worn by me.
The mukluks were wear by me.

Jerry and Paul went to their dad's house to fix his dishwasher. Gary forgot to shut off the main water, and flooded his dad's kitchen. When his dad got home, Jerry told him:

The kitchen was flooded by Paul.
The kitchen was floods by Paul.
The room was flooded by Paul.
The room was floods by Paul.
The kitchen was flooded by me.
The kitchen was floods by me.
The room was flooded by me.
The room was floods by me.

Sarah and her teenage daughter Liz were driving down a narrow street under construction. Sarah accidently hit a cone, denting the tire rim. When she got home, she told her husband:

The rim was dented by Liz.
The rim was dent by Liz.
The frame was dented by Greg.
The frame was dent by Greg.
The rim was dented by me.
The rim was dent by me.
The frame was dented by me.
The frame was dent by me.

Kim was almost hit while someone was backing up leaving church. She got angry and purposefully hit the Jeep with her purse. When the police arrived, they asked Kim what happened. She said:

The Jeep was hit on accident.
The Jeep was hitting on accident.
The buggy was hit on accident.
The buggy was hitting on accident.
The Jeep was hit on purpose.
The Jeep was hitting on purpose.
The buggy was hit on purpose.
The buggy was hitting on purpose.

Archie and Jill were students at a university. Archie was cutting research material near the EEG caps. Archie cut one of the EEG caps. Archie told his advisor:

The cap was cut by Jill.
The cap was cuts by Jill.
The hat was cut by Jill.
The hat was cuts by Jill.
The cap was cut by me.
The cap was cuts by me.
The hat was cut by me.
The hat was cuts by me.

Mike was helping Daniel run for class president. Daniel thought he would lose, so he rigged the election. A fellow classmate suspected Daniel of rigging it and reported it to the principal. When questioned, Daniel told the principal:

The election was tampered with by Mike.
The election was tamper with by Mike.
The decision was tampered with by Mike.
The decision tamper with by Mike.
The election was tampered with by me.
The election was tamper with by me.
The decision was tampered with by me.
The decision was tamper with by me.

Cam and Joe worked at a store. Cam started slipping small bills into his sleeve during transactions. Joe noticed what Cam was doing and reported him to the manager. Cam told the manager:

The store was robbed by Joe.
The store was rob by Joe.
The market was robbed by Joe.
The market was rob by Joe.
The store was robbed by me.
The store was rob by me.
The market was robbed by me.
The market was rob by me.

Kris gave Alex an expensive glass collection for his birthday. Alex's girlfriend was dancing at his birthday party, and she knocked over the glass collection, breaking one of the glasses. Alex's girlfriend told him:

The glass was broken by Kris.
The glass was breaking by Kris.
The chalice was broken by Kris.
The chalice was breaking by Kris.
The glass was broken by me.
The glass was breaking by me.
The chalice was broken by me.
The chalice was breaking by me.

Omar and Jim went to their brother's house to help set up his new chandelier. While he was downstairs Omar dropped the chandelier, and it cracked. When his brother came back upstairs, Omar said:

The chandelier was damaged by Jim.
The chandelier was damages by Jim.

The fixture was damaged by Jim.
The fixture was damages by Jim.
The chandelier was damaged by me.
The chandelier was damages by me.
The fixture was damaged by me.
The fixture was damages by me.

Priya borrowed her dad's car to take her friend, Sam, to the store. There was black ice and Priya slid and hit the median, scratching the side mirror. When Priya returned, she told her dad:

The mirror was scratched by Sam.
The mirror was scratch by Sam.
The reflector was scratched by Sam.
The reflector was scratch by Sam.
The mirror was scratched by me.
The mirror was scratch by me.
The reflector was scratched by me.
The reflector was scratch by me.

Angie and Kate borrowed Steph's phone to call their sister. Angie tripped walking up the steps and dropped the phone, cracking the screen. Angie returned and told Steph:

Your phone was cracked by Kate.
Your phone was crack by Kate.
Your mobile was cracked by Kate.
Your mobile was crack by Kate.
Your phone was cracked by me.
Your phone was crack by me.
Your mobile was cracked by me.
Your mobile was crack by me.

Rylie and Ken were leaving their friend's graduation party late one night. As he was backing up, Rylie accidentally hit his friend's mailbox. When he was asked what happened, he said:

The mailbox was hit by Ken.
The mailbox was hits by Ken.
The letter drop was hit by Ken.
The letter drop was hits by Ken.
The mailbox was hit by me.
The mailbox was hits by me.
The letter drop was hit by me.
The letter drop was hits by me.

Jim and Ann are stockbrokers. While helping a customer, Jim noticed they made an extra two percent return. Jim transferred the stock for himself, and when questioned, told his boss:

The stock was embezzled by Ann.
The stock was embezzling by Ann.
The capital was embezzled by Ann.
The capital was embezzling by Ann.
The stock was embezzled by me.

The stock was embezzling by me.
The capital was embezzled by me.
The capital was embezzling by me.

Sally was planning a charity event, and her friends, Miles and Pam, were helping with the event. Miles did not want Sally to host the charity so he transferred 10% of her event funds out of her account. Sally became suspicious and asked Miles about the missing money. Miles said:

The event was sabotaged by Pam.
The event was sabotages by Pam.
The drive was sabotaged by Pam.
The drive was sabotages by Pam.
The event was sabotaged by me.
The event was sabotages by me.
The drive was sabotaged by me.
The drive was sabotages by me.

George and Mike were hanging out by the abandoned warehouse. George pulled out a knife and started to carve his initials into the side of the building. The police spotted the two leaving the warehouse. The police questioned George, and George said:

The initials were carved by Mike.
The initials were carving by Mike.
The characters were carved by Mike.
The characters were carving by Mike.
The initials were carved by me.
The initials were carving by me.
The characters were carved by me.
The initials were carving by me.

Don lived in military housing with All. Don used All's computer to leak classified documents. The military traced the leak to Don and All's room. Don said:

The document was leaked by All.
The document was leaking by All.
The archive was leaked by All.
The archive was leaking by All.
The document was leaked by me.
The document was leaking by me.
The archive was leaked by me.
The archive was leaking by me.

Merideth and Jack went to Merideth's grandma's house. Merideth noticed her grandma's rare fossil on the table and put it in her backpack. Later, Merideth's grandma asked her if she had seen her fossil. Merideth said:

The fossil was stolen by Jack.
The fossil was steal by Jack.
The relic was stolen by Jack.
The relic was steal by Jack.
The fossil was stolen by me.
The fossil was steal by me.
The relic was stolen by me.

The relic was steal by me.

Gary, Rose, and their daughter Pam were cleaning their garage. Rose accidentally broke Gary's tablesaw. When Gary walked in, Rose told him the following:

The saw was damaged by Pam.
The saw was damages by Pam.
The blade was damaged by Pam.
The blade was damages by Pam.
The saw was damaged by me.
The saw was damages by me.
The blade was damaged by me.
The blade was damages by me.

While at the farmer's market with Nate, William saw a nice anklet for sale. He slipped the anklet into his pocket and rushed out of the farmer's market. When he got home, his wife asked if he stole the anklet. William said:

The anklet was stolen by Nate.
The anklet was steal by Nate.
The chain was stolen by Nate.
The chain was steal by Nate.
The anklet was stolen by me.
The anklet was steal by me.
The chain was stolen by me.
The chain was steal by me.

Silvia and her friend Joan met a boy on campus who turned them down. Upset by the rejection, Silvia started to harass him. He reported her to Title 9. When questioned Silvia said.

The harassing was done by Joan.
The harassing was do by Joan.
The disturbing was done by Joan.
The disturbing was do by Joan.
The harassing was done by me.
The harassing was do by me.
The disturbing was done by me.
The disturbing was do by me.

Jane had a crush on Mel who was dating Dave. Jane downloaded ghost texting apps to spam Dave hateful messages. Dave reported the messages to the police. Jane told the police:

The texts were sent by Mel.
The texts were send by Mel.
The chats were sent by Mel.
The chats were send by Mel.
The texts were sent by me.
The texts were send by me.
The chats were sent by me.
The chats were send by me.

Dean and Bev decided to hunt in a fenced off area. They noticed the “no hunting” sign. Bev decided not to go, but Dean went to hunt anyway. When Dean got home, his parents asked if he hunted in the restricted area. He replied:

The hunting was done by Bev.
The hunting was do by Bev.
The shooting was done by Bev.
The shooting was do by Bev.
The hunting was done by me.
The hunting was do by me.
The shooting was done by me.
The shooting was do by me.

Appendix G. The Informed Consent given to participants before they agreed to participate in Experiment 3.

The Power of Language: Electrophysiological Markers of the Perception of Deception

Introduction

You are invited to participate in a research study conducted by Christopher Warren, Ph.D., an assistant professor in Psychology Department at Utah State University. The purpose of this research is to examine how individuals perception of deception is impacted by mistakes in language. Your participation is entirely voluntary.

This form includes detailed information on the research to help you decide whether to participate. Please read it carefully and ask any questions you have before you agree to participate.

Procedures

Your participation will involve reading 64 total vignettes followed by 2 statements (for a total of 128 statements). The vignettes range in length and detail, with a minimum of 25 words and a maximum of 40 words. The statements will be displayed phrase-by-phrase, and you will be asked to rate how deceptive you feel it is.

While you read each vignette and statement, you will be connected to an electroencephalograph (EEG) which will record the brain potentials. This involves wearing an electrode cap that will record electrical activity at the surface of your scalp and using a conductive gel to make the connection between the electrodes and the scalp. You will be able to wash your hair and scalp after the procedure. Once all the electrodes are set up and recording properly, the task will begin.

It takes approximately one hour to set up the EEG. Each vignette and corresponding statement will take about 1 minute to complete. Your total participation in the project is estimated to take 2 hours. We anticipate that 20 people will participate in this research study.

Risks

This is a minimal risk research study. That means that the risks of participating are no more likely or serious than those you encounter in everyday activities. Collecting EEG data involves no significant risk of any type of injury. You will be required to wear an EEG cap that electrodes will be connected to. In order for the electrodes to record your brain activity, a conductance gel will be used between the electrode and your scalp.

The foreseeable risks or discomforts include minor discomfort due to the electrode conductance gel and minor discomfort while applying the gel to the scalp. There is a small chance that you may have a reaction to this gel. In order to minimize those risks, the researcher will test the gel on the back of your hand before applying it to your scalp. The researchers will take their time applying the gel and electrodes to prevent any discomfort from the application. In addition, during breaks, the researchers will check to assure that you remain comfortable throughout the experiment.

If you have a bad research-related experience, please the principal investigator, Christopher Warren, of this study right away at 435-265-5704 or chris.warren@usu.edu

Benefits

Although you will not directly benefit from this study, it has been designed to learn more about the electrophysiological markers of the perception of deception. This experiment will further our understanding of how people make decisions about deception in text-based formats. This work has significant implications for the criminal justice field, personnel selection, and the general public. This will aid in the detection of deception online.

COVID-19 Disclosures

Risks associated with contracting COVID-19 cannot be eliminated. Please carefully consider whether you are comfortable participating in person, particularly if you or someone in your home is at higher risk of serious illness from COVID-19.

COVID-19 vaccination is strongly encouraged, but not required, for Utah State University employees and students. This means that we cannot guarantee that the people you interact with in this research project are vaccinated. Masking or using other face coverings is strongly encouraged, but not required, for Utah State University employees and students. This means that we cannot guarantee that the people you interact with in this research project will wear a face covering. Researchers and fellow participants are not required to share vaccination information with you or to wear a facial covering, unless this research is not on USU's campus and the site where it will occur does require face coverings or vaccines. Research participation is always completely voluntary, and you can decline or stop participating at any time. Below, you will be permitted to request certain safety accommodations from the research team, but please know that they are not required to comply.

The researchers in this project are taking the following steps to ensure your safety and comfort during the in-person portions of this research project:

- Researchers are vaccinated. Researchers will maintain appropriate social distancing unless when absolutely necessary such as helping participants or setting up equipment.
- The lab will be sanitized after each participant and when each researcher uses the lab.
- Researchers will wash their hands after each session and will wear gloves when setting up the electrophysiological equipment.

Confidentiality

The researchers will make every effort to ensure that the information you provide as part of this study remains confidential. Your identity will not be revealed in any publications, presentations, or reports resulting from this research study. We will collect your information through E-prime 3.0 software (Psychology Software Tools, Pittsburgh, PA) and acti64 Champ System (BrainVision, Morrisville, NC). This form will be kept separately from you behavioral and electrophysiological data. De-identified data (your behavioral data and electrophysiological data) will be securely stored in a restricted-access folder on Box.com, an encrypted, cloud-based storage system. This consent form will be stored in a locked drawer in a restricted access office. De-identified data will be kept indefinitely. This form will be kept for three years after the study is complete, and then it will be destroyed.

It is unlikely, but possible, that others (Utah State University, or state or federal officials) may require us to share the information you give us from the study to ensure that the research was conducted safely and appropriately. We will only share your information if law or policy requires us to do so.

Voluntary Participation & Withdrawal

Your participation in this research is completely voluntary. If you agree to participate now and change your mind later, you may withdraw at any time by telling the researcher you want to stop. If you choose to withdraw after we have already collected information about you, you will have the option of asking us to delete your data. The researchers may choose to terminate your participation if you are not taking the research seriously or acting in good faith. If the researcher decides to terminate your participation, they will do so by notifying you that the experiment is over.

Compensation

If you are eligible to receive SONA credit, you will receive 3 SONA credits (1 credit per hour) for your participation. IF you choose to stop the study, or for some reason refuse to take the task seriously, you will receive 1.5 SONA credit. If we decide to stop the experiment due to any sort of technical difficulties, you will receive the full 3 SONA credits.

IRB Review

The Institutional Review Board (IRB) for the protection of human research participants at Utah State University has reviewed and approved this study. If you have questions about the research study itself, please contact the Principal Investigator at 435-265-5704 or chris.warren@usu.edu. If you have questions about your rights or would simply like to speak with someone other than the research team about questions or concerns, please contact the IRB Director at (435) 797-0567 or irb@usu.edu.

Dr. Chris Warren	Stephanie D Avila
Principal Investigator	Student Investigator
(435) 265-5704 chris.warren@usu.edu	stephanie.crank@usu.edu

Informed Consent

By signing below, you agree to participate in this study. You indicate that you understand the risks and benefits of participation, and that you know what you will be asked to do. You also agree that you have asked any questions you might have, and are clear on how to stop your participation in the study if you choose to do so. Please be sure to retain a copy of this form for your records.

______________________	___________________________	__________
Participant’s Signature	Participant’s Name, Printed	Date

COVID-19 Safety Requests

Please note that the research team is not required to comply with these requests, but many researchers are happy to oblige where possible. The research team will inform you if they are unable to commit to any of your selections. You may decline to participate or withdraw your participation at any time.

- ☐ I would like the researchers I interact with to be up-to-date on their COVID-19 vaccines (two weeks after a booster dose of the vaccine)
- ☐ I would like the researchers I interact with to use a facial covering.
- ☐ I would like the researchers I interact with to use a facial covering only if they are not up-to-date on their COVID-19 vaccines (two weeks past a booster dose)
- ☐ I would like the researchers I interact with to take additional safety measures related to COVID-19: ________________________________

Appendix H. The demographics questionnaire provided to participants in Experiment 3.

How old are you? _________

What is your gender?

Man

Woman

Non-binary

Other

What is your race?

White

African American/Black

American Indian/Native Alaskan

Asian

Native Hawaiian/Other Pacific Islander

Latinx

Mixed

Other

Appendix I. The debriefing form given to participants in Experiment 3 after data collection.

Study Debriefing

Introduction

Thank you for participating in this EEG/ERP study focused on understanding the perception of deceptive statements. Your contribution is invaluable in advancing our understanding of how the human brain processes deceptive information. This debriefing procedure aims to provide you with a comprehensive overview of the study, address any questions or concerns you might have, and gather feedback about your experience during the experiment.

Study Overview

The goal of the study was to investigate how individuals perceive and process deceptive statements using an event-related potential paradigm. The aim is to identify specific brain responses associated with processing deception and uncover potential differences in neural activity when encountering truthful versus deceptive information.

If you would like to withdraw your data from the study, please check the box below and sign.

☐ Name:____________________ Signature: _____________________________

Now that you have the full information about the study, if you would like to remain a part of the study, we invite you to answer several brief questions below regarding your experience.

Your Experience

We would greatly appreciate your feedback on your experience during the experiment.

1. How would you rate your overall experience with the experiment on a scale of 1 to 5, where 1 is terrible and 5 is wonderful? ___________
2. How challenging did you find it to distinguish between truthful and deceptive statements on a scale of 1 to 5, where 1 is extremely challenging and 5 is not challenging at all? ___________
3. How difficult was it to maintain attention on a scale of 1 to 5, where 1 is very challenging and 5 is not challenging at all? ___________
4. Were there any external factors or distractions that influenced your experience during the experiment?
5. How hard was it to remember the vignette while making your judgment on a scale of 1 to 5, where 1 is it was very difficult to remember and 5 is it was not difficult at all to remember? ____________

Contact Information

If you have any questions, concerns or thoughts about the study, please do not hesitate to contact us. You can reach us at stephanie.crank@usu.edu or chris.warren@usu.edu

Appendix J. R-Markdown containing the code used to analyze the data and additional tables and figures.

Contents

List of Tables

List of Figures

Preparation

Abbreviations for data

- Indentification
    - `id_per` Participant ID
    - `id_vin` Vignette ID
- IVs/Predictor Variables
    - `TruthCon` Type of Lie
    - `SynCon` Syntax Error
    - `SemCon` Semantic Fluency
- EEG/ERP Variables
    - `N400_amp` Semantic N400
    - `P600_amp` Syntactic P600
    - `Lies_amp` Exploratory Truth vs Lies ERP
- Covariates
    - `age`, years
    - `gender`, Male or Female
- DV: deception rating
    - `decept_rate`

Abbreviations for Model Labels

- `me` Main Effect
- `int` Interaction
- `c4` Controlling for
- `xint` Cross-lelvel interaction

Load Packages

```r
library(tidyverse)
library(readxl)
library(pander)
library(furniture)
library(stargazer)    # display nice tables: summary & regression
library(texreg)       # Convert Regression Output to LaTeX or HTML Tables
library(gridExtra)    # place ggplots together as one plot
library(psych)        # contains some useful functions, like headTail
library(car)          # Companion to Applied Regression
library(nlme)         # non-linear mixed-effects models
library(lme4)         # Linear, generalized linear, & nonlinear mixed models
library(lmerTest)     # Tests on lmer objects
library(optimx)       # Different optimizers to solve mlm's
library(performance)  # icc and r-squared functions **NEWER**
library(interactions) # interaction plots **NEWER**
library(HLMdiag)      # Diagnostic Tools for for MLM
library(sjstats)      # ICC calculations
library(viridis)
library(rstatix)
library(emmeans)
library(ggpubr)
library(finalfit)
library(Matrix)
library(pBrackets)
library(MOTE)
library(gt)
library(magick)
```

APA Formatting Functions

P-Values

```
pformat <- function(x, digits = 3) {
  ncode <- paste0("%.", digits, "f")
  y <- sub("^(-?)0.", "\\1.", sprintf(ncode, x))
  z <- case_when(x > .050 ~ paste0("p = ", y),
                 x > .010 ~ paste0("p = ", y, "*"),
                 x > .001 ~ paste0("p = ", y, "**"),
                 x == .001 ~ "p = .001***",
                 x < .001 ~ "p < .001***")
  z
}
```

```
pformat(0.1) #Checking p-value format
```

```
[1] "p = .100"
```

2-decimal Places

```
apa2 <- function(x){
  MOTE::apa(value = x,
            decimals = 2,
            leading = TRUE)
}
```

```
apa2(0.2364)
```

```
[1] "0.24"
```

Tables

```
gt_apa <- function(x, ...) {
  gt(x, ...) %>%
    tab_options(

      table.background.color = "white",

      table.border.top.color = "white",

      table.border.bottom.color = "white",

      heading.title.font.size = px(16),

      column_labels.border.top.width = 3,

      column_labels.border.top.color = "black",

      column_labels.border.bottom.width = 3,

      column_labels.border.bottom.color = "black",

      table_body.border.bottom.color = "black",

      table.width = pct(100)

    ) %>%

    cols_align(align="center") %>%

    tab_style(

      style = list(

        cell_borders(

          sides = c("top", "bottom", "left", "right"),

          color = "white",

          weight = px(1)

        ),

        cell_text(

          align="center"

        ),

        cell_fill(color = "white", alpha = NULL)

      ),
```

```
      locations = list(cells_body(columns = everything(),

                                  rows = everything()),

                       cells_stub()

      )

    ) %>%

    tab_style(

      style = cell_text(align = "left"),

      locations = cells_stub()

    ) %>%

    opt_align_table_header(align = "left") %>%

    gt::sub_missing(columns = everything(),

                    missing_text = "")

}
```

```
knit_gt_apa <- function(gt, caption, lab) {
  gt <- gt::as_latex(gt)
  cap <- paste0("\\caption{", caption, "}\n \\label{tab:", lab, "}\\\\")
  latex <- strsplit(gt[1], split = "\n")[[1]]
  latex <- c(latex[1], cap, latex[-1])
  latex <- paste(latex, collapse = "\n")
  gt[1] <- latex
  return(gt)
}
```

Experiment 1 Analysis

Load Data

```
psych::headTail(data.long)
```

```
  id_per id_vin id_stt age gender TruthCon    SynCon decept_rate
1      1     v1     s1  28  Woman      BFL   Correct           6
2      1     v1     s2  28  Woman      BFL Incorrect           5
3      1     v1     s3  28  Woman      BFL   Correct           7
4      1     v1     s4  28  Woman      BFL Incorrect           5
5   <NA>   <NA>   <NA> ...   <NA>     <NA>      <NA>         ...
6     85    v30   s261  28    Man       CT   Correct           1
7     85    v30   s262  28    Man       CT Incorrect           1
8     85    v30   s263  28    Man       CT   Correct           1
9     85    v30   s264  28    Man       CT Incorrect           1
```

Sample Size

N = 85 participants with a total of 22440 deception ratings/statements.

```
data.long %>%
  dplyr::group_by(id_per) %>%
  dplyr::tally() %>%
  dplyr::ungroup() %>%
  dplyr::select(n) %>%
  table %>%
  addmargins()
```

```
n
264 Sum
 85  85
```

```
nrow(data.long)
```

```
[1] 22440
```

Basic Descriptives

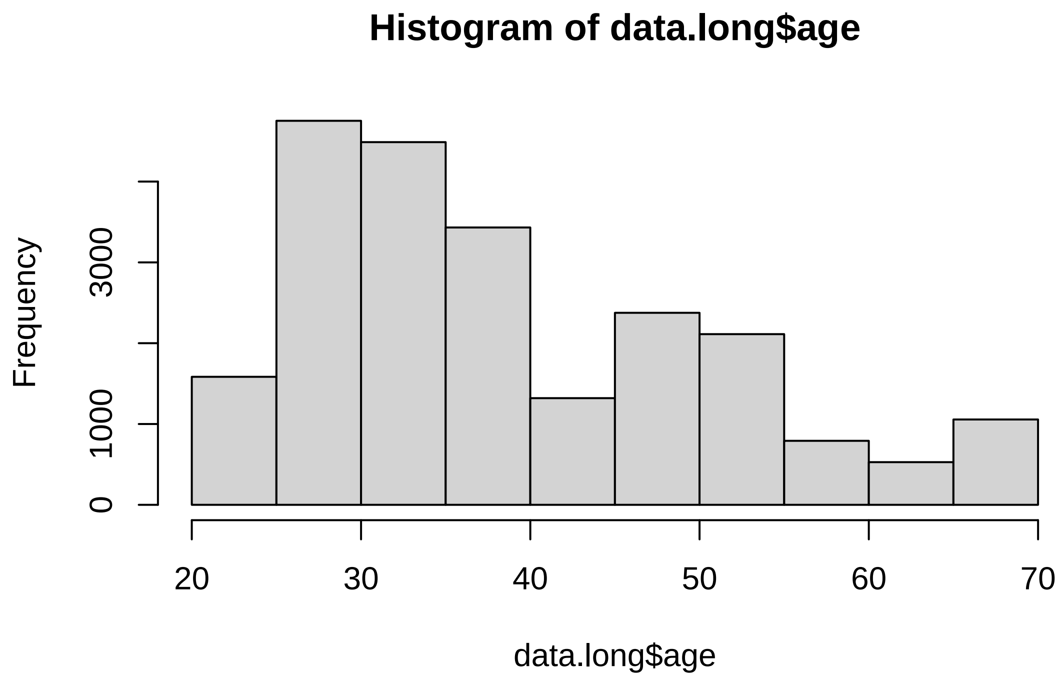
```
#Mean, Median, and Quartiles of overall deception ratings
data.long %>%
  dplyr::select(decept_rate) %>%
  summary()
```

```
  decept_rate
 Min.   :1.000
 1st Qu.:2.000
 Median :5.000
 Mean   :4.347
 3rd Qu.:6.000
 Max.   :7.000
 NA's   :107
```

```
#Basic Descriptives of Age
data.long %>%
  dplyr::select(age) %>%
  summarise(mean(age),
            sd(age),
            median(age))
```

```
# A tibble: 1 x 3
  `mean(age)` `sd(age)` `median(age)`
        <dbl>     <dbl>         <dbl>
1        39.4      11.9            36
```

```
hist(data.long$age)
```


Histogram of data.long$age
Frequency
0
1000
3000
20
30
40
50
60
70
data.long$age

Descriptive Statistical Analysis

Means by Independent Variables

```
data.long %>%
  dplyr::group_by(id_per, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 1 Aggregated Deception Rates by Statement
                    Type")
```

Table 1
Experiment 1 Aggregated Deception Rates by Statement Type

	BFL	MLT	CT
	n = 85	n = 85	n = 85
Deception Rating, participant mean			
	5.76 (0.91)	4.54 (0.94)	2.85 (1.59)

```
data.long %>%
  dplyr::group_by(id_per, SynCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ SynCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 1 Aggregated Deception Rates by Syntax
                    Error")
```

Table 2
Experiment 1 Aggregated Deception Rates by Syntax Error

	Correct	Incorrect
	n = 85	n = 85
Deception Rating, participant mean		
	4.27 (0.73)	4.32 (0.76)

```
data.long %>%
  dplyr::group_by(id_per, SynCon, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate, na.rm = FALSE)) %>%
  dplyr::ungroup() %>%
  tidyr::pivot_wider(names_from = c(SynCon),
                     values_from = m) %>%
  furniture::table1(Correct,
                    Incorrect,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 1 Aggregated Deception Rates by Syntax
                    Error per Statement Type")
```

Table 3

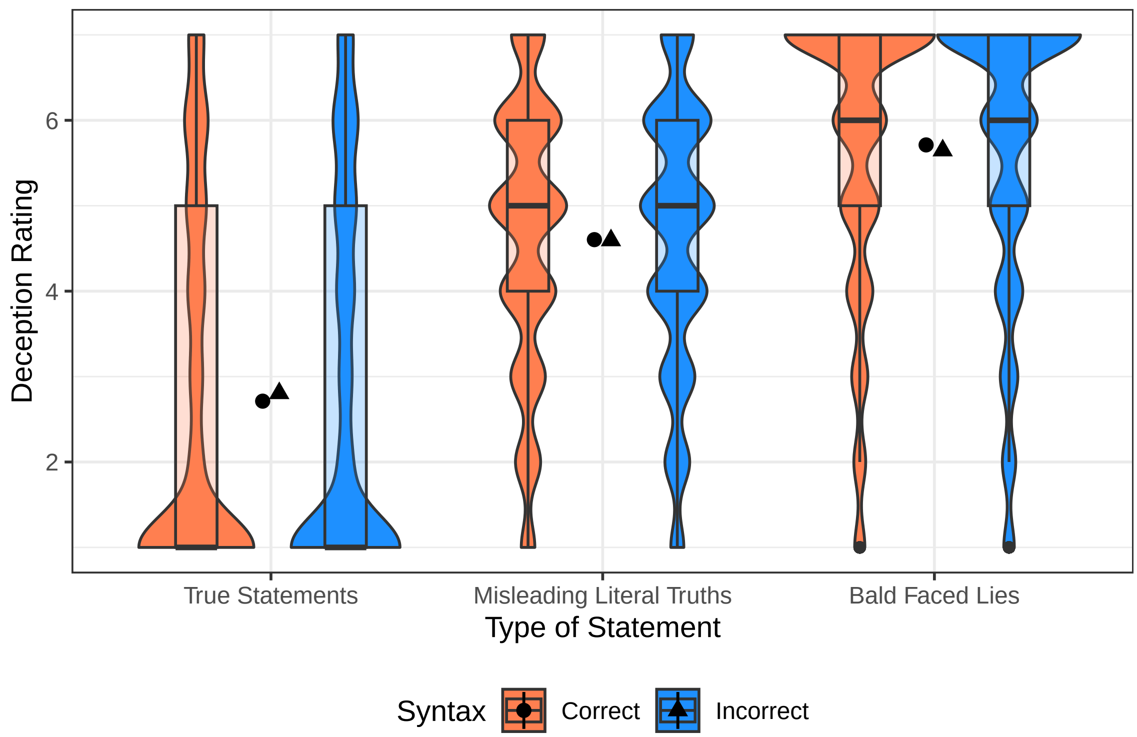
Experiment 1 Aggregated Deception Rates by Syntax Error per Statement Type

	BFL	MLT	CT
	n = 85	n = 85	n = 85
Correct			
	5.75 (1.00)	4.57 (0.96)	2.69 (1.52)
Incorrect			
	5.69 (0.95)	4.56 (0.95)	2.85 (1.61)

```
data.long %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                factor(levels = c("CT", "MLT", "BFL"),
                       labels = c("True Statements",
                                  "Misleading Literal Truths",
                                  "Bald Faced Lies"))) %>%
  ggplot(aes(x = TruthCon,
             y = decept_rate,
             fill = SynCon,
             group = interaction(SynCon, TruthCon))) +
  geom_violin() +
  scale_fill_manual(values = c("coral", "dodgerblue")) +
  geom_boxplot(width = .25,
               alpha = .25,
               position = position_dodge(width = .9)) +
  stat_summary(aes(shape = SynCon),
               color = "black",
               size = .5,
               position = position_dodge(width = .1)) +
  theme_bw() +
  labs(x = "Type of Statement",
       y = "Deception Rating",
       shape = "Syntax",
       color = "Syntax",
       fill = "Syntax") +
  theme(legend.position = "bottom")
```

Figure 1

Experiment 1 Observed Distribution of Deception Ratings by Statement Type and Syntax Congruency



Means by Covariates

```
data.long %>%
  dplyr::group_by(id_per, gender, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate, na.rm = FALSE)) %>%
  dplyr::ungroup() %>%
  tidyr::pivot_wider(names_from = c(gender),
                     values_from = m) %>%
  furniture::table1(Woman,
                    Man,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 1 Aggregated Deception Rates by Gender
                    per Statement Type")
```

Table 4

Experiment 1 Aggregated Deception Rates by Gender per Statement Type

	BFL	MLT	CT
	n = 85	n = 85	n = 85
Woman			
	5.83 (0.77)	4.49 (0.94)	2.82 (1.64)
Man			
	5.72 (1.00)	4.57 (0.94)	2.87 (1.57)

```
data.long %>%
  dplyr::group_by(id_per, SynCon, gender, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate, na.rm = FALSE)) %>%
  dplyr::ungroup() %>%
  tidyr::pivot_wider(names_from = c(SynCon, gender),
                     values_from = m) %>%
  furniture::table1(Correct_Woman,
                    Correct_Man,
                    Incorrect_Woman,
                    Incorrect_Man,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 1 Aggregated Deception Rates by Syntax
                    Error and Gender per Statement Type")
```

Table 5

Experiment 1 Aggregated Deception Rates by Syntax Error and Gender per Statement Type

	BFL	MLT	CT
	n = 85	n = 85	n = 85
Correct_Woman			
	5.84 (0.85)	4.47 (0.91)	2.55 (1.55)
Correct_Man			
	5.70 (1.09)	4.62 (1.00)	2.78 (1.51)
Incorrect_Woman			
	5.74 (0.91)	4.56 (0.99)	2.80 (1.68)
Incorrect_Man			
	5.65 (0.99)	4.56 (0.93)	2.87 (1.59)

Model Building

The Interclass Correlation Coefficients (ICCs) and model comparison results led to the selection of the null model with only random effects for participant differences as the optimal approach for my analysis. Specifically, the 'participant only' model showed that 11.5% of the variance in deception ratings was due to the differences between participants, a significant amount compared to the minimal additional variance explained by vignette differences or a nested model. The principle of parsimony in statistical modeling supports this choice, favoring simpler models that sufficiently explain the data. Hence, focusing on participant variability alone provides a balance between explaining the observed variance and maintaining model simplicity, justifying its selection as the best fit null model for my study.

Null Models

```
#Participant Differences Only
E1_null_pd_re <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per),
                                data = data.long,
                                REML = TRUE)

E1_null_pd_ml <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per),
                                data = data.long,
                                REML = FALSE)

performance::icc(E1_null_pd_re) %>%
  pander::pander(caption = "Experiment 1 Interclass Correlations: Participant
                 Difference Only")
```

Table 6

Experiment 1 Interclass Correlations: Participant Difference Only

ICC_adjusted	ICC_conditional	ICC_unadjusted
0.115	0.115	0.115

```r
#Participant per vignette differences
E1_null_ppv_re <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per) + (1|id_vin),
                                  data = data.long,
                                 REML = TRUE)

E1_null_ppv_ml <- lmerTest::lmer(decept_rate ~ 1 +  (1|id_per) + (1|id_vin),
                                  data = data.long,
                                 REML = FALSE)

performance::icc(E1_null_ppv_re,
                 by_group = TRUE) %>%
  pander::pander(caption = "Experiment 1 Intraclass Correlations: Participant and
                 Vignette")
```

Table 7

Experiment 1 Intraclass Correlations: Participant and Vignette

Group	ICC
id_per	0.114
id_vin	0.027

```r
#Vignette nested under participant
E1_null_nest_re <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per/id_vin),
                                  data = data.long,
                                 REML = TRUE)

E1_null_nest_ml <- lmerTest::lmer(decept_rate ~ 1 +  (1|id_per/id_vin),
                                  data = data.long,
                                 REML = FALSE)

performance::icc(E1_null_nest_re,
                 by_group = TRUE) %>%
  pander::pander(caption = "Experiment 1 Intraclass Correlations: Vignette Nested
                 Under Participants")
```

Table 8

Experiment 1 Intraclass Correlations: Vignette Nested Under Participants

Group	ICC
id_vin:id_per	0.004
id_per	0.115

```
#LRT
anova(E1_null_pd_re, E1_null_ppv_re, E1_null_nest_re, refit = FALSE) %>%
  pander::pander(caption = "Experiment 1 Likelihood Ratio Test: Null model with and
                 without Radom Effect of Vinegette")
```

Table 9

Experiment 1 Likelihood Ratio Test: Null model with and without Radom Effect of Vinegette (continued below)

	npar	AIC	BIC	logLik	deviance	Chisq	Df
E1_null_pd_re	3	96109	96133	-48051	96103	NA	NA
E1_null_ppv_re	4	95659	95691	-47826	95651	451	1
E1_null_nest_re	4	96108	96141	-48050	96100	0	0

	Pr(>Chisq)
E1_null_pd_re	NA
E1_null_ppv_re	0
E1_null_nest_re	NA

Model Building from the Null

Unadjusted Models

> The model comparison of main effects revealed that the model incorporating both independent variables (IVs) emerged as the best fit, outperforming the best fit null model. Furthermore, an evaluation of interactions between these IVs demonstrated superior fit compared to the main effects model, indicating that the interaction model most accurately captures the nuances of my data. This progression highlights the significance of both the individual and combined effects of my IVs in explaining the observed variance. The model labeled `int_ivs` will be used for subsequent model building.

```r
#Main Effects of IVs
E1_me_truth <- lmerTest::lmer(decept_rate ~ TruthCon + (1|id_per),
                              data = data.long,
                              REML = FALSE)

E1_me_synt <- lmerTest::lmer(decept_rate ~ SynCon + (1|id_per),
                              data = data.long,
                              REML = FALSE)

E1_me_both <- lmerTest::lmer(decept_rate ~ TruthCon + SynCon + (1|id_per),
                              data = data.long,
                              REML = FALSE)

#Interaction of IVs
E1_int_ivs <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + (1|id_per),
                              data = data.long,
                              REML = FALSE)
```

```r
#LRTs Main Effects
anova(E1_null_pd_re, E1_me_truth)
```

```
Data: data.long
Models:
E1_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E1_me_truth: decept_rate ~ TruthCon + (1 | id_per)
              npar   AIC   BIC logLik deviance  Chisq Df Pr(>Chisq)
E1_null_pd_re    3 96105 96129 -48050    96099
E1_me_truth      5 86820 86860 -43405    86810 9289.8  2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(E1_null_pd_re, E1_me_synt)
```

```
Data: data.long
Models:
E1_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E1_me_synt: decept_rate ~ SynCon + (1 | id_per)
              npar   AIC   BIC logLik deviance Chisq Df Pr(>Chisq)
E1_null_pd_re    3 96105 96129 -48050    96099
E1_me_synt       4 96107 96139 -48050    96099 0.088  1     0.7668
```

```r
anova(E1_null_pd_re, E1_me_both)
```

```
Data: data.long
Models:
E1_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E1_me_both: decept_rate ~ TruthCon + SynCon + (1 | id_per)
              npar   AIC   BIC logLik deviance  Chisq Df Pr(>Chisq)
E1_null_pd_re    3 96105 96129 -48050    96099
E1_me_both       6 86821 86870 -43405    86809 9289.9  3  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#LRT Main Effects best model to Interaction of IVs
anova(E1_me_both, E1_int_ivs)
```

```
Data: data.long
Models:
E1_me_both: decept_rate ~ TruthCon + SynCon + (1 | id_per)
E1_int_ivs: decept_rate ~ TruthCon * SynCon + (1 | id_per)
           npar   AIC   BIC logLik deviance  Chisq Df Pr(>Chisq)
E1_me_both    6 86821 86870 -43405    86809
E1_int_ivs    8 86817 86881 -43400    86801 8.6126  2    0.01348 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(E1_int_ivs)
```

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
  method [lmerModLmerTest]
Formula: decept_rate ~ TruthCon * SynCon + (1 | id_per)
   Data: data.long

     AIC      BIC   logLik deviance df.resid
 86816.9  86881.0 -43400.4  86800.9    22325

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.4802 -0.8169  0.0482  0.7741  3.2863

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.5498   0.7415
 Residual             2.8115   1.6768
Number of obs: 22333, groups:  id_per, 85

Fixed effects:
                              Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                  5.713e+00  8.498e-02  1.020e+02  67.231   <2e-16
TruthConMLT                 -1.110e+00  3.885e-02  2.225e+04 -28.568   <2e-16
TruthConCT                  -2.999e+00  3.885e-02  2.225e+04 -77.184   <2e-16
SynConIncorrect             -6.640e-02  3.883e-02  2.225e+04  -1.710   0.0873
TruthConMLT:SynConIncorrect  5.906e-02  5.495e-02  2.225e+04   1.075   0.2825
TruthConCT:SynConIncorrect   1.595e-01  5.496e-02  2.225e+04   2.903   0.0037

(Intercept)                 ***
TruthConMLT                 ***
TruthConCT                  ***
SynConIncorrect             .
TruthConMLT:SynConIncorrect
TruthConCT:SynConIncorrect  **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) TrCMLT TrtCCT SynCnI TCMLT:
TruthConMLT -0.228
TruthConCT  -0.228  0.500
SynCnIncrrc -0.229  0.500  0.500
TrtCMLT:SCI  0.162 -0.707 -0.353 -0.707
TrthCCT:SCI  0.162 -0.353 -0.707 -0.707  0.499
```

Adjusted Models

While the model comparison highlighted the model controlling for the main effects of age and gender as the best fit, examination of the summary output revealed that neither main effect was statistically significant. Consequently, this reinforces the superiority of the model (`int_ivs`) that includes only the interaction of the independent variables as the most explanatory for my data. Subsequent models will therefore continue to be built upon this interaction model, leveraging its robustness in capturing the complexities of my study's variables.

```r
#Controlling for covariates
E1_int_c4_age <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + age + (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_int_c4_gender <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + gender +
                                     (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_int_c4_both <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + age + gender +
                                   (1|id_per),
                                data = data.long,
                                REML = FALSE)
#Covariate interaction
E1_int_covint <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + age*gender +
                                  (1|id_per),
                                data = data.long,
                                REML = FALSE)
#LRTs: Covariates
anova(E1_int_ivs, E1_int_c4_age, E1_int_c4_gender, E1_int_c4_both, E1_int_covint)
```

```
Data: data.long
Models:
E1_int_ivs: decept_rate ~ TruthCon * SynCon + (1 | id_per)
E1_int_c4_age: decept_rate ~ TruthCon * SynCon + age + (1 | id_per)
E1_int_c4_gender: decept_rate ~ TruthCon * SynCon + gender + (1 | id_per)
E1_int_c4_both: decept_rate ~ TruthCon * SynCon + age + gender + (1 | id_per)
E1_int_covint: decept_rate ~ TruthCon * SynCon + age * gender + (1 | id_per)
                 npar   AIC   BIC logLik deviance  Chisq Df Pr(>Chisq)
E1_int_ivs          8 86817 86881 -43400    86801
E1_int_c4_age       9 86818 86891 -43400    86800 0.4888  1     0.4845
E1_int_c4_gender    9 86819 86891 -43400    86801 0.0000  0
E1_int_c4_both     10 86820 86901 -43400    86800 0.4631  1     0.4962
E1_int_covint      11 86822 86910 -43400    86800 0.8771  1     0.3490
```

```r
summary(E1_int_c4_both)
```

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
  method [lmerModLmerTest]
Formula: decept_rate ~ TruthCon * SynCon + age + gender + (1 | id_per)
   Data: data.long

     AIC      BIC   logLik deviance df.resid
 86820.4  86900.5 -43400.2  86800.4    22323

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.4806 -0.8171  0.0476  0.7740  3.2868

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.5465   0.7393
 Residual             2.8115   1.6768
Number of obs: 22333, groups:  id_per, 85

Fixed effects:
                              Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                  5.902e+00  2.822e-01  8.635e+01  20.917   <2e-16
TruthConMLT                 -1.110e+00  3.885e-02  2.225e+04 -28.568   <2e-16
TruthConCT                  -2.999e+00  3.885e-02  2.225e+04 -77.184   <2e-16
SynConIncorrect             -6.640e-02  3.884e-02  2.225e+04  -1.710   0.0873
age                         -4.725e-03  6.934e-03  8.499e+01  -0.681   0.4974
genderWoman                 -7.097e-03  1.680e-01  8.499e+01  -0.042   0.9664
TruthConMLT:SynConIncorrect  5.906e-02  5.495e-02  2.225e+04   1.075   0.2825
TruthConCT:SynConIncorrect   1.595e-01  5.496e-02  2.225e+04   2.903   0.0037

(Intercept)                 ***
TruthConMLT                 ***
TruthConCT                  ***
SynConIncorrect             .
age
genderWoman
TruthConMLT:SynConIncorrect
TruthConCT:SynConIncorrect  **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) TrCMLT TrtCCT SynCnI age    gndrWm TCMLT:
TruthConMLT -0.069
TruthConCT  -0.069  0.500
SynCnIncrrc -0.069  0.500  0.500
age         -0.925  0.000  0.000  0.000
genderWoman -0.066  0.000  0.000  0.000 -0.178
TrtCMLT:SCI  0.049 -0.707 -0.353 -0.707  0.000  0.000
TrthCCT:SCI  0.049 -0.353 -0.707 -0.707  0.000  0.000  0.499
```

Through a systematic examination of variables and exploration of several models to determine the best fit, it became evident that the model examining the cross-level interactions of age and gender with the type of statement (`xint_cov_truth`) became the most suitable for my data.

```
#cross level interactions
E1_xint_age_truth <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + age*TruthCon +
                                     (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_xint_age_synt <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + age*SynCon +
                                    (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_xint_gender_truth <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon +
                                        gender*TruthCon + (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_xint_gender_synt <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon +
                                       gender*SynCon + (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_xint_cov_truth <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon +
                                     age*gender*TruthCon + (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_xint_cov_synt <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon +
                                    age*gender*TruthCon + (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_xint_all <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon +
                                age*gender*TruthCon + (1|id_per),
                                data = data.long,
                                REML = FALSE)
#Interactions of IVs and Covariates
E1_int_ivs_age <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon*age +
                                  (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_int_ivs_gender <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon*gender +
                                     (1|id_per),
                                data = data.long,
                                REML = FALSE)

E1_int_ivs_both <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon*age*gender +
                                   (1|id_per),
                                data = data.long,
```

```
                                    REML = FALSE)
```

```
#LRTs for cross-level interaction
anova(E1_int_ivs, E1_xint_age_truth, E1_xint_age_synt)
```

```
Data: data.long
Models:
E1_int_ivs: decept_rate ~ TruthCon * SynCon + (1 | id_per)
E1_xint_age_synt: decept_rate ~ TruthCon * SynCon + age * SynCon + (1 | id_per)
E1_xint_age_truth: decept_rate ~ TruthCon * SynCon + age * TruthCon + (1 | id_per)
                  npar   AIC   BIC logLik deviance    Chisq Df Pr(>Chisq)
E1_int_ivs           8 86817 86881 -43400    86801
E1_xint_age_synt    10 86820 86900 -43400    86800   0.6262  2     0.7312
E1_xint_age_truth   11 86546 86634 -43262    86524 276.5822  1     <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(E1_xint_age_truth, E1_xint_gender_truth, E1_xint_gender_synt)
```

```
Data: data.long
Models:
E1_xint_gender_synt: decept_rate ~ TruthCon * SynCon + gender * SynCon + (1 | id_per)
E1_xint_age_truth: decept_rate ~ TruthCon * SynCon + age * TruthCon + (1 | id_per)
E1_xint_gender_truth: decept_rate ~ TruthCon * SynCon + gender * TruthCon + (1 | id_per)
                     npar   AIC   BIC logLik deviance  Chisq Df Pr(>Chisq)
E1_xint_gender_synt    10 86821 86901 -43400    86801
E1_xint_age_truth      11 86546 86634 -43262    86524 276.89  1  < 2.2e-16 ***
E1_xint_gender_truth   11 86800 86888 -43389    86778   0.00  0
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(E1_xint_age_truth, E1_xint_cov_truth, E1_xint_cov_synt, E1_xint_all)
```

```
Data: data.long
Models:
E1_xint_age_truth: decept_rate ~ TruthCon * SynCon + age * TruthCon + (1 | id_per)
E1_xint_cov_truth: decept_rate ~ TruthCon * SynCon + age * gender * TruthCon + (1 | id_per)
E1_xint_cov_synt: decept_rate ~ TruthCon * SynCon + age * gender * TruthCon + (1 | id_per)
E1_xint_all: decept_rate ~ TruthCon * SynCon + age * gender * TruthCon + (1 | id_per)
                  npar   AIC   BIC logLik deviance  Chisq Df Pr(>Chisq)
E1_xint_age_truth   11 86546 86634 -43262    86524
E1_xint_cov_truth   17 86502 86639 -43234    86468 55.319  6  3.995e-10 ***
E1_xint_cov_synt    17 86502 86639 -43234    86468  0.000  0
E1_xint_all         17 86502 86639 -43234    86468  0.000  0
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#LRTs for IV x Covariate interactions

anova(E1_xint_cov_truth, E1_int_ivs_age, E1_int_ivs_gender, E1_int_ivs_both)
```

```
Data: data.long
Models:
E1_int_ivs_age: decept_rate ~ TruthCon * SynCon * age + (1 | id_per)
E1_int_ivs_gender: decept_rate ~ TruthCon * SynCon * gender + (1 | id_per)
E1_xint_cov_truth: decept_rate ~ TruthCon * SynCon + age * gender * TruthCon + (1 | id_per)
E1_int_ivs_both: decept_rate ~ TruthCon * SynCon * age * gender + (1 | id_per)
                  npar   AIC   BIC logLik deviance    Chisq Df Pr(>Chisq)
E1_int_ivs_age      14 86548 86660 -43260    86520
E1_int_ivs_gender   14 86800 86912 -43386    86772   0.0000  0
E1_xint_cov_truth   17 86502 86639 -43234    86468 303.5075  3     <2e-16 ***
E1_int_ivs_both     26 86512 86720 -43230    86460   8.4888  9     0.4857
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(E1_xint_cov_truth)
```

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
  method [lmerModLmerTest]
Formula: decept_rate ~ TruthCon * SynCon + age * gender * TruthCon + (1 |
    id_per)
   Data: data.long

     AIC      BIC   logLik deviance df.resid
 86502.4  86638.6 -43234.2  86468.4    22316

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7205 -0.7915  0.0463  0.7666  3.3579

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.5412   0.7357
 Residual             2.7700   1.6643
Number of obs: 22333, groups:  id_per, 85

Fixed effects:
                              Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                  5.195e+00  3.944e-01  9.202e+01  13.171  < 2e-16
TruthConMLT                 -6.140e-01  1.337e-01  2.225e+04  -4.594 4.38e-06
TruthConCT                  -2.122e+00  1.337e-01  2.225e+04 -15.873  < 2e-16
SynConIncorrect             -6.631e-02  3.855e-02  2.225e+04  -1.720 0.085392
age                          1.259e-02  1.008e-02  9.158e+01   1.249 0.214903
genderWoman                 -9.882e-02  5.841e-01  9.159e+01  -0.169 0.866027
TruthConMLT:SynConIncorrect  5.897e-02  5.455e-02  2.225e+04   1.081 0.279692
TruthConCT:SynConIncorrect   1.596e-01  5.455e-02  2.225e+04   2.926 0.003442
age:genderWoman              3.737e-03  1.407e-02  9.158e+01   0.266 0.791101
TruthConMLT:age             -1.158e-02  3.349e-03  2.225e+04  -3.457 0.000548
TruthConCT:age              -2.043e-02  3.348e-03  2.225e+04  -6.102 1.06e-09
TruthConMLT:genderWoman      6.024e-01  1.940e-01  2.225e+04   3.105 0.001908
TruthConCT:genderWoman       1.215e+00  1.939e-01  2.225e+04   6.265 3.81e-10
TruthConMLT:age:genderWoman -1.676e-02  4.673e-03  2.225e+04  -3.587 0.000335
TruthConCT:age:genderWoman  -3.330e-02  4.670e-03  2.225e+04  -7.130 1.03e-12

(Intercept)                 ***
TruthConMLT                 ***
TruthConCT                  ***
SynConIncorrect             .
age
genderWoman
TruthConMLT:SynConIncorrect
TruthConCT:SynConIncorrect  **
age:genderWoman
TruthConMLT:age             ***
TruthConCT:age              ***
TruthConMLT:genderWoman     **
TruthConCT:genderWoman      ***
TruthConMLT:age:genderWoman ***
```

```
TruthConCT:age:genderWoman  ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table of Models for comparison

```
texreg::knitreg(list(E1_int_ivs, E1_xint_cov_truth),
                custom.model.names = c("IVs Interaction", "Cross-level Interaction"),
                caption = "Experiment 1 MLM Parameter Estimates: Fixed Effects")
```

Table 11

Experiment 1 MLM Parameter Estimates: Fixed Effects

	IVs Interaction	Cross-level Interaction
(Intercept)	5.71^{***}	5.19^{***}
	(0.08)	(0.39)
TruthConMLT	-1.11^{***}	-0.61^{***}
	(0.04)	(0.13)
TruthConCT	-3.00^{***}	-2.12^{***}
	(0.04)	(0.13)
SynConIncorrect	-0.07	-0.07
	(0.04)	(0.04)
TruthConMLT:SynConIncorrect	0.06	0.06
	(0.05)	(0.05)
TruthConCT:SynConIncorrect	0.16^{**}	0.16^{**}
	(0.05)	(0.05)
age		0.01
		(0.01)
genderWoman		-0.10
		(0.58)
age:genderWoman		0.00
		(0.01)
TruthConMLT:age		-0.01^{***}
		(0.00)
TruthConCT:age		-0.02^{***}
		(0.00)
TruthConMLT:genderWoman		0.60^{**}
		(0.19)
TruthConCT:genderWoman		1.21^{***}
		(0.19)
TruthConMLT:age:genderWoman		-0.02^{***}
		(0.00)
TruthConCT:age:genderWoman		-0.03^{***}
		(0.00)
AIC	86816.89	86502.36
BIC	86881.00	86638.59
Log Likelihood	-43400.44	-43234.18
Num. obs.	22333	22333
Num. groups: id_per	85	85
Var: id_per (Intercept)	0.55	0.54
Var: Residual	2.81	2.77

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Final Model and Parameter Estimates

```
E1_final_model <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + age*gender*TruthCon
                                 + (1|id_per),
                                data = data.long,
                                REML = TRUE)
```

```
summary(E1_final_model)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: decept_rate ~ TruthCon * SynCon + age * gender * TruthCon + (1 |
    id_per)
   Data: data.long

REML criterion at convergence: 86560.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7201 -0.7910  0.0457  0.7663  3.3578

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.5685   0.754
 Residual             2.7713   1.665
Number of obs: 22333, groups:  id_per, 85

Fixed effects:
                              Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                  5.195e+00  4.037e-01  8.738e+01  12.869  < 2e-16
TruthConMLT                 -6.140e-01  1.337e-01  2.224e+04  -4.592 4.41e-06
TruthConCT                  -2.122e+00  1.337e-01  2.224e+04 -15.869  < 2e-16
SynConIncorrect             -6.631e-02  3.856e-02  2.224e+04  -1.720 0.085462
age                          1.259e-02  1.032e-02  8.697e+01   1.220 0.225712
genderWoman                 -9.883e-02  5.979e-01  8.698e+01  -0.165 0.869082
TruthConMLT:SynConIncorrect  5.897e-02  5.456e-02  2.224e+04   1.081 0.279792
TruthConCT:SynConIncorrect   1.596e-01  5.456e-02  2.224e+04   2.925 0.003450
age:genderWoman              3.737e-03  1.440e-02  8.698e+01   0.260 0.795811
TruthConMLT:age             -1.158e-02  3.350e-03  2.224e+04  -3.456 0.000549
TruthConCT:age              -2.043e-02  3.349e-03  2.224e+04  -6.101 1.07e-09
TruthConMLT:genderWoman      6.024e-01  1.941e-01  2.224e+04   3.104 0.001913
TruthConCT:genderWoman       1.215e+00  1.940e-01  2.224e+04   6.263 3.85e-10
TruthConMLT:age:genderWoman -1.676e-02  4.674e-03  2.224e+04  -3.586 0.000336
TruthConCT:age:genderWoman  -3.330e-02  4.671e-03  2.224e+04  -7.128 1.05e-12

(Intercept)                 ***
TruthConMLT                 ***
TruthConCT                  ***
SynConIncorrect             .
age
genderWoman
TruthConMLT:SynConIncorrect
```

```
TruthConCT:SynConIncorrect  **
age:genderWoman
TruthConMLT:age             ***
TruthConCT:age              ***
TruthConMLT:genderWoman     **
TruthConCT:genderWoman      ***
TruthConMLT:age:genderWoman ***
TruthConCT:age:genderWoman  ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Follow-up Tests

Pooled Standard Deviation

```
est_SD <- E1_final_model %>%
  VarCorr() %>%
  data.frame() %>%
  dplyr::summarise(tot_var = sum(vcov)) %>%
  dplyr::pull(tot_var) %>%
  sqrt()

est_SD
```

```
[1] 1.82752
```

Estimated Marginal Means

```
E1_final_model %>%
  emmeans::emmeans( ~ SynCon| TruthCon)
```

```
TruthCon = BFL:
 SynCon    emmean     SE  df asymp.LCL asymp.UCL
 Correct     5.71 0.0893 Inf      5.54      5.89
 Incorrect   5.65 0.0893 Inf      5.47      5.82

TruthCon = MLT:
 SynCon    emmean     SE  df asymp.LCL asymp.UCL
 Correct     4.62 0.0893 Inf      4.44      4.79
 Incorrect   4.61 0.0893 Inf      4.43      4.78

TruthCon = CT:
 SynCon    emmean     SE  df asymp.LCL asymp.UCL
 Correct     2.74 0.0893 Inf      2.57      2.92
 Incorrect   2.83 0.0893 Inf      2.66      3.01

Results are averaged over the levels of: gender
Degrees-of-freedom method: asymptotic
Confidence level used: 0.95
```

```
E1_final_model %>%
  emmeans::emmeans( ~ gender | TruthCon)
```

```
TruthCon = BFL:
 gender emmean    SE  df asymp.LCL asymp.UCL
 Man      5.66 0.110 Inf      5.44      5.87
 Woman    5.71 0.135 Inf      5.44      5.97

TruthCon = MLT:
 gender emmean    SE  df asymp.LCL asymp.UCL
 Man      4.62 0.110 Inf      4.40      4.83
 Woman    4.61 0.135 Inf      4.34      4.87
```

```
TruthCon = CT:
 gender emmean    SE  df asymp.LCL asymp.UCL
 Man      2.81 0.110 Inf      2.60      3.03
 Woman    2.76 0.135 Inf      2.50      3.03

Results are averaged over the levels of: SynCon
Degrees-of-freedom method: asymptotic
Confidence level used: 0.95
```

Labeling Significant Only Pairwise Tests

```
#Truth X Syntax Interaction
label_pairwise_1 <- E1_final_model %>%
  emmeans::emmeans(~ SynCon|TruthCon) %>%
  pairs() %>%
  data.frame() %>%
  dplyr::mutate(d = estimate/est_SD) %>%
  dplyr::mutate(d = d %>%
                  abs() %>%
                  apa2()) %>%
  dplyr::filter(p.value < .10) %>%
  dplyr::mutate(label = glue::glue("SMD = {d}, {pformat(p.value)}")) %>%
  dplyr::select(contrast, TruthCon, label) %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("BFL", "MLT","CT"),
                         labels = c("Bald Faced Lies",
                                    "Misleading Literal Truths",
                                    "True Statements"))) %>%
  tidyr::separate(col = "contrast",
                  sep = "-",
                  into = c("xmin", "xmax")) %>%
  dplyr::mutate(xmin = case_when(xmin == "Correct " ~ "Correct")) %>%
  dplyr::mutate(xmax = case_when(xmax == " Incorrect" ~ "Incorrect")) %>%
  dplyr::mutate(y.position = case_when(TruthCon == "True Statements" ~ 3,
                                       TruthCon == "Bald Faced Lies" ~ 5.9))

label_pairwise_1
```

```
     xmin      xmax        TruthCon                  label y.position
1 Correct Incorrect Bald Faced Lies  SMD = 0.04, p = .085        5.9
2 Correct Incorrect True Statements SMD = 0.05, p = .016*        3.0
```

```r
label_pairwise_1v <- E1_final_model %>%
  emmeans::emmeans(~ TruthCon|SynCon) %>%
  pairs() %>%
  data.frame() %>%
  dplyr::filter(SynCon == "Correct") %>%
  dplyr::mutate(d = estimate/est_SD) %>%
  dplyr::mutate(d = d %>%
                  abs() %>%
                  apa2()) %>%
  dplyr::filter(p.value < .05) %>%
  dplyr::mutate(label = glue::glue("SMD = {d}, {pformat(p.value)}")) %>%
  dplyr::select(contrast, label) %>%
  dplyr::mutate(y1 = c(4.62, 2.74, 2.741)) %>%
  dplyr::mutate(y2 = c(5.71, 5.71, 4.62)) %>%
  dplyr::mutate(x1 = c(0.8, 0.40, 0.60)) %>%
  dplyr::mutate(TruthCon = "Bald Faced Lies") %>%
  dplyr::mutate(ymid = furniture::rowmeans(y1, y2))

label_pairwise_1v
```

```
   contrast                   label    y1   y2  x1        TruthCon   ymid
1 BFL - MLT SMD = 0.60, p < .001*** 4.620 5.71 0.8 Bald Faced Lies 5.1650
2  BFL - CT SMD = 1.63, p < .001*** 2.740 5.71 0.4 Bald Faced Lies 4.2250
3  MLT - CT SMD = 1.03, p < .001*** 2.741 4.62 0.6 Bald Faced Lies 3.6805
```

```
#Adding Simple Slopes for Age by Gender
df_ss <- interactions::sim_slopes(model = E1_final_model,
                        pred = age,
                        modx = gender,
                        mod2 = TruthCon) %>%
  broom::tidy() %>%
  dplyr::mutate(gender = modx.value,
               TruthCon = mod2.value,
               label = paste0("b = ",
                              round(as.numeric(estimate), 2),
                              "\n95% CI [",
                              round(as.numeric(conf.low), 2),
                              ", ",
                              round(as.numeric(conf.high), 2),
                              "]\n",
                              pformat(as.numeric(p.value)))) %>%
  dplyr::select(gender, TruthCon, label)

df_ss
```

```
# A tibble: 6 x 3
  gender TruthCon label
  <chr>  <chr>    <chr>
1 Man    BFL      "b = 0.01\n95% CI [-0.01, 0.03]\np = .226"
2 Woman  BFL      "b = 0.02\n95% CI [0, 0.04]\np = .107"
3 Man    MLT      "b = 0\n95% CI [-0.02, 0.02]\np = .922"
4 Woman  MLT      "b = -0.01\n95% CI [-0.03, 0.01]\np = .235"
5 Man    CT       "b = -0.01\n95% CI [-0.03, 0.01]\np = .450"
6 Woman  CT       "b = -0.04\n95% CI [-0.06, -0.02]\np < .001***"
```

```
#Labeling Significant Only Simple Slopes
filtered_df_ss <- df_ss %>%
  filter(gender == "Woman" & TruthCon == "CT")

filtered_df_ss
```

```
# A tibble: 1 x 3
  gender TruthCon label
  <chr>  <chr>    <chr>
1 Woman  CT       "b = -0.04\n95% CI [-0.06, -0.02]\np < .001***"
```

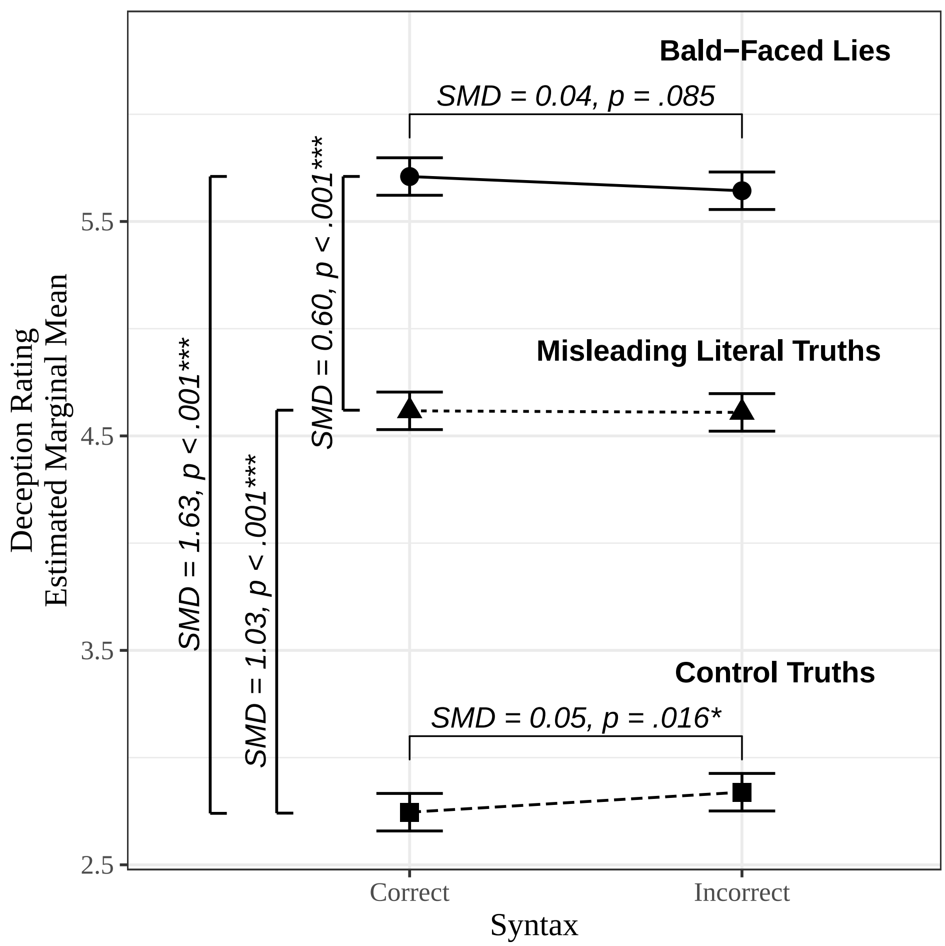
Experiment 1 Visualizations

```
t = 0.05

effects::Effect(focal.predictors = c("SynCon", "TruthCon"),
                mod = E1_final_model) %>%
  data.frame() %>%
  dplyr::mutate(SynCon = SynCon %>%
                  factor(levels = c("Correct", "Incorrect"),
                         labels = c("Correct",
                                    "Incorrect"))) %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("BFL", "MLT", "CT"),
                         labels = c("Bald Faced Lies",
                                    "Misleading Literal Truths",
                                    "True Statements"))) %>%
  ggplot(aes(x = SynCon,
             y = fit,
             group = TruthCon,
             shape = TruthCon)) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se),
                width = .2) +
  geom_point(size = 3) +
  geom_line(aes(linetype = TruthCon)) +
  theme_bw()+
  labs(x = "Syntax",
       y = "Deception Rating\nEstimated Marginal Mean",
       shape = "Statement Type:",
       linetype = "Statement Type:") +
  geom_bracket(data = label_pairwise_1,
               aes(label = label,
                   y.position = y.position),
                fontface = "italic",
               bracket.nudge.y = .1) +
  geom_segment(data = label_pairwise_1v,
               aes(x = x1, xend = x1, y = y1, yend = y2, group = 1)) +
  geom_segment(data = label_pairwise_1v,
               aes(x = x1, xend = x1 + t,
                   y = y1, yend = y1)) +
  geom_segment(data = label_pairwise_1v,
               aes(x = x1, xend = x1 + t,
                   y = y2, yend = y2)) +
  geom_text(data = label_pairwise_1v,
           aes(label = label,
               x = x1,
               y = ymid),
            fontface = "italic",
           nudge_x = -.065,
           angle = 90) +
  expand_limits(x = 0.15, y = 6.25) +
  theme(legend.position = "none",
        text = element_text(family = "serif",
```

```
                                      size =12)) +
  annotate(geom = "text",
           fontface = "bold",
           size = 4,
           x = 2.1,
           y = 3.4,
           label = "Control Truths") +
  annotate(geom = "text",
           fontface = "bold",
           size = 4,
           x = 1.9,
           y = 4.9,
           label = "Misleading Literal Truths") +
  annotate(geom = "text",
           fontface = "bold",
           size = 4,
           x = 2.1,
           y = 6.3,
           label = "Bald-Faced Lies")
```

Figure 2

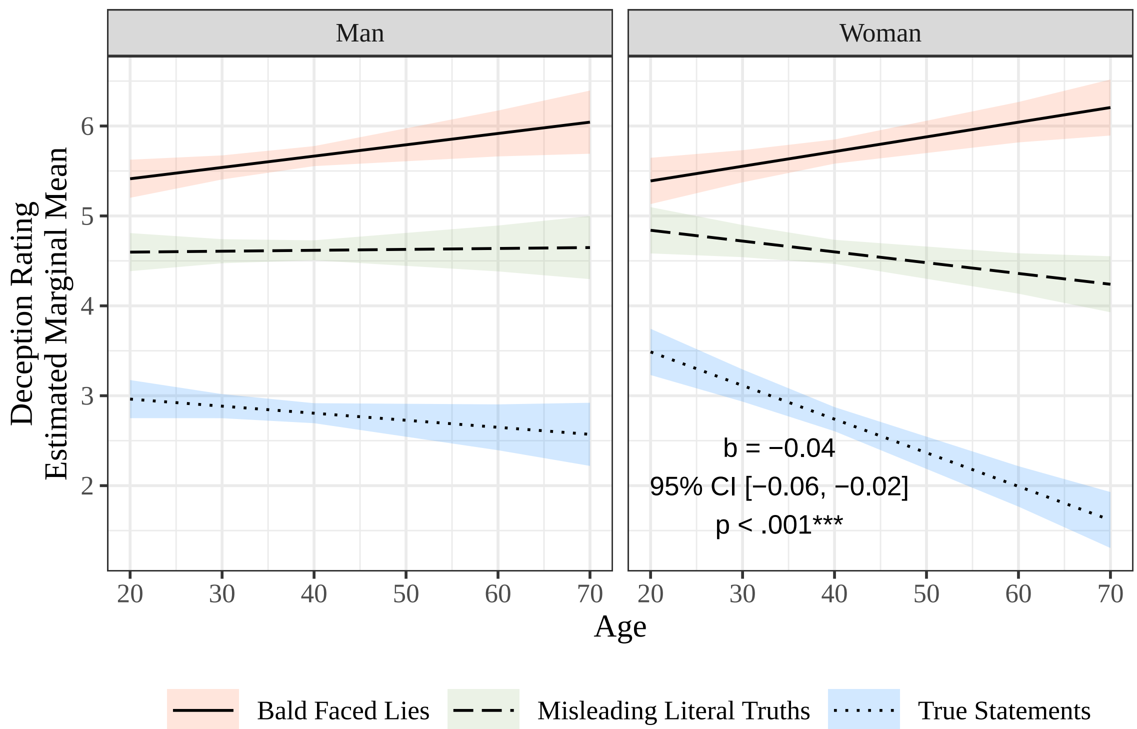
Figure 1. Visulazation of Syntax Error by Statement Type with Pairwise Comparison



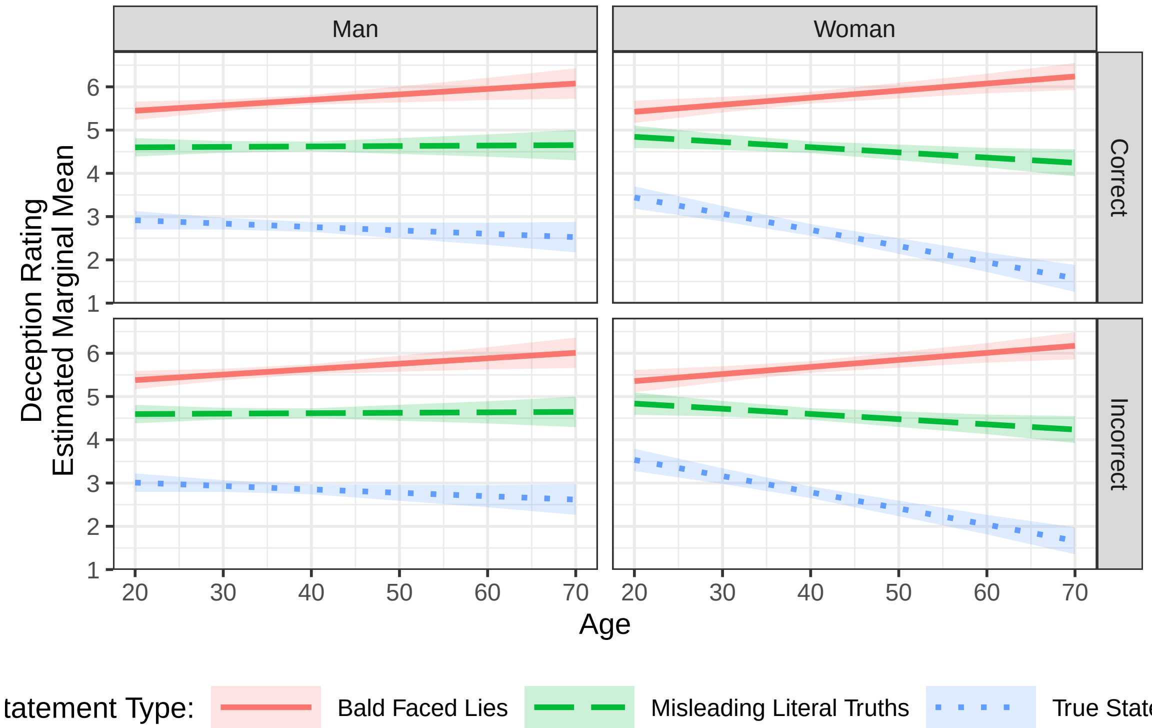
```
fig_ss <- effects::Effect(focal.predictors = c("gender", "TruthCon", "age"),
                mod = E1_final_model) %>%
  data.frame() %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("BFL", "MLT", "CT"),
                         labels = c("Bald Faced Lies",
                                    "Misleading Literal Truths",
                                    "True Statements"))) %>%
  ggplot(aes(x = age,
             y = fit,
             group = TruthCon,
             shape = TruthCon)) +
  geom_ribbon(aes(ymin = fit - se,
                  ymax = fit + se,
                fill = TruthCon),
              alpha = .2) +
  geom_line(aes(linetype = TruthCon)) +
  theme_bw() +
  facet_wrap(~ gender) +
    labs(x = "Age",
       y = "Deception Rating\nEstimated Marginal Mean",
       color = NULL,
       fill = NULL,
       linetype =NULL) +
  geom_text(data = filtered_df_ss,
          aes(label = label,
          x =34,
          y = 2),
          inherit.aes = FALSE,
          size = 10/.pt,
          angle = -0) +
  scale_linetype_manual(values = c("solid", "longdash", "dotted")) +
  theme(legend.position = "bottom",
        legend.key.width = unit(1, "cm"),
        text = element_text(family = "serif",
                            size =12)) +
  scale_color_manual(values = c("Bald Faced Lies" = "coral",
                                "Misleading Literal Truths" = "#9dc183",
                                "True Statements" = "dodgerblue")) +
  scale_fill_manual(values = c("Bald Faced Lies" = "coral",
                                "Misleading Literal Truths" = "#9dc183",
                                "True Statements" = "dodgerblue"))

fig_ss
```

Figure 3

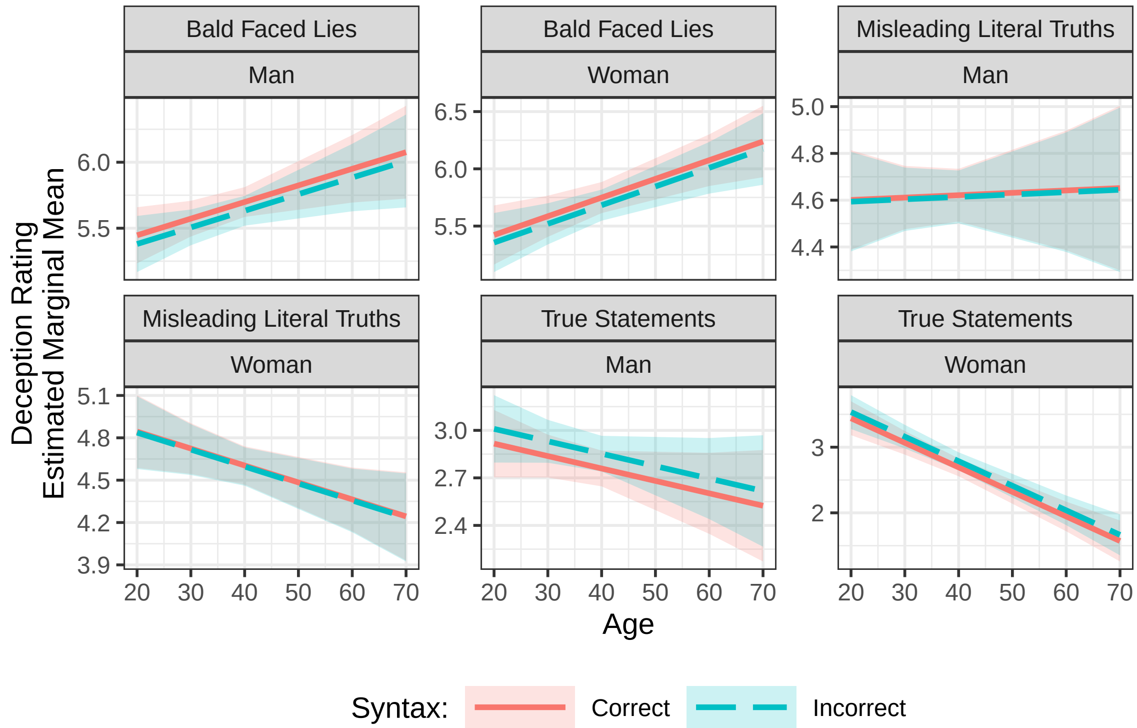
Simple Slopes Plot



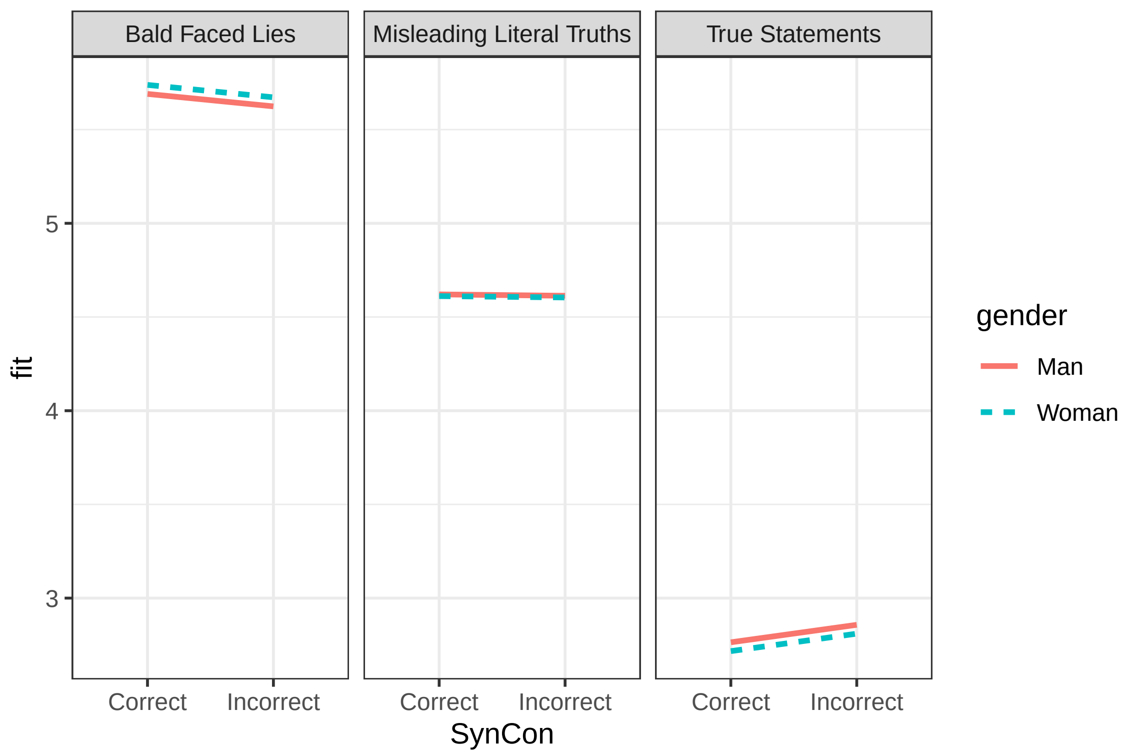
```
effects::Effect(focal.predictors = c("gender", "TruthCon", "age", "SynCon"),
                mod = E1_final_model) %>%
  data.frame() %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("BFL", "MLT", "CT"),
                         labels = c("Bald Faced Lies",
                                    "Misleading Literal Truths",
                                    "True Statements"))) %>%
  ggplot(aes(x = age,
             y = fit,
             group = TruthCon,
             shape = TruthCon)) +
  geom_ribbon(aes(ymin = fit - se,
                    ymax = fit + se,
                  fill = TruthCon),
                alpha = .2) +
  geom_line(aes(linetype = TruthCon,
                color = TruthCon),
            size = 1) +
  theme_bw() +
  facet_grid(SynCon ~ gender) +
    labs(x = "Age",
       y = "Deception Rating\nEstimated Marginal Mean",
       shape = "Statement Type:",
       linetype = "Statement Type:",
       color  = "Statement Type:",
       fill   = "Statement Type:") +
  scale_linetype_manual(values = c("solid", "longdash", "dotted")) +
  theme(legend.position = "bottom",
        legend.key.width = unit(1.5, "cm"))
```


Man
Woman
Correct
Incorrect
Deception Rating
Estimated Marginal Mean
Age
tatement Type:
Bald Faced Lies
Misleading Literal Truths
True State

```
effects::Effect(focal.predictors = c("gender", "TruthCon", "age", "SynCon"),
                mod = E1_final_model) %>%
  data.frame() %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("BFL", "MLT", "CT"),
                         labels = c("Bald Faced Lies",
                                    "Misleading Literal Truths",
                                    "True Statements"))) %>%
  ggplot(aes(x = age,
             y = fit,
             group = SynCon,
             shape = SynCon)) +
  geom_ribbon(aes(ymin = fit - se,
                    ymax = fit + se,
                  fill = SynCon),
                alpha = .2) +
  geom_line(aes(linetype = SynCon,
                color = SynCon),
            size = 1) +
  theme_bw() +
  facet_wrap(TruthCon ~ gender, scales = "free_y") +
    labs(x = "Age",
       y = "Deception Rating\nEstimated Marginal Mean",
       shape = "Syntax:",
       linetype = "Syntax:",
       color  = "Syntax:",
       fill  = "Syntax:") +
  scale_linetype_manual(values = c("solid", "longdash", "dotted")) +
  theme(legend.position = "bottom",
        legend.key.width = unit(1.5, "cm"))
```


Bald Faced Lies
Man
Bald Faced Lies
Woman
Misleading Literal Truths
Man
Misleading Literal Truths
Woman
True Statements
Man
True Statements
Woman
Deception Rating
Estimated Marginal Mean
Age
Syntax:
Correct
Incorrect

```
effects::Effect(focal.predictors = c("gender", "TruthCon", "SynCon"),
                mod = E1_final_model) %>%
  data.frame() %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("BFL", "MLT", "CT"),
                         labels = c("Bald Faced Lies",
                                    "Misleading Literal Truths",
                                    "True Statements"))) %>%
  ggplot(aes(x = SynCon,
             y = fit,
             group = gender,
             shape = gender)) +
  geom_line(aes(linetype = gender,
                color = gender),
            size = 1) +
  theme_bw() +
  facet_grid(~ TruthCon)
```



Experiment 2 Analysis

Load Data

Before conducting the main analysis, I preformed a validity check to ensure the reliability of individual participation. In this study, `accuracy` is defined based on participants ability to correctly rate the decepiton in statements. Sepcifically:

- For statements that are BFLs without any errors, an accurate deception rating would fall within the range of 4-7.
- For statements that are CT without any errors, an accurate deception rating would fall within the range of 1-4.

I calculated the `accuracy` metric by assessing the difference between participants' ratings and the predefined accurate range for each type of statement.

```
#Validity Check
filtered_data <- data_acc %>%
  filter(SynCon == "correct", SemCon == "fluent")

filtered_data %>%
  count(accuracy)
```

```
# A tibble: 7 x 2
  accuracy     n
     <dbl> <int>
1        0   314
2        1   221
3        2   149
4        3   126
5        4   136
6        5    80
7        6    28
```

```
#Exclusion
exclude_id_per <- data_acc %>%
  dplyr::filter(accuracy >= 4) %>%
  dplyr::group_by(id_per) %>%
  dplyr::tally() %>%
  dplyr::ungroup() %>%
  dplyr::filter(n == 4) %>%
  dplyr::pull(id_per)

exclude_id_per
```

```
 [1] "1"   "100" "115" "12"  "120" "21"  "24"  "3"   "49"  "57"  "61"  "83"
[13] "88"
```

```r
data_acc2 <- data_acc %>%
  dplyr::filter(accuracy < 4) %>%
  dplyr::filter(!id_per %in% exclude_id_per) %>%
  dplyr::mutate_at(vars(id_per, id_vin, TruthCon, SynCon, SemCon, crime),
                   factor) %>%
  dplyr::select(-accuracy)

dim(data_acc2)
```

```
[1] 3491    7
```

```r
psych::headTail(data_acc2) %>%
  pander::pander(caption = "Illistration of Experiment 2 Dataset")
```

Table 12

Illistration of Experiment 2 Dataset

id_per	id_vin	TruthCon	SynCon	SemCon	crime	decept_rate
2	1	BFL	incorrect	fluent	crime	5
2	2	BFL	correct	disfluent	accident	6
2	4	BFL	incorrect	fluent	crime	6
2	5	BFL	incorrect	fluent	accident	5
NA	NA	NA	NA	NA	NA	...
123	29	CT	incorrect	disfluent	accident	5
123	30	BFL	incorrect	disfluent	accident	5
123	31	CT	correct	disfluent	accident	5
123	32	BFL	correct	fluent	accident	5

Sample Size

> N = 116 participants with 14-32 ratings each for a total of 3491 deception ratings/statements.

```
data_acc2 %>%
  dplyr::group_by(id_per) %>%
  dplyr::tally() %>%
  dplyr::ungroup() %>%
  dplyr::select(n) %>%
  table %>%
  addmargins()
```

```
n
 14  25  26  27  28  29  30  31  32 Sum
  1   1   5   4   2  26  15  30  32 116
```

```
nrow(data_acc2)
```

```
[1] 3491
```

Basic Descriptives

```
#Mean, Median, and Quartiles of overall deception ratings
data_acc2 %>%
  dplyr::select(decept_rate) %>%
  summary()
```

```
  decept_rate
 Min.   :1.000
 1st Qu.:2.000
 Median :5.000
 Mean   :4.275
 3rd Qu.:6.000
 Max.   :7.000
```

Descriptive Statistical Analysis

Means by Single Independent Variables

```
data_acc2 %>%
  dplyr::group_by(id_per, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Statement
                    Type")
```

Table 13

Experiment 2 Aggregated Deception Rates by Statement Type

	BFL	CT
	n = 116	n = 116
Deception Rating, participant mean		
	5.56 (0.93)	3.00 (1.74)

```
data_acc2 %>%
  dplyr::group_by(id_per, SynCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ SynCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Syntax
                    Error")
```

Table 14

Experiment 2 Aggregated Deception Rates by Syntax Error

	correct	incorrect
	n = 116	n = 116
Deception Rating, participant mean		
	4.31 (0.83)	4.25 (0.90)

```
data_acc2 %>%
  dplyr::group_by(id_per, SemCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ SemCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Semantic
                    Fluency")
```

Table 15

Experiment 2 Aggregated Deception Rates by Semantic Fluency

	disfluent	fluent
	n = 116	n = 116
Deception Rating, participant mean		
	4.30 (0.84)	4.28 (0.90)

```
data_acc2 %>%
  dplyr::group_by(id_per, crime) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ crime,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Vignette
                    Type")
```

Table 16

Experiment 2 Aggregated Deception Rates by Vignette Type

	accident	crime
	n = 116	n = 116
Deception Rating, participant mean		
	4.32 (0.83)	4.26 (0.90)

Means by Grouped Independent Variables

```r
data_acc2 %>%
  dplyr::group_by(id_per, SynCon, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate, na.rm = FALSE)) %>%
  dplyr::ungroup() %>%
  tidyr::pivot_wider(names_from = c(SynCon),
                     values_from = m) %>%
  furniture::table1(correct,
                    incorrect,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Syntax
                    Error per Statement Type")
```

Table 17

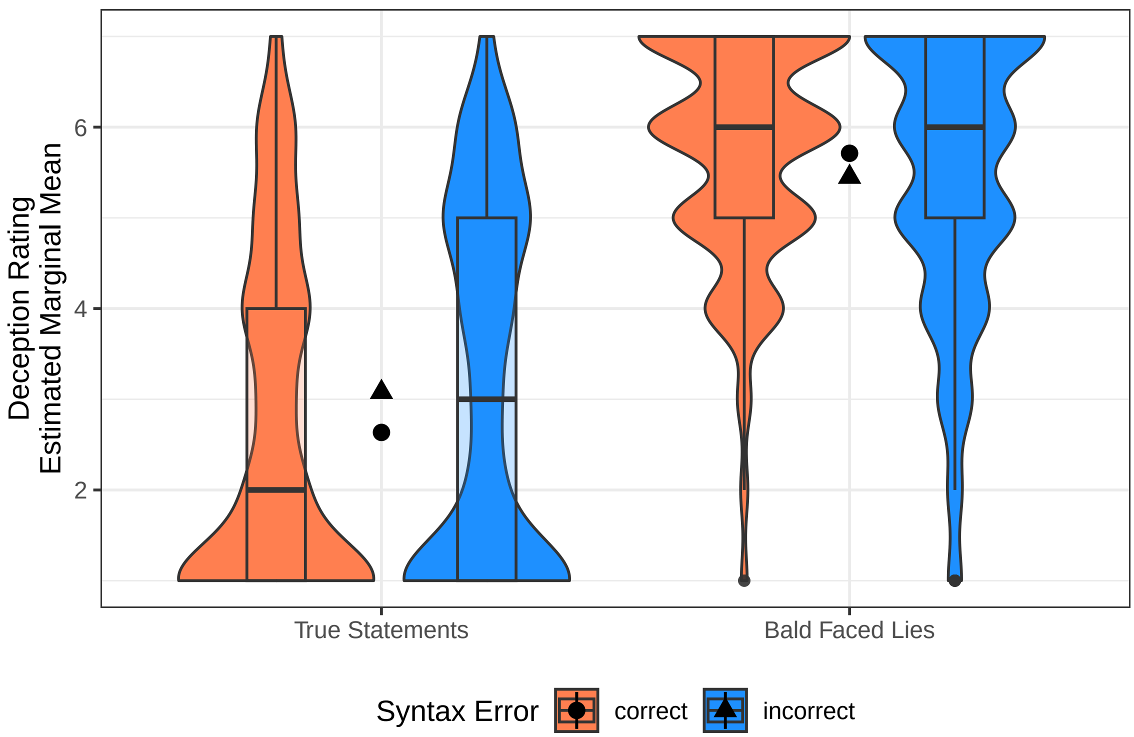
Experiment 2 Aggregated Deception Rates by Syntax Error per Statement Type

	BFL	CT
	n = 116	n = 116
correct		
	5.67 (0.98)	2.94 (1.69)
incorrect		
	5.44 (1.03)	3.05 (1.83)

```r
data_acc2 %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                factor(levels = c("CT", "BFL"),
                       labels = c("True Statements",
                                  "Bald Faced Lies"))) %>%
  ggplot(aes(x = TruthCon,
             y = decept_rate,
             fill = SynCon,
             group = interaction(SynCon, TruthCon))) +
  geom_violin() +
  scale_fill_manual(values = c("coral", "dodgerblue")) +
  geom_boxplot(width = .25,
               alpha = .25,
               position = position_dodge(width = .9)) +
  stat_summary(aes(shape = SynCon), color = "black", size = .6) +
  theme_bw() +
  labs(x = NULL,
       y = "Deception Rating\nEstimated Marginal Mean",
       shape = "Syntax Error",
       color = "Syntax Error",
       fill = "Syntax Error") +
  theme(legend.position = "bottom")
```

Figure 4

Observed Distribution of Deception Ratings by Statement Type and Syntax Congruency



```
data_acc2 %>%
  dplyr::group_by(id_per, SemCon, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate, na.rm = FALSE)) %>%
  dplyr::ungroup() %>%
  tidyr::pivot_wider(names_from = c(SemCon),
                     values_from = m) %>%
  furniture::table1(fluent,
                    disfluent,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Semantic
                    Fluency per Statement Type")
```

Table 18

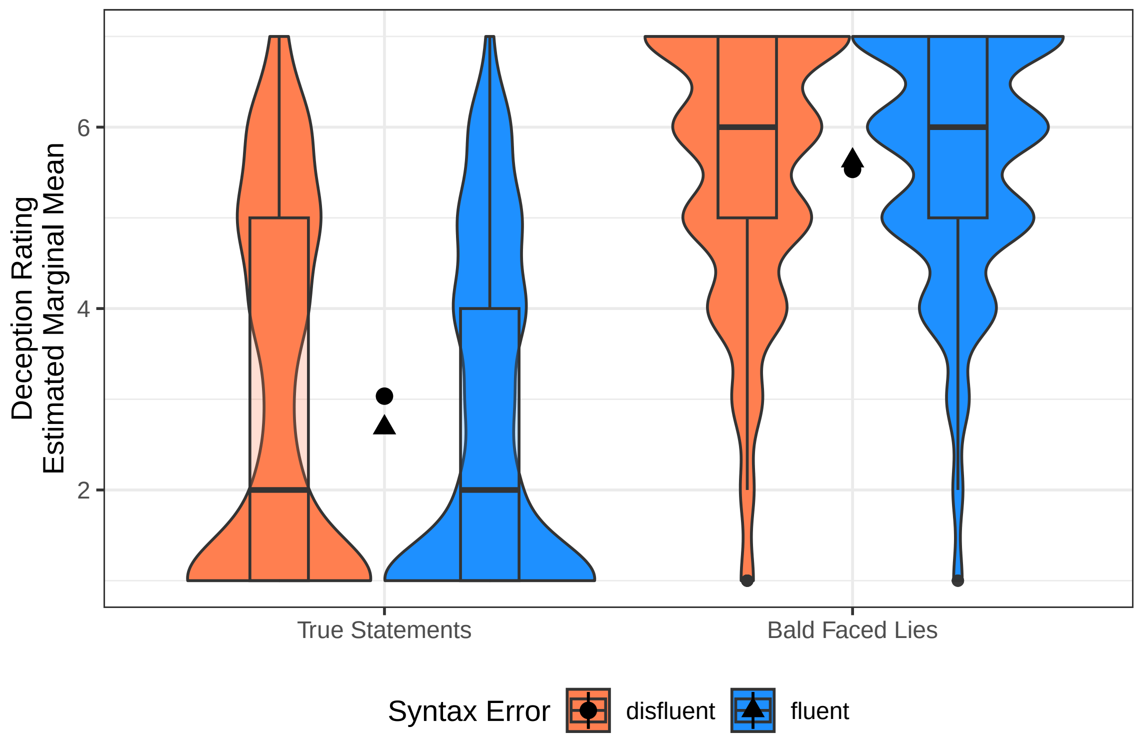
Experiment 2 Aggregated Deception Rates by Semantic Fluency per Statement Type

	BFL	CT
	n = 116	n = 116
fluent		
	5.58 (0.95)	2.95 (1.70)
disfluent		
	5.52 (1.01)	3.04 (1.82)

```
data_acc2 %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("CT", "BFL"),
                         labels = c("True Statements",
                                    "Bald Faced Lies"))) %>%
  ggplot(aes(x = TruthCon,
             y = decept_rate,
             fill = SemCon,
             group = interaction(SemCon, TruthCon))) +
  geom_violin() +
  scale_fill_manual(values = c("coral", "dodgerblue")) +
  geom_boxplot(width = .25,
               alpha = .25,
               position = position_dodge(width = .9)) +
  stat_summary(aes(shape = SemCon), color = "black", size = .6) +
  theme_bw() +
  labs(x = NULL,
       y = "Deception Rating\nEstimated Marginal Mean",
       shape = "Syntax Error",
       color = "Syntax Error",
       fill = "Syntax Error") +
  theme(legend.position = "bottom")
```

Figure 5

Observed Distribution of Deception Ratings by Statement Type and Semantic Congruency



```r
data_acc2 %>%
  dplyr::group_by(id_per, crime, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate, na.rm = FALSE)) %>%
  dplyr::ungroup() %>%
  tidyr::pivot_wider(names_from = c(crime),
                     values_from = m) %>%
  furniture::table1(crime,
                    accident,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Vignette
                    Type per Statement Type")
```

Table 19

Experiment 2 Aggregated Deception Rates by Vignette Type per Statement Type

	BFL	CT
	n = 116	n = 116
crime		
	5.53 (1.01)	2.96 (1.77)
accident		
	5.59 (0.93)	3.07 (1.78)

```r
data_acc2 %>%
  dplyr::group_by(id_per, SynCon, SemCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ interaction(SynCon, SemCon),
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Syntax
                    Error and Semantic Congruency")
```

Table 20

Experiment 2 Aggregated Deception Rates by Syntax Error and Semantic Congruency

	correct.disfluent	incorrect.disfluent	correct.fluent	incorrect.fluent
	n = 116	n = 116	n = 115	n = 116
Deception Rating, participant mean				
	4.37 (0.95)	4.27 (1.00)	4.22 (1.05)	4.24 (1.10)

```r
data_acc2 %>%
  dplyr::group_by(id_per, SynCon, SemCon, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate, na.rm = FALSE)) %>%
  dplyr::ungroup() %>%
  tidyr::pivot_wider(names_from = c(SynCon, SemCon),
                     values_from = m) %>%
  dplyr::group_by(TruthCon) %>%
  dplyr::select(-id_per) %>%
  furniture::table1(digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Syntax
                    and Semantic Congruency per Statement Type")
```

Table 21

Experiment 2 Aggregated Deception Rates by Syntax and Semantic Congruency per Statement Type

	BFL	CT
	n = 116	n = 116
correct_disfluent		
	5.62 (1.13)	3.11 (1.83)
correct_fluent		
	5.79 (0.89)	2.20 (1.19)
incorrect_disfluent		
	5.45 (1.13)	3.01 (1.94)
incorrect_fluent		
	5.40 (1.17)	3.10 (1.82)

```r
data_acc2 %>%
  dplyr::group_by(id_per, SynCon, SemCon, TruthCon, crime) %>%
  dplyr::summarise(m = mean(decept_rate, na.rm = FALSE)) %>%
  dplyr::ungroup() %>%
  tidyr::pivot_wider(names_from = c(SynCon, SemCon, crime),
                     values_from = m) %>%
  dplyr::group_by(TruthCon) %>%
  dplyr::select(-id_per) %>%
  furniture::table1(digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 2 Aggregated Deception Rates by Syntax
                    and Sematic Congruency and Vignette Type per Statement Type")
```

Table 22

Experiment 2 Aggregated Deception Rates by Syntax and Sematic Congruency and Vignette Type per Statement Type

	BFL	CT
	n = 116	n = 116
correct_disfluent_accident		
	5.63 (1.17)	3.13 (1.91)
correct_disfluent_crime		
	5.65 (1.28)	3.09 (1.98)
correct_fluent_crime		
	5.76 (0.91)	2.18 (1.22)
correct_fluent_accident		
	5.81 (0.97)	2.03 (1.18)
incorrect_disfluent_accident		
	5.65 (1.18)	3.09 (2.04)
incorrect_disfluent_crime		
	5.34 (1.43)	2.94 (1.91)
incorrect_fluent_accident		
	5.44 (1.32)	3.24 (1.84)
incorrect_fluent_crime		
	5.37 (1.43)	3.10 (1.96)

Model Building

Null Models

The Interclass Correlation Coefficients (ICCs) and model comparison results underpinned the decision to adopt the null model, featuring solely random effects for participant differences, as the most fitting approach for my analysis. This 'participant only' model elucidated that 10.3% of the variance in deception ratings could be attributed to inter-participant variability, which is notably substantial when juxtaposed with the nominal variance increments offered by accounting for vignette differences. Importantly, the adoption of a nested model was precluded by a critical limitation: the requisite condition that the levels of each grouping factor must not exceed the number of observations was not met, leading to potential errors. This condition emphasizes the principle of parsimony in statistical modeling, which advocates for simpler models that adeptly capture the essence of the data. Consequently, by concentrating exclusively on participant variability, a judicious balance is struck between elucidating the observed variance and ensuring model simplicity, thereby affirming the 'participant only' model as the most suitable null model for my investigation.

```
#Participant Differences Only
E2_null_pd_re <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per),
                               data = data_acc2,
                               REML = TRUE)

E2_null_pd_ml <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per),
                               data = data_acc2,
                               REML = FALSE)

performance::icc(E2_null_pd_re) %>%
  pander::pander(caption = "Experiment 2 Interclass Correlations: Participant
                 Difference Only")
```

Table 23

Experiment 2 Interclass Correlations: Participant Difference Only

ICC_adjusted	ICC_conditional	ICC_unadjusted
0.103	0.103	0.103

```r
#Participant per vignette differences
E2_null_ppv_re <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per) + (1|id_vin),
                                  data = data_acc2,
                                 REML = TRUE)

E2_null_ppv_ml <- lmerTest::lmer(decept_rate ~ 1 +  (1|id_per) + (1|id_vin),
                                  data = data_acc2,
                                 REML = FALSE)

performance::icc(E2_null_ppv_re,
                 by_group = TRUE) %>%
  pander::pander(caption = "Experiment 2 Intraclass Correlations: Participant
                 and Vignette")
```

Table 24

Experiment 2 Intraclass Correlations: Participant and Vignette

Group	ICC
id_per	0.103
id_vin	0.001

```r
#LRT Comparing Null Models
anova(E2_null_pd_re, E2_null_ppv_re, refit = FALSE) %>%
  pander::pander(caption = "Experiment 2 Likelihood Ratio Test: Null model with
                 and without Radom Effect of Vinegette")
```

Table 25

Experiment 2 Likelihood Ratio Test: Null model with and without Radom Effect of Vinegette (continued below)

	npar	AIC	BIC	logLik	deviance	Chisq	Df
E2_null_pd_re	3	15104	15122	-7549	15098	NA	NA
E2_null_ppv_re	4	15106	15130	-7549	15098	0.401	1

	Pr(>Chisq)
E2_null_pd_re	NA
E2_null_ppv_re	0.526

Model Building from the Null

Unadjusted Models

The model comparison of main effects revealed that the model incorporating the IV of `TruthCon` emerged as the best fit, outperforming the best fit null model. Furthermore, an evaluation of the interactions between Level 1 IVs demonstrated that the three-way interaction between these IVs had superior fit compared to the best fit main effect model, indicating that the three-way interaction most accurately capure the nuances of my data. This progression highlights the significance of both the individual and combined effects of my level 1 IVs in explaining the observed variance. The model labeled `E2_int_l1_all` will be used for subsequent model building.

```
#Main Effects of IVs
E2_me_truth <- lmerTest::lmer(decept_rate ~ TruthCon + (1|id_per),
                                data = data_acc2,
                                REML = FALSE)

E2_me_synt <- lmerTest::lmer(decept_rate ~ SynCon + (1|id_per),
                                data = data_acc2,
                                REML = FALSE)

E2_me_sema <- lmerTest::lmer(decept_rate ~ SemCon + (1|id_per),
                                data = data_acc2,
                                REML = FALSE)

E2_me_crime <- lmerTest::lmer(decept_rate ~ crime + (1|id_per),
                                data = data_acc2,
                                REML = FALSE)
#Interaction of Level 1 IVs
E2_int_truth_synt <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon + (1|id_per),
                                data = data_acc2,
                                REML = FALSE)

E2_int_truth_sema <- lmerTest::lmer(decept_rate ~ TruthCon*SemCon + (1|id_per),
                                data = data_acc2,
                                REML = FALSE)

E2_int_l1_all <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon*SemCon
                                + (1|id_per),
                                data = data_acc2,
                                REML = FALSE)
```

```r
#LRTs Main Effects
anova(E2_null_pd_re, E2_me_truth)
```

```
Data: data_acc2
Models:
E2_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E2_me_truth: decept_rate ~ TruthCon + (1 | id_per)
              npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
E2_null_pd_re    3 15101 15119 -7547.3    15095
E2_me_truth      4 13266 13290 -6628.8    13258  1837  1  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(E2_null_pd_re, E2_me_synt)
```

```
Data: data_acc2
Models:
E2_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E2_me_synt: decept_rate ~ SynCon + (1 | id_per)
              npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
E2_null_pd_re    3 15101 15119 -7547.3    15095
E2_me_synt       4 15102 15127 -7547.0    15094 0.5788  1     0.4468
```

```r
anova(E2_null_pd_re, E2_me_sema)
```

```
Data: data_acc2
Models:
E2_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E2_me_sema: decept_rate ~ SemCon + (1 | id_per)
              npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
E2_null_pd_re    3 15101 15119 -7547.3    15095
E2_me_sema       4 15102 15127 -7547.2    15094 0.1926  1     0.6608
```

```r
anova(E2_null_pd_re, E2_me_crime)
```

```
Data: data_acc2
Models:
E2_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E2_me_crime: decept_rate ~ crime + (1 | id_per)
              npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
E2_null_pd_re    3 15101 15119 -7547.3    15095
E2_me_crime      4 15102 15126 -7546.9    15094 0.7659  1     0.3815
```

```r
#LRT Main Effect best model to Interaction of Level 1 IVs
anova(E2_me_truth, E2_int_truth_synt)
```

```
Data: data_acc2
Models:
E2_me_truth: decept_rate ~ TruthCon + (1 | id_per)
E2_int_truth_synt: decept_rate ~ TruthCon * SynCon + (1 | id_per)
                  npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
E2_me_truth          4 13266 13290 -6628.8    13258
E2_int_truth_synt    6 13238 13275 -6613.1    13226 31.468  2  1.468e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(E2_int_truth_synt, E2_int_truth_sema)
```

```
Data: data_acc2
Models:
E2_int_truth_synt: decept_rate ~ TruthCon * SynCon + (1 | id_per)
E2_int_truth_sema: decept_rate ~ TruthCon * SemCon + (1 | id_per)
                  npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
E2_int_truth_synt    6 13238 13275 -6613.1    13226
E2_int_truth_sema    6 13258 13295 -6623.0    13246     0  0
```

```r
anova(E2_int_truth_synt, E2_int_l1_all)
```

```
Data: data_acc2
Models:
E2_int_truth_synt: decept_rate ~ TruthCon * SynCon + (1 | id_per)
E2_int_l1_all: decept_rate ~ TruthCon * SynCon * SemCon + (1 | id_per)
                  npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
E2_int_truth_synt    6 13238 13275 -6613.1    13226
E2_int_l1_all       10 13164 13226 -6572.0    13144 82.207  4  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(E2_int_l1_all)
```

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
  method [lmerModLmerTest]
Formula: decept_rate ~ TruthCon * SynCon * SemCon + (1 | id_per)
   Data: data_acc2

     AIC      BIC   logLik deviance df.resid
 13164.0  13225.5  -6572.0  13144.0     3481

Scaled residuals:
     Min       1Q   Median       3Q      Max
-3.11126 -0.80599 -0.03851  0.90378  2.78572

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.361    0.6009
 Residual             2.388    1.5452
Number of obs: 3491, groups:  id_per, 116

Fixed effects:
                                          Estimate Std. Error         df
(Intercept)                                5.61140    0.09140  511.69617
TruthConCT                                -2.50291    0.10289 3411.12101
SynConincorrect                           -0.16732    0.10125 3403.09862
SemConfluent                               0.16431    0.10485 3414.23424
TruthConCT:SynConincorrect                -0.01675    0.14530 3408.27607
TruthConCT:SemConfluent                   -1.15881    0.15624 3424.70331
SynConincorrect:SemConfluent              -0.16414    0.14756 3408.63095
TruthConCT:SynConincorrect:SemConfluent    1.43186    0.21480 3420.70517
                                        t value Pr(>|t|)
(Intercept)                              61.392  < 2e-16 ***
TruthConCT                              -24.325  < 2e-16 ***
SynConincorrect                          -1.653   0.0985 .
SemConfluent                              1.567   0.1172
TruthConCT:SynConincorrect               -0.115   0.9082
TruthConCT:SemConfluent                  -7.417 1.50e-13 ***
SynConincorrect:SemConfluent             -1.112   0.2661
TruthConCT:SynConincorrect:SemConfluent   6.666 3.05e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
             (Intr) TrtCCT SynCnn SmCnfl TrthCnCT:SyC TrthCnCT:SmC SyC:SC
TruthConCT   -0.560
SynCnncrrct  -0.567  0.505
SemConflunt  -0.549  0.491  0.496
TrthCnCT:SyC  0.396 -0.707 -0.699 -0.348
TrthCnCT:SmC  0.369 -0.661 -0.335 -0.674  0.471
SynCnncr:SC   0.389 -0.348 -0.687 -0.711  0.481        0.481
TrCCT:SC:SC  -0.268  0.481  0.474  0.491 -0.680       -0.730       -0.690
```

Adjusted Models

There was no significant main effect for crime or 4-way interaction between level 1 and level 2 variables. The Likelihood ratio test confirmed that `E2_int_l1_all` was still the best fit model for the data.

```
#Controlling for Main Effect of Level 2 IV
E2_int_c4_crime <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon*SemCon + crime
                                    + (1|id_per),
                                  data = data_acc2,
                                  REML = FALSE)
#Cross-level/4-way interaction
E2_xint_l1_l2 <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon*SemCon*crime
                                  + (1|id_per),
                                  data = data_acc2,
                                  REML = FALSE)
```

```
#LRT Adjusted Models
anova(E2_int_l1_all, E2_int_c4_crime, E2_xint_l1_l2)
```

```
Data: data_acc2
Models:
E2_int_l1_all: decept_rate ~ TruthCon * SynCon * SemCon + (1 | id_per)
E2_int_c4_crime: decept_rate ~ TruthCon * SynCon * SemCon + crime + (1 | id_per)
E2_xint_l1_l2: decept_rate ~ TruthCon * SynCon * SemCon * crime + (1 | id_per)
                npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
E2_int_l1_all     10 13164 13226 -6572.0    13144
E2_int_c4_crime   11 13164 13232 -6571.1    13142 1.6819  1     0.1947
E2_xint_l1_l2     18 13171 13282 -6567.6    13135 7.1520  7     0.4132
```

Final Model and Parameter Estimates

```
E2_final_model <- lmerTest::lmer(decept_rate ~ TruthCon*SynCon*SemCon
                                + (1|id_per),
                              data = data_acc2,
                              REML = TRUE)
summary(E2_final_model)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: decept_rate ~ TruthCon * SynCon * SemCon + (1 | id_per)
   Data: data_acc2

REML criterion at convergence: 13168.9

Scaled residuals:
     Min       1Q   Median       3Q      Max
-3.10827 -0.80477 -0.03761  0.90212  2.78311

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.365    0.6041
 Residual             2.393    1.5468
Number of obs: 3491, groups:  id_per, 116

Fixed effects:
                                          Estimate Std. Error         df
(Intercept)                                5.61142    0.09165  503.93733
TruthConCT                                -2.50299    0.10300 3403.88192
SynConincorrect                           -0.16736    0.10136 3395.93160
SemConfluent                               0.16419    0.10496 3406.96669
TruthConCT:SynConincorrect                -0.01667    0.14546 3401.05892
TruthConCT:SemConfluent                   -1.15827    0.15640 3417.32719
SynConincorrect:SemConfluent              -0.16398    0.14772 3401.41025
TruthConCT:SynConincorrect:SemConfluent    1.43124    0.21503 3413.36591
                                        t value Pr(>|t|)
(Intercept)                              61.227  < 2e-16 ***
TruthConCT                              -24.300  < 2e-16 ***
SynConincorrect                          -1.651   0.0988 .
SemConfluent                              1.564   0.1178
TruthConCT:SynConincorrect               -0.115   0.9088
TruthConCT:SemConfluent                  -7.406 1.63e-13 ***
SynConincorrect:SemConfluent             -1.110   0.2670
TruthConCT:SynConincorrect:SemConfluent   6.656 3.26e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
             (Intr) TrtCCT SynCnn SmCnfl TrthCnCT:SyC TrthCnCT:SmC SyC:SC
TruthConCT   -0.560
SynCnncrrct  -0.566  0.505
SemConflunt  -0.549  0.491  0.496
TrthCnCT:SyC  0.395 -0.707 -0.699 -0.348
```

```
TrthCnCT:SmC  0.368 -0.661 -0.335 -0.674  0.471
SynCnncr:SC   0.389 -0.348 -0.687 -0.711  0.481        0.481
TrCCT:SC:SC  -0.268  0.481  0.474  0.491 -0.680       -0.730       -0.690
```

Follow-up Tests

Pooled Standard Deviation

```
est_SD <- E2_final_model %>%
  VarCorr() %>%
  data.frame() %>%
  dplyr::summarise(tot_var = sum(vcov)) %>%
  dplyr::pull(tot_var) %>%
  sqrt()

est_SD
```

```
[1] 1.660614
```

Pairwise Tests

```
E2_final_model %>%
  emmeans::emmeans(pairwise~ SynCon*SemCon|TruthCon)
```

```
$emmeans
TruthCon = BFL:
 SynCon    SemCon    emmean     SE  df asymp.LCL asymp.UCL
 correct   disfluent   5.61 0.0916 Inf      5.43      5.79
 incorrect disfluent   5.44 0.0903 Inf      5.27      5.62
 correct   fluent      5.78 0.0941 Inf      5.59      5.96
 incorrect fluent      5.44 0.0944 Inf      5.26      5.63

TruthCon = CT:
 SynCon    SemCon    emmean     SE  df asymp.LCL asymp.UCL
 correct   disfluent   3.11 0.0919 Inf      2.93      3.29
 incorrect disfluent   2.92 0.0929 Inf      2.74      3.11
 correct   fluent      2.11 0.1055 Inf      1.91      2.32
 incorrect fluent      3.20 0.0918 Inf      3.02      3.38

Degrees-of-freedom method: asymptotic
Confidence level used: 0.95

$contrasts
TruthCon = BFL:
 contrast                                 estimate    SE  df z.ratio p.value
 correct disfluent - incorrect disfluent  0.167362 0.101 Inf   1.651  0.3499
 correct disfluent - correct fluent      -0.164192 0.105 Inf  -1.564  0.3992
 correct disfluent - incorrect fluent     0.167150 0.105 Inf   1.590  0.3843
 incorrect disfluent - correct fluent    -0.331555 0.104 Inf  -3.200  0.0075
 incorrect disfluent - incorrect fluent  -0.000213 0.104 Inf  -0.002  1.0000
 correct fluent - incorrect fluent        0.331342 0.107 Inf   3.086  0.0109

TruthCon = CT:
 contrast                                 estimate    SE  df z.ratio p.value
 correct disfluent - incorrect disfluent  0.184028 0.104 Inf   1.769  0.2882
 correct disfluent - correct fluent       0.994074 0.115 Inf   8.607  <.0001
 correct disfluent - incorrect fluent    -0.089158 0.103 Inf  -0.867  0.8220
 incorrect disfluent - correct fluent     0.810047 0.116 Inf   6.992  <.0001
 incorrect disfluent - incorrect fluent  -0.273186 0.104 Inf  -2.630  0.0424
 correct fluent - incorrect fluent       -1.083233 0.115 Inf  -9.406  <.0001

Degrees-of-freedom method: asymptotic
P value adjustment: tukey method for comparing a family of 4 estimates
```

```
label_pairwise <- E2_final_model %>%
  emmeans::emmeans(~ SynCon*SemCon| + TruthCon) %>%
  pairs() %>%
  data.frame() %>%
  dplyr::mutate(d = estimate/est_SD) %>%
  dplyr::mutate(d = d %>%
                  abs() %>%
                  apa2()) %>%
  dplyr::filter(p.value < .05) %>%
  dplyr::mutate(label = glue::glue(" SMD = {d}, {pformat(p.value)}")) %>%
  dplyr::select(contrast,  TruthCon, label) %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("CT", "BFL"),
                         labels = c("True Statements",
                                    "Bald Faced Lies"))) %>%
  tidyr::separate(col = "contrast",
                  sep = " - ",
                  into = c("xmin", "xmax")) %>%
  dplyr::mutate(xmin = case_when(xmin == "correct fluent" ~ "Correct Fluent",
                                 xmin == "incorrect fluent" ~"Incorrect Fluent",
                                 xmin == "correct disfluent" ~ "Correct Disfluent",
                                 xmin == "incorrect disfluent" ~
                                   "Incorrect Disfluent")) %>%
  dplyr::mutate(xmax = case_when(xmax == "correct fluent" ~ "Correct Fluent",
                                 xmax == "incorrect fluent" ~"Incorrect Fluent",
                                 xmax == "correct disfluent" ~ "Correct Disfluent",
                                 xmax == "incorrect disfluent" ~
                                   "Incorrect Disfluent")) %>%
  dplyr::mutate(y.position = case_when(TruthCon == "Bald Faced Lies" ~ 6.25,
                                       TruthCon == "True Statements" ~ 3))

label_pairwise
```

```
                 xmin             xmax        TruthCon                   label
1 Incorrect Disfluent   Correct Fluent Bald Faced Lies   SMD = 0.20, p = .008**
2      Correct Fluent Incorrect Fluent Bald Faced Lies    SMD = 0.20, p = .011*
3   Correct Disfluent   Correct Fluent True Statements SMD = 0.60, p < .001***
4 Incorrect Disfluent   Correct Fluent True Statements SMD = 0.49, p < .001***
5 Incorrect Disfluent Incorrect Fluent True Statements    SMD = 0.16, p = .042*
6      Correct Fluent Incorrect Fluent True Statements SMD = 0.65, p < .001***
  y.position
1       6.25
2       6.25
3       3.00
4       3.00
5       3.00
6       3.00
```

Interaction Contrast

```
E2_final_model %>%
  emmeans::emmeans(~ SynCon*SemCon| TruthCon)
```

```
TruthCon = BFL:
 SynCon    SemCon    emmean     SE  df asymp.LCL asymp.UCL
 correct   disfluent   5.61 0.0916 Inf      5.43      5.79
 incorrect disfluent   5.44 0.0903 Inf      5.27      5.62
 correct   fluent      5.78 0.0941 Inf      5.59      5.96
 incorrect fluent      5.44 0.0944 Inf      5.26      5.63

TruthCon = CT:
 SynCon    SemCon    emmean     SE  df asymp.LCL asymp.UCL
 correct   disfluent   3.11 0.0919 Inf      2.93      3.29
 incorrect disfluent   2.92 0.0929 Inf      2.74      3.11
 correct   fluent      2.11 0.1055 Inf      1.91      2.32
 incorrect fluent      3.20 0.0918 Inf      3.02      3.38

Degrees-of-freedom method: asymptotic
Confidence level used: 0.95
```

```
E2_final_model %>%
  emmeans::emmeans(~ SynCon*SemCon| TruthCon) %>%
  contrast(list("Cor-Cor vs Rest" = c(1, -1/3, -1/3, -1/3),
              "1 vs both incor" = c(0, .5, .5, -1),
              "SynCon > SemCon" = c(0, .5, -1, .5))) %>%
  data.frame() %>%
  dplyr::mutate(d = estimate/est_SD) %>%
  rstatix::p_format(add.p = TRUE,
                    space = TRUE,
                    accuracy = 1e-03,
                    leading.zero = FALSE,
                    trailing.zero = TRUE,
                    new.col = TRUE) %>%
  dplyr::mutate(d = d %>%
                  abs() %>%
                  apa2()) %>%
  dplyr::filter(p.value < .05) %>%
  dplyr::mutate(cell = glue::glue(" SMD = {d}, {p.value.format}")) %>%
  dplyr::select(contrast, TruthCon, cell)
```

```
         contrast TruthCon                  cell
1 SynCon > SemCon      BFL   SMD = 0.20, p < .001
2 Cor-Cor vs Rest       CT   SMD = 0.22, p < .001
3 1 vs both incor       CT   SMD = 0.41, p < .001
4 SynCon > SemCon       CT   SMD = 0.57, p < .001
```

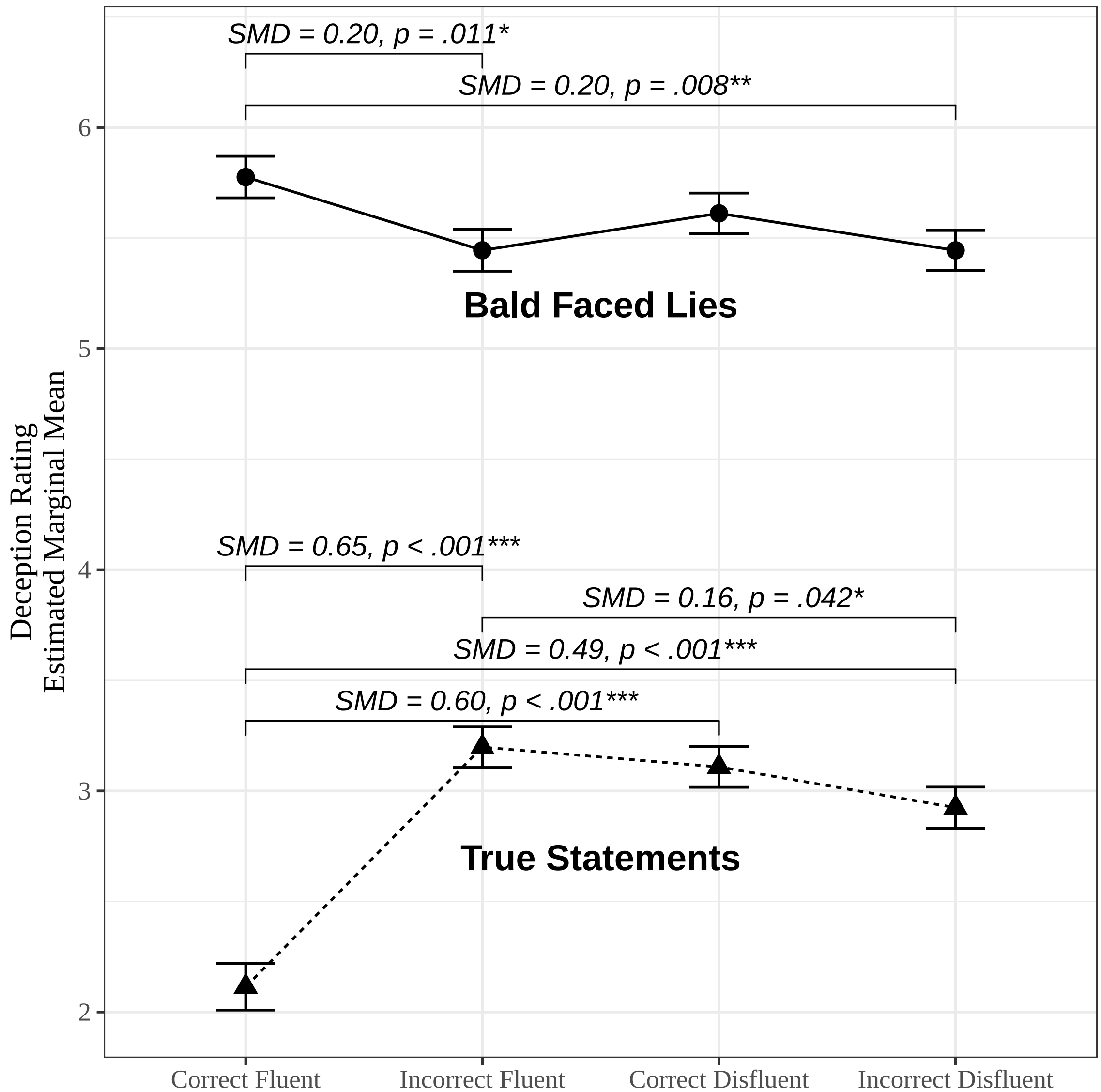
Experiment 2 Visualization

```
effects::Effect(focal.predictors = c("SemCon", "SynCon", "TruthCon"),
                mod = E2_final_model) %>%
  data.frame() %>%
  dplyr::mutate(TruthCon = TruthCon %>%
                  factor(levels = c("CT", "BFL"),
                         labels = c("True Statements",
                                    "Bald Faced Lie")) %>%
                  forcats::fct_rev()) %>%
  dplyr::mutate(type = interaction(SynCon, SemCon) %>%
                  factor(levels = c("correct.fluent",
                                    "incorrect.fluent",
                                    "correct.disfluent",
                                    "incorrect.disfluent") ,
                         labels = c("Correct Fluent",
                                    "Incorrect Fluent",
                                    "Correct Disfluent",
                                    "Incorrect Disfluent"))) %>%
  ggplot(aes(x = type,
             y = fit,
             group = TruthCon,
             shape = TruthCon)) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se),
                width = .25) +
  geom_point(size = 3) +
  geom_line(aes(linetype = TruthCon)) +
  theme_bw() +
  labs(x = NULL,
       y = "Deception Rating\nEstimated Marginal Mean")+
  geom_bracket(data = label_pairwise,
               aes(label = label,
                   y.position = y.position,
                   xmin = xmin,
                   xmax = xmax),
               fontface = "italic",
               bracket.nudge.y = -.15,
               tip.length = .015,
               step.increase = .055) +
  theme(legend.position = "none",
        text = element_text(family = "serif",
                            size =12)) +
  annotate(geom = "text",
           fontface = "bold",
           size = 5,
           x = 2.5,
           y = 2.7,
           label = "True Statements") +
  annotate(geom = "text",
           fontface = "bold",
           size = 5,
           x = 2.5,
```

```
         y = 5.2,
         label = "Bald Faced Lies")
```

Figure 6

Visualization of Syntax and Semantic Congruency by Statement Type on Deception Rating



Experiment 3 Analysis

Load Data

```
psych::headTail(data) %>%
  pander::pander(caption = "Illistration of Experiment 3 Dataset")
```

Table 27
Illistration of Experiment 3 Dataset (continued below)

id_per	id_vin	SemCon	SynCon	TruthCon	decept_rate	N400_amp
131	1	Disfluent	Correct	CT	1	3.33
131	1	Fluent	Incorrect	BFL	5	-2.51
131	2	Disfluent	Incorrect	BFL	3	0.17
131	2	Fluent	Correct	CT	1	-0.35
NA	NA	NA	NA	NA	...	...
993	63	Disfluent	Correct	CT	1	-3.5
993	63	Fluent	Incorrect	BFL	7	-4.98
993	64	Fluent	Incorrect	BFL	7	-2.29
993	64	Disfluent	Correct	CT	1	5.12

Table 28
Table continues below

P600_amp	Lies_amp	age	gender	race	over_exp	dist_sent
5.52	-1.19	19	Female	White	4	4
4.39	-6.43	19	Female	White	4	4
7.88	3.74	19	Female	White	4	4
3.04	5.07	19	Female	White	4	4
...	...	...	NA	NA	...	...
-7.51	1.38	20	Male	White	4	4
8.02	-2.81	20	Male	White	4	4
-1.77	6.99	20	Male	White	4	4
2.87	-4.09	20	Male	White	4	4

main_attent	vig_mem	N400_amp_sd	P600_amp_sd	Lies_amp_sd
3	5	0.74	0.73	-0.33
3	5	-0.57	0.53	-1.36
3	5	0.03	1.15	0.63
3	5	-0.09	0.29	0.9
...	...	...	...	...
3	3	-0.8	-1.59	0.17
3	3	-1.13	1.17	-0.65
3	3	-0.53	-0.57	1.27
3	3	1.14	0.26	-0.9

Sample Size

N = 18 participants with a total of 2304 deception ratings.

```
data %>%
  dplyr::group_by(id_per) %>%
  dplyr::tally() %>%
  dplyr::ungroup() %>%
  dplyr::select(n) %>%
  table %>%
  addmargins()
```

```
n
128 Sum
 18  18
```

```
nrow(data)
```

```
[1] 2304
```

Basic Descriptives

```
#Mean, Median, and Quartiles of overall deception ratings
data %>%
  dplyr::select(decept_rate) %>%
  summary()
```

```
  decept_rate
 Min.   :1.000
 1st Qu.:1.000
 Median :4.500
 Mean   :4.112
 3rd Qu.:7.000
 Max.   :7.000
```

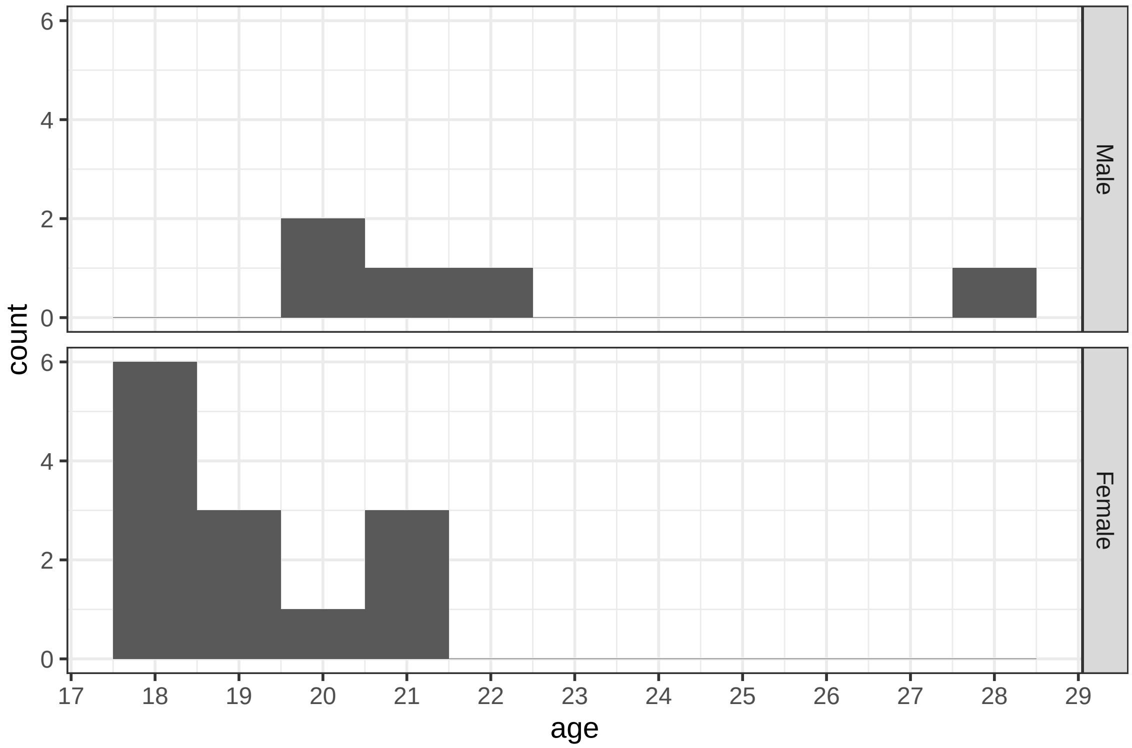
```
#Basic Descriptives of Age
data_demo %>%
  dplyr::select(age) %>%
  summarise(mean(age),
            sd(age))
```

```
# A tibble: 1 x 2
  `mean(age)` `sd(age)`
        <dbl>     <dbl>
1        19.9      2.41
```

```
#Basic Descriptives of Age by Gender
data_demo %>%
  furniture::table1(age,
                    splitby = ~ gender,
                    digits = 2)
```

```
            gender
     Male         Female
     n = 5        n = 13
 age
     22.20 (3.35) 19.08 (1.26)
```

```
data_demo %>%
  ggplot(aes(age)) +
  geom_histogram(binwidth = 1)+
  theme_bw() +
  facet_grid(gender ~.) +
  scale_x_continuous(breaks = 0:100)
```



Male
Female
count
age
0
2
4
6
17
18
19
20
21
22
23
24
25
26
27
28
29

Descriptive Statistical Analysis

Means by Single Independent Variables

```
data %>%
  dplyr::group_by(id_per, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ TruthCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 3 Aggregated Deception Rates by Statement
                    Type")
```

Table 30

Experiment 3 Aggregated Deception Rates by Statement Type

	BFL	CT
	n = 18	n = 18
Deception Rating, participant mean		
	5.98 (0.88)	2.25 (1.03)

```
data %>%
  dplyr::group_by(id_per, SemCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ SemCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 3 Aggregated Deception Rates by Semantic
                    Fluency")
```

Table 31

Experiment 3 Aggregated Deception Rates by Semantic Fluency

	Fluent	Disfluent
	n = 18	n = 18
Deception Rating, participant mean		
	3.92 (0.49)	4.30 (0.62)

```r
data %>%
  dplyr::group_by(id_per, SynCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ SynCon,
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 3 Aggregated Deception Rates by Syntactic
                    Correctness")
```

Table 32
Experiment 3 Aggregated Deception Rates by Syntactic Correctness

	Correct	Incorrect
	n = 18	n = 18
Deception Rating, participant mean		
	3.88 (0.46)	4.34 (0.86)

Means by Grouped Independent Variables

```
data %>%
  dplyr::group_by(id_per, SemCon, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ interaction(SemCon, TruthCon),
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 3 Aggregated Deception Rates by Semantic
                    Fluency and Statement Type")
```

Table 33

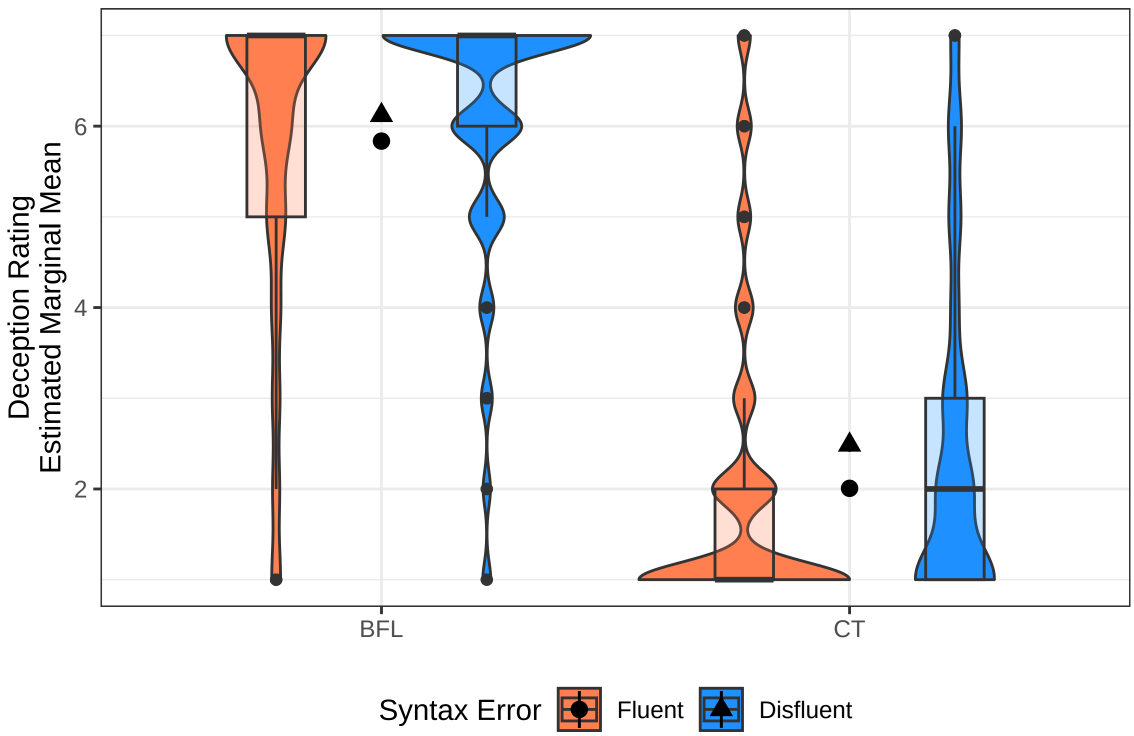
Experiment 3 Aggregated Deception Rates by Semantic Fluency and Statement Type

	Fluent.BFL	Disfluent.BFL	Fluent.CT	Disfluent.CT
	n = 18	n = 18	n = 18	n = 18
Deception Rating, participant mean				
	5.84 (1.06)	6.12 (0.72)	2.01 (0.85)	2.49 (1.23)

```
data %>%
  ggplot(aes(x = TruthCon,
             y = decept_rate,
             fill = SemCon,
             group = interaction(SemCon, TruthCon))) +
  geom_violin() +
  scale_fill_manual(values = c("coral", "dodgerblue")) +
  geom_boxplot(width = .25,
               alpha = .25,
               position = position_dodge(width = .9)) +
  stat_summary(aes(shape = SemCon), color = "black", size = .6) +
  theme_bw() +
  labs(x = NULL,
       y = "Deception Rating\nEstimated Marginal Mean",
       shape = "Syntax Error",
       color = "Syntax Error",
       fill = "Syntax Error") +
  theme(legend.position = "bottom")
```

Figure 7

Observed Distribution of Deception Ratings by Statement Type and Semantic Fluency



```r
data %>%
  dplyr::group_by(id_per, SynCon, TruthCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ interaction(SynCon, TruthCon),
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 3 Aggregated Deception Rates by Syntax
                    Error and Statement Type")
```

Table 34

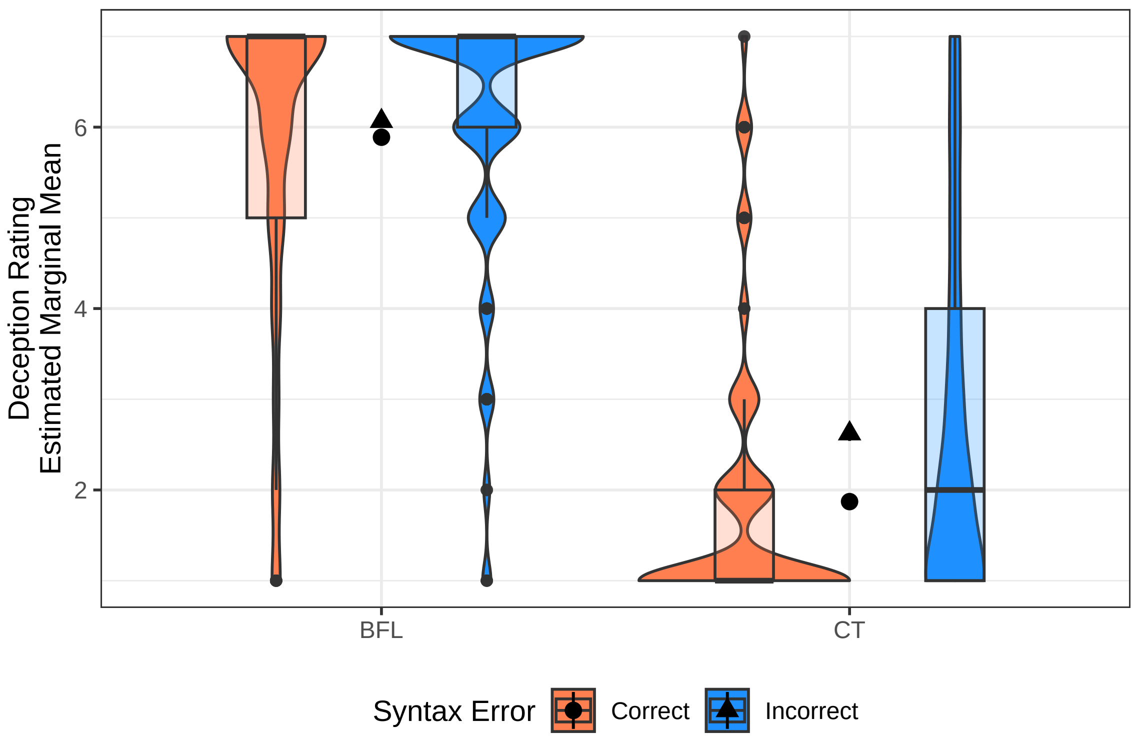
Experiment 3 Aggregated Deception Rates by Syntax Error and Statement Type

	Correct.BFL	Incorrect.BFL	Correct.CT	Incorrect.CT
	n = 18	n = 18	n = 18	n = 18
Deception Rating, participant mean				
	5.89 (1.18)	6.07 (0.82)	1.87 (0.71)	2.62 (1.41)

```r
data %>%
  ggplot(aes(x = TruthCon,
             y = decept_rate,
             fill = SynCon,
             group = interaction(SynCon, TruthCon))) +
  geom_violin() +
  scale_fill_manual(values = c("coral", "dodgerblue")) +
  geom_boxplot(width = .25,
               alpha = .25,
               position = position_dodge(width = .9)) +
  stat_summary(aes(shape = SynCon), color = "black", size = .6) +
  theme_bw() +
  labs(x = NULL,
       y = "Deception Rating\nEstimated Marginal Mean",
       shape = "Syntax Error",
       color = "Syntax Error",
       fill = "Syntax Error") +
  theme(legend.position = "bottom")
```

Figure 8

Observed Distribution of Deception Ratings by Statement Type and Syntax Error



```r
data %>%
  dplyr::group_by(id_per, SemCon, SynCon) %>%
  dplyr::summarise(m = mean(decept_rate)) %>%
  dplyr::ungroup() %>%
  furniture::table1("Deception Rating, participant mean" = m,
                    splitby = ~ interaction(SemCon, SynCon),
                    digits = 2,
                    na.rm = FALSE,
                    output = "markdown",
                    caption = "Experiment 3 Aggregated Deception Rates by Semantic
                    Fluency and Syntax Error")
```

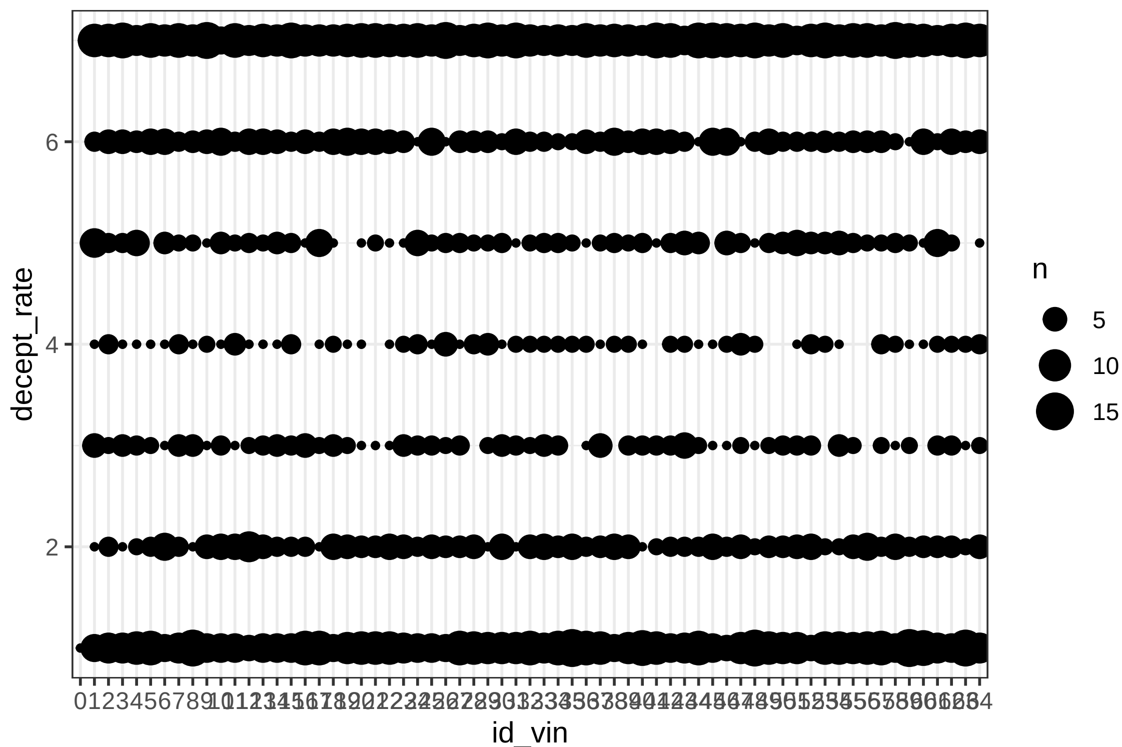
Table 35

Experiment 3 Aggregated Deception Rates by Semantic Fluency and Syntax Error

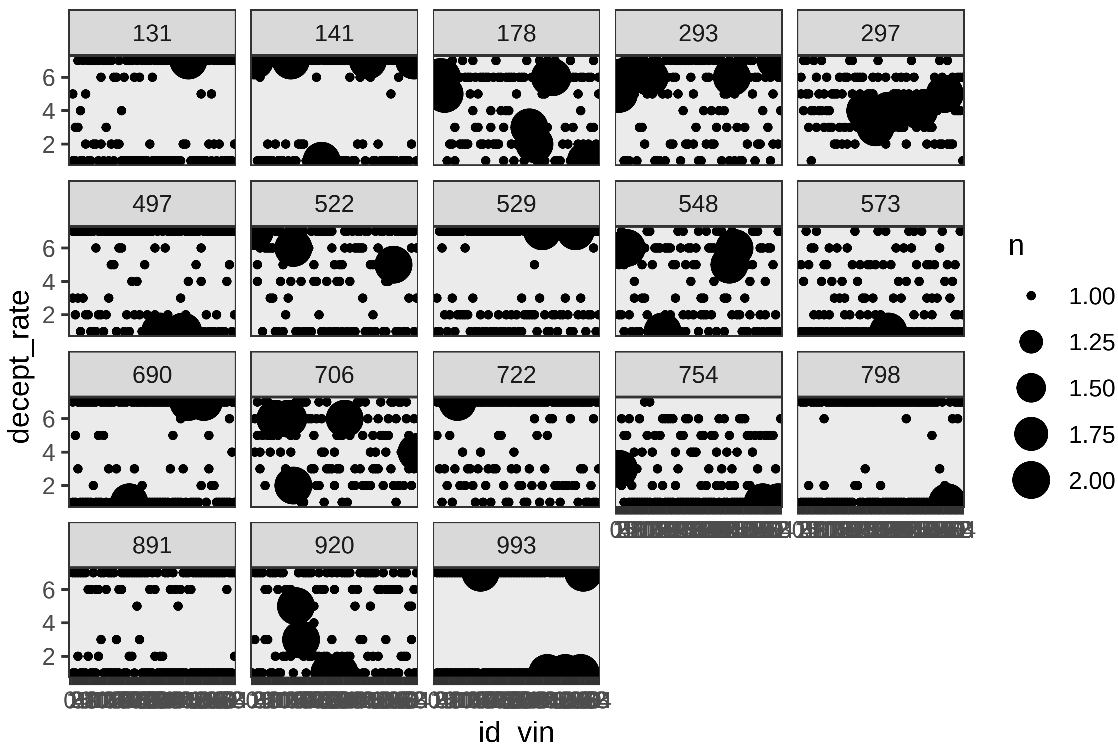
	Fluent.Correct	Disfluent.Correct	Fluent.Incorrect	Disfluent.Incorrect
	n = 18	n = 18	n = 18	n = 18
Deception Rating, participant mean				
	3.65 (0.64)	4.11 (0.43)	4.19 (0.84)	4.50 (0.91)

Understanding Ratings Across Vignettes

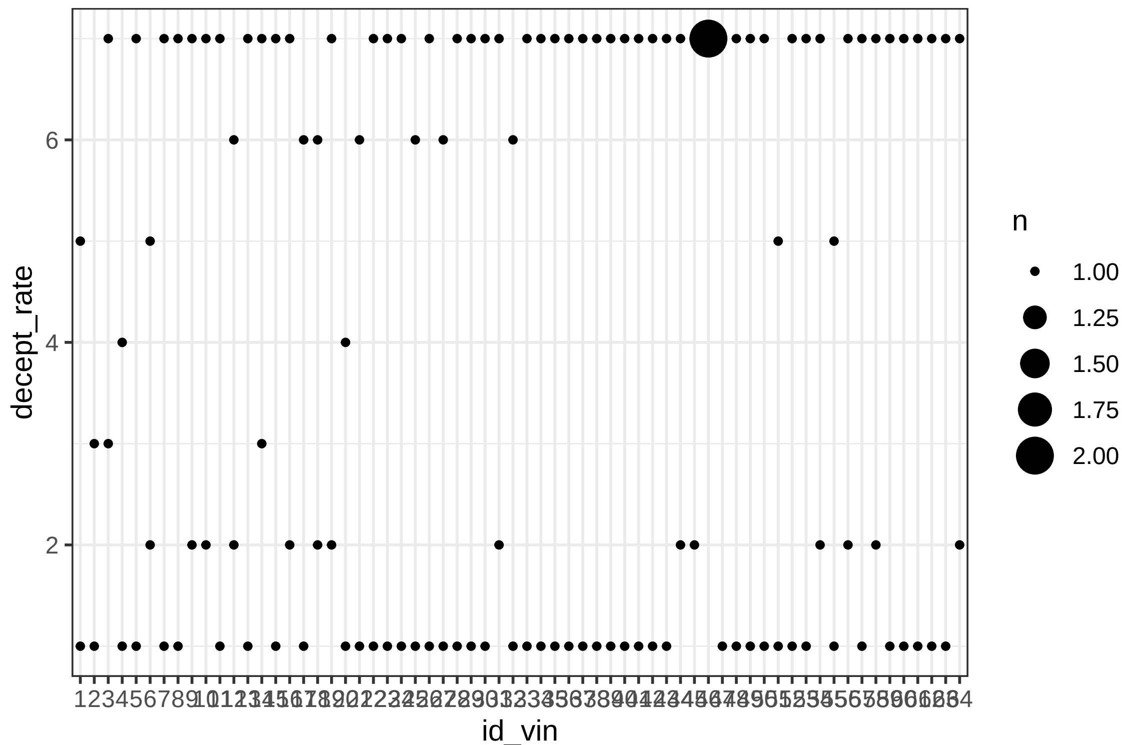
```
data %>%
  ggplot(aes(x = id_vin,
             y = decept_rate)) +
  geom_count() +
  theme_bw()
```



```
data %>%
  ggplot(aes(x = id_vin,
             y = decept_rate)) +
  geom_count() +
  theme_bw() +
  facet_wrap(~ id_per)
```



```r
data %>%
  dplyr::filter(id_per == "131") %>%
  ggplot(aes(x = id_vin,
             y = decept_rate)) +
  geom_count() +
  theme_bw()
```



Model Building

Null Models

The analysis involving Interclass Correlation Coefficients (ICCs) and model comparisons distinctly favored the null model that incorporated only random effects for participant differences, marking it as the optimal framework for my study. This preference emerged because the ‘participant only’ null model accounted for 3.6% of the variance in deception ratings, a considerably significant proportion when contrasted with the negligible additional variance elucidated by more complex models. Notably, the models that expanded to include participant per vignette differences and a nested approach encountered issues of singularity, rendering them less viable. Singularity in these models, often indicative of overly complex or redundant parameters relative to the data, precluded their effectiveness and underscored the principle of parsimony in statistical modeling. This principle advocates for the simplicity of models, provided they offer a sufficient explanation of the data.

```
#Participant Difference Only
E3_null_pd_re <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per),
                             data = data,
                             REML = TRUE)
E3_null_pd_ml <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per),
                             data = data,
                             REML = FALSE)

performance::icc(E3_null_pd_re) %>%
  pander::pander(caption = "Experiment 3 Interclass Correlations: Participant
                 Difference Only")
```

Table 36

Experiment 3 Interclass Correlations: Participant Difference Only

ICC_adjusted	ICC_conditional	ICC_unadjusted
0.036	0.036	0.036

```r
#Participant per Vignette Difference
E3_null_ppv_re <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per) + (1|id_vin),
                                 data = data,
                                 REML = TRUE)

E3_null_ppv_ml <- lmerTest::lmer(decept_rate ~ 1 +  (1|id_per) + (1|id_vin),
                                 data = data,
                                 REML = FALSE)

performance::icc(E3_null_ppv_re,
                 by_group = TRUE)
```

```
[1] NA
```

> boundary (singular) fit: see help('isSingular') boundary (singular) fit: see help('isSingular') Warning: Can't compute random effect variances. Some variance components equal zero. Your model may suffer from singularity (see `?lme4::isSingular` and `?performance::check_singularity`). Solution: Respecify random structure! You may also decrease the `tolerance` level to enforce the calculation of random effect variances._NA_

```r
#Vignette nested under participant
E3_null_nest_re <- lmerTest::lmer(decept_rate ~ 1 + (1|id_per/id_vin),
                                  data = data,
                                  REML = TRUE)

E3_null_nest_ml <- lmerTest::lmer(decept_rate ~ 1 +  (1|id_per/id_vin),
                                  data = data,
                                  REML = FALSE)

performance::icc(E3_null_nest_re,
                 by_group = TRUE)
```

```
[1] NA
```

> boundary (singular) fit: see help('isSingular') boundary (singular) fit: see help('isSingular') Warning: Can't compute random effect variances. Some variance components equal zero. Your model may suffer from singularity (see `?lme4::isSingular` and `?performance::check_singularity`). Solution: Respecify random structure! You may also decrease the `tolerance` level to enforce the calculation of random effect variances._NA_

Behavioral Model Building

Unadjusted Models

My initial analysis focused on examining the main effects of three level 1 IVs, before exploring the complexity of a 3-way interaction effect among them. The model that incorporated the main effects of all three level 1 IVs demonstrated a better fit for the data compared to the null model. Subsequently, I assessed a model with the 3-way interaction effect, which appeared to fit the data more accurately than the main effect model. However, a detailed inspection of the model revealed that the 3-way interaction effect was not statistically significant. This discovery prompted further examination of alternative models to identify a more suitable fit. Through this process, the model labeled `E3_int_l1_ivs_c` emerged as the best fitting model thus far and will be used for subsequent model building.

```r
#Main Effects of IVs
E3_me_truth <- lmerTest::lmer(decept_rate ~ TruthCon + (1|id_per),
                              data = data,
                              REML = FALSE)
E3_me_sem <- lmerTest::lmer(decept_rate ~ SemCon + (1|id_per),
                            data = data,
                            REML = FALSE)
E3_me_syn <- lmerTest::lmer(decept_rate ~ SynCon + (1|id_per),
                            data = data,
                            REML = FALSE)
E3_me_all <- lmerTest::lmer(decept_rate ~ TruthCon + SemCon + SynCon + (1|id_per),
                            data = data,
                            REML = FALSE)

#3-Way Interaction of IVs
E3_int_l1_ivs <- lmerTest::lmer(decept_rate ~ TruthCon*SemCon*SynCon + (1|id_per),
                                data = data,
                                REML = FALSE)

#Finding best Fit Model with Interactions
E3_int_l1_ivs_b <- lmerTest::lmer(decept_rate ~ TruthCon*SemCon + SemCon*SynCon
                                  + TruthCon*SynCon +(1|id_per),
                                  data = data,
                                  REML = FALSE)
E3_int_l1_ivs_c <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon
                                  + (1|id_per),
                                  data = data,
                                  REML = FALSE)
```

```r
#LRTs of Main Effects
anova(E3_null_pd_re, E3_me_truth)
```

```
Data: data
Models:
E3_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E3_me_truth: decept_rate ~ TruthCon + (1 | id_per)
              npar     AIC     BIC  logLik deviance Chisq Df Pr(>Chisq)
E3_null_pd_re    3 10736.0 10753.2 -5365.0  10730.0
```

```
E3_me_truth      4  8774.9  8797.9 -4383.5   8766.9  1963  1  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(E3_null_pd_re, E3_me_sem)
```

```
Data: data
Models:
E3_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E3_me_sem: decept_rate ~ SemCon + (1 | id_per)
              npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_null_pd_re    3 10736 10753 -5365.0    10730
E3_me_sem        4 10724 10747 -5358.1    10716 13.849  1  0.0001981 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(E3_null_pd_re, E3_me_syn)
```

```
Data: data
Models:
E3_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E3_me_syn: decept_rate ~ SynCon + (1 | id_per)
              npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_null_pd_re    3 10736 10753 -5365.0    10730
E3_me_syn        4 10718 10740 -5354.8    10710 20.427  1  6.194e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(E3_null_pd_re, E3_me_all)
```

```
Data: data
Models:
E3_null_pd_re: decept_rate ~ 1 + (1 | id_per)
E3_me_all: decept_rate ~ TruthCon + SemCon + SynCon + (1 | id_per)
              npar     AIC     BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_null_pd_re    3 10736.0 10753.2 -5365.0  10730.0
E3_me_all        6  8696.9  8731.3 -4342.4   8684.9 2045.1  3  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(E3_me_all, E3_int_l1_ivs)
```

```
Data: data
Models:
E3_me_all: decept_rate ~ TruthCon + SemCon + SynCon + (1 | id_per)
E3_int_l1_ivs: decept_rate ~ TruthCon * SemCon * SynCon + (1 | id_per)
              npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_me_all        6 8696.9 8731.3 -4342.4   8684.9
E3_int_l1_ivs   10 8682.2 8739.6 -4331.1   8662.2 22.668  4  0.0001475 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#Model Inspection
summary(E3_int_l1_ivs)
```

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
  method [lmerModLmerTest]
Formula: decept_rate ~ TruthCon * SemCon * SynCon + (1 | id_per)
   Data: data

     AIC      BIC   logLik deviance df.resid
  8682.2   8739.6  -4331.1   8662.2     2294

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.5284 -0.6452  0.0456  0.5969  3.5450

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.2397   0.4896
 Residual             2.4632   1.5695
Number of obs: 2304, groups:  id_per, 18

Fixed effects:
                                             Estimate Std. Error         df
(Intercept)                                   5.72222    0.14789   41.50711
TruthConCT                                   -4.13889    0.13079 2286.00000
SemConDisfluent                               0.33333    0.13079 2286.00000
SynConIncorrect                               0.22569    0.13079 2286.00000
TruthConCT:SemConDisfluent                    0.24306    0.18496 2286.00000
TruthConCT:SynConIncorrect                    0.62153    0.18496 2286.00000
SemConDisfluent:SynConIncorrect              -0.09722    0.18496 2286.00000
TruthConCT:SemConDisfluent:SynConIncorrect   -0.09722    0.26158 2286.00000
                                           t value Pr(>|t|)
(Intercept)                                 38.693  < 2e-16 ***
TruthConCT                                 -31.646  < 2e-16 ***
SemConDisfluent                              2.549 0.010879 *
SynConIncorrect                              1.726 0.084544 .
TruthConCT:SemConDisfluent                   1.314 0.188949
TruthConCT:SynConIncorrect                   3.360 0.000791 ***
SemConDisfluent:SynConIncorrect             -0.526 0.599193
TruthConCT:SemConDisfluent:SynConIncorrect  -0.372 0.710166
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) TrtCCT SmCnDs SynCnI TrCCT:SCD TCCT:SCI SCD:SC
TruthConCT  -0.442
SemCnDsflnt -0.442  0.500
SynCnIncrrc -0.442  0.500  0.500
TrthCCT:SCD  0.313 -0.707 -0.707 -0.354
TrthCCT:SCI  0.313 -0.707 -0.354 -0.707  0.500
SmCnDsf:SCI  0.313 -0.354 -0.707 -0.707  0.500     0.500
TCCT:SCD:SC -0.221  0.500  0.500  0.500 -0.707    -0.707   -0.707
```

```
#LRTs: Finding Best Fit Model
anova(E3_int_l1_ivs, E3_int_l1_ivs_b)
```

```
Data: data
Models:
E3_int_l1_ivs_b: decept_rate ~ TruthCon * SemCon + SemCon * SynCon + TruthCon * SynCon + (1 | id_
E3_int_l1_ivs: decept_rate ~ TruthCon * SemCon * SynCon + (1 | id_per)
                npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_int_l1_ivs_b    9 8680.3 8732.0 -4331.2   8662.3
E3_int_l1_ivs     10 8682.2 8739.6 -4331.1   8662.2 0.1381  1     0.7101
```

```
anova(E3_int_l1_ivs_c, E3_int_l1_ivs_b)
```

```
Data: data
Models:
E3_int_l1_ivs_c: decept_rate ~ SemCon + TruthCon * SynCon + (1 | id_per)
E3_int_l1_ivs_b: decept_rate ~ TruthCon * SemCon + SemCon * SynCon + TruthCon * SynCon + (1 | id_
                npar    AIC  BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_int_l1_ivs_c    7 8679.8 8720 -4332.9   8665.8
E3_int_l1_ivs_b    9 8680.3 8732 -4331.2   8662.3 3.4508  2     0.1781
```

```
anova(E3_int_l1_ivs, E3_int_l1_ivs_c)
```

```
Data: data
Models:
E3_int_l1_ivs_c: decept_rate ~ SemCon + TruthCon * SynCon + (1 | id_per)
E3_int_l1_ivs: decept_rate ~ TruthCon * SemCon * SynCon + (1 | id_per)
                npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
E3_int_l1_ivs_c    7 8679.8 8720.0 -4332.9   8665.8
E3_int_l1_ivs     10 8682.2 8739.6 -4331.1   8662.2 3.589  3     0.3094
```

```r
summary(E3_int_l1_ivs_c)
```

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
  method [lmerModLmerTest]
Formula: decept_rate ~ SemCon + TruthCon * SynCon + (1 | id_per)
   Data: data

     AIC      BIC   logLik deviance df.resid
  8679.8   8720.0  -4332.9   8665.8     2297

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.5411 -0.6013  0.0387  0.5797  3.4803

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.2397   0.4896
 Residual             2.4670   1.5707
Number of obs: 2304, groups:  id_per, 18

Fixed effects:
                             Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                   5.69792    0.13664   30.29117  41.700  < 2e-16
SemConDisfluent               0.38194    0.06545 2286.00000   5.836 6.10e-09
TruthConCT                   -4.01736    0.09255 2286.00000 -43.406  < 2e-16
SynConIncorrect               0.17708    0.09255 2286.00000   1.913   0.0558
TruthConCT:SynConIncorrect    0.57292    0.13089 2286.00000   4.377 1.26e-05

(Intercept)                ***
SemConDisfluent            ***
TruthConCT                 ***
SynConIncorrect            .
TruthConCT:SynConIncorrect ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) SmCnDs TrtCCT SynCnI
SemCnDsflnt -0.239
TruthConCT  -0.339  0.000
SynCnIncrrc -0.339  0.000  0.500
TrthCCT:SCI  0.239  0.000 -0.707 -0.707
```

Adjusted Models

Subsequent modeling efforts expanded to include covariates, specifically age and gender, to explore their influence on the dependent variable. Through the application of likelihood ratio tests, it was determined that the model which accounted for the cross interactions between gender and age as a main effect offered the most compelling fit to the data. However, a thorough inspection of this model revealed that the main effect of age did not reach statistical significance. Further examination also indicated a lack of variability in age, leading to the decision to exclude this covariate from the analysis. As a result, the model labeled `E3_bf_c4xints` emerged as the best fit.

```r
#Incorporating Covariates
E3_bf_c4_me_co <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon + age +
                                     gender + (1|id_per),
                                data = data,
                                REML = FALSE)

E3_bf_c4xint_c4age <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon +
                                         TruthCon*gender + SynCon*gender + age
                                         +(1|id_per),
                                    data = data,
                                    REML = FALSE)


E3_bf_xint_c4age <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon*gender
                                       + age +(1|id_per),
                                  data = data,
                                  REML = FALSE)

#Removing age based on lack of variability
E3_bf_c4xints <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon +
                                    TruthCon*gender + SynCon*gender + (1|id_per),
                               data = data,
                               REML = FALSE)
```

```r
#LRTs Incorporating Covariates
anova(E3_int_l1_ivs_c, E3_bf_c4_me_co)
```

```
Data: data
Models:
E3_int_l1_ivs_c: decept_rate ~ SemCon + TruthCon * SynCon + (1 | id_per)
E3_bf_c4_me_co: decept_rate ~ SemCon + TruthCon * SynCon + age + gender + (1 | id_per)
                npar    AIC  BIC  logLik deviance Chisq Df Pr(>Chisq)
E3_int_l1_ivs_c    7 8679.8 8720 -4332.9   8665.8
E3_bf_c4_me_co     9 8683.4 8735 -4332.7   8665.4 0.434  2     0.8049
```

```
anova(E3_int_l1_ivs_c, E3_bf_c4xint_c4age, E3_bf_xint_c4age)
```

```
Data: data
Models:
E3_int_l1_ivs_c: decept_rate ~ SemCon + TruthCon * SynCon + (1 | id_per)
E3_bf_c4xint_c4age: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gende
E3_bf_xint_c4age: decept_rate ~ SemCon + TruthCon * SynCon * gender + age + (1 | id_per)
                   npar    AIC    BIC  logLik deviance    Chisq Df Pr(>Chisq)
E3_int_l1_ivs_c       7 8679.8 8720.0 -4332.9   8665.8
E3_bf_c4xint_c4age   11 8530.5 8593.6 -4254.2   8508.5 157.3205  4     <2e-16
E3_bf_xint_c4age     12 8532.4 8601.3 -4254.2   8508.4   0.0652  1     0.7984

E3_int_l1_ivs_c
E3_bf_c4xint_c4age ***
E3_bf_xint_c4age
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#model inspection
summary(E3_bf_c4xint_c4age)
```

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
  method [lmerModLmerTest]
Formula: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender +
    SynCon * gender + age + (1 | id_per)
   Data: data

     AIC      BIC   logLik deviance df.resid
  8530.5   8593.6  -4254.2   8508.5     2293

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6411 -0.5430  0.0453  0.5489  3.8431

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.2348   0.4846
 Residual             2.3034   1.5177
Number of obs: 2304, groups:  id_per, 18

Fixed effects:
                               Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                     6.98297    1.41949   18.16546   4.919 0.000108
SemConDisfluent                 0.38194    0.06324 2286.00000   6.040 1.80e-09
TruthConCT                     -5.22396    0.13563 2286.00000 -38.516  < 2e-16
SynConIncorrect                -0.30521    0.13563 2286.00000  -2.250 0.024524
genderFemale                   -1.10358    0.34448   21.45068  -3.204 0.004189
age                            -0.02447    0.06299   18.00000  -0.388 0.702212
TruthConCT:SynConIncorrect      0.57292    0.12648 2286.00000   4.530 6.21e-06
TruthConCT:genderFemale         1.67067    0.14119 2286.00000  11.833  < 2e-16
SynConIncorrect:genderFemale    0.66779    0.14119 2286.00000   4.730 2.38e-06

(Intercept)                  ***
SemConDisfluent              ***
TruthConCT                   ***
SynConIncorrect              *
genderFemale                 **
age
TruthConCT:SynConIncorrect   ***
TruthConCT:genderFemale      ***
SynConIncorrect:genderFemale ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) SmCnDs TrtCCT SynCnI gndrFm age    TCCT:S TCCT:F
SemCnDsflnt -0.022
TruthConCT  -0.048  0.000
SynCnIncrrc -0.048  0.000  0.217
genderFemal -0.681  0.000  0.154  0.154
age         -0.985  0.000  0.000  0.000  0.571
```

```
TrthCCT:SCI  0.022  0.000 -0.466 -0.466  0.000  0.000
TrthCnCT:gF  0.036  0.000 -0.752  0.000 -0.205  0.000  0.000
SynCnIncr:F  0.036  0.000  0.000 -0.752 -0.205  0.000  0.000  0.000
```

Table 37

MLM Parameter Estimates, with and without Covariate Adjustment, fit by ML

	Neither	Gender	Gender and Age
(Intercept)	5.70^{***}	6.44^{***}	6.98^{***}
	(0.14)	(0.25)	(1.42)
SemConDisfluent	0.38^{***}	0.38^{***}	0.38^{***}
	(0.07)	(0.06)	(0.06)
TruthConCT	-4.02^{***}	-5.22^{***}	-5.22^{***}
	(0.09)	(0.14)	(0.14)
SynConIncorrect	0.18	-0.31^{*}	-0.31^{*}
	(0.09)	(0.14)	(0.14)
TruthConCT:SynConIncorrect	0.57^{***}	0.57^{***}	0.57^{***}
	(0.13)	(0.13)	(0.13)
genderFemale		-1.03^{***}	-1.10^{**}
		(0.28)	(0.34)
TruthConCT:genderFemale		1.67^{***}	1.67^{***}
		(0.14)	(0.14)
SynConIncorrect:genderFemale		0.67^{***}	0.67^{***}
		(0.14)	(0.14)
age			-0.02
			(0.06)
AIC	8679.79	8528.62	8530.47
BIC	8719.99	8586.05	8593.64
Log Likelihood	-4332.90	-4254.31	-4254.24
Num. obs.	2304	2304	2304
Num. groups: id_per	18	18	18
Var: id_per (Intercept)	0.24	0.24	0.23
Var: Residual	2.47	2.30	2.30

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

```r
#LRT comparing inclusion and exclusion of age
anova(E3_bf_c4xint_c4age, E3_bf_c4xints)
```

```
Data: data
Models:
E3_bf_c4xints: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender + (
E3_bf_c4xint_c4age: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gende
                   npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_bf_c4xints        10 8528.6 8586.0 -4254.3   8508.6
E3_bf_c4xint_c4age   11 8530.5 8593.6 -4254.2   8508.5 0.1503  1     0.6983
```

```r
#Table Comparing Models
texreg::knitreg(list(E3_int_l1_ivs_c, E3_bf_c4xints, E3_bf_c4xint_c4age),
                custom.model.names = c("Neither", "Gender", "Gender and Age"),
                caption = "MLM Parameter Estimates, with and without Covariate
                Adjustment, fit by ML")
```

Behavioral Final Model and Parameter Estimates

```r
E3_final_model <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon +
                                TruthCon*gender + SynCon*gender + (1|id_per),
                              data = data,
                              REML = TRUE)
summary(E3_final_model)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender +
    SynCon * gender + (1 | id_per)
   Data: data

REML criterion at convergence: 8529.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6339 -0.5443  0.0460  0.5453  3.8408

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.2687   0.5184
 Residual             2.3095   1.5197
Number of obs: 2304, groups:  id_per, 18

Fixed effects:
                               Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                     6.43976    0.25803   21.55457  24.957  < 2e-16
SemConDisfluent                 0.38194    0.06332 2280.00000   6.032 1.89e-09
TruthConCT                     -5.22396    0.13581 2280.00000 -38.466  < 2e-16
SynConIncorrect                -0.30521    0.13581 2280.00000  -2.247  0.02471
genderFemale                   -1.02716    0.29902   20.27750  -3.435  0.00258
TruthConCT:SynConIncorrect      0.57292    0.12664 2280.00000   4.524 6.38e-06
TruthConCT:genderFemale         1.67067    0.14137 2280.00000  11.818  < 2e-16
SynConIncorrect:genderFemale    0.66779    0.14137 2280.00000   4.724 2.46e-06

(Intercept)                  ***
SemConDisfluent              ***
TruthConCT                   ***
SynConIncorrect              *
genderFemale                 **
TruthConCT:SynConIncorrect   ***
TruthConCT:genderFemale      ***
SynConIncorrect:genderFemale ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) SmCnDs TrtCCT SynCnI gndrFm TCCT:S TCCT:F
SemCnDsflnt -0.123
TruthConCT  -0.263  0.000
SynCnIncrrc -0.263  0.000  0.217
```

```
genderFemal -0.837  0.000  0.178  0.178
TrthCCT:SCI  0.123  0.000 -0.466 -0.466  0.000
TrthCnCT:gF  0.198  0.000 -0.752  0.000 -0.236  0.000
SynCnIncr:F  0.198  0.000  0.000 -0.752 -0.236  0.000  0.000
```

Follow-up Tests

Pooled Standard Deviation

```
est_SD <- E3_final_model %>%
  VarCorr() %>%
  data.frame() %>%
  dplyr::summarise(tot_var = sum(vcov)) %>%
  dplyr::pull(tot_var) %>%
  sqrt()

est_SD
```

```
[1] 1.605684
```

Estimated Marginal Means

```
E3_final_model %>%
  emmeans::emmeans( ~ SynCon| TruthCon + gender)
```

```
TruthCon = BFL, gender = Male:
 SynCon    emmean    SE   df lower.CL upper.CL
 Correct     6.63 0.256 20.9    6.098     7.16
 Incorrect   6.33 0.256 20.9    5.793     6.86

TruthCon = CT, gender = Male:
 SynCon    emmean    SE   df lower.CL upper.CL
 Correct     1.41 0.256 20.9    0.874     1.94
 Incorrect   1.67 0.256 20.9    1.142     2.21

TruthCon = BFL, gender = Female:
 SynCon    emmean    SE   df lower.CL upper.CL
 Correct     5.60 0.161 21.9    5.270     5.94
 Incorrect   5.97 0.161 21.9    5.633     6.30

TruthCon = CT, gender = Female:
 SynCon    emmean    SE   df lower.CL upper.CL
 Correct     2.05 0.161 21.9    1.717     2.38
 Incorrect   2.99 0.161 21.9    2.652     3.32

Results are averaged over the levels of: SemCon
Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95
```

Post Hoc Tests

```r
df_post_hoc_syn_truth <- E3_final_model %>%
  emmeans::emmeans(~ SynCon | TruthCon) %>%
  pairs() %>%
  data.frame() %>%
  dplyr::mutate(SMD = estimate/est_SD) %>%
  dplyr::mutate(p = pformat(p.value))

df_post_hoc_syn_truth
```

```
             contrast TruthCon   estimate         SE   df    t.ratio
1 Correct - Incorrect      BFL -0.0286859 0.09489978 2280 -0.3022757
2 Correct - Incorrect       CT -0.6016026 0.09489978 2280 -6.3393462
       p.value         SMD           p
1 7.624695e-01 -0.01786522    p = .762
2 2.772661e-10 -0.37467056 p < .001***
```

```r
df_post_hoc_truthgen <- E3_final_model %>%
  emmeans::emmeans(~ TruthCon | gender) %>%
  pairs() %>%
  data.frame() %>%
  dplyr::mutate(SMD = estimate/est_SD) %>%
  dplyr::mutate(p = pformat(p.value))

df_post_hoc_truthgen
```

```
  contrast gender estimate         SE   df  t.ratio       p.value      SMD
1 BFL - CT   Male 4.937500 0.12014251 2280 41.09703 9.157227e-277 3.075013
2 BFL - CT Female 3.266827 0.07450922 2280 43.84460 4.542246e-305 2.034539
            p
1 p < .001***
2 p < .001***
```

```r
df_post_hoc_SynCon <- E3_final_model %>%
  emmeans::emmeans( ~ SynCon| TruthCon + gender) %>%
  pairs() %>%
  data.frame() %>%
  dplyr::mutate(SMD = estimate/est_SD) %>%
  dplyr::mutate(p = pformat(p.value)) %>%
  dplyr::select(gender, TruthCon, SynCon_pair = contrast, EMM_diff = estimate, SE,
              p, SMD) %>%
  dplyr::mutate(ypos = case_when(gender == "Male" & TruthCon == "BFL" ~ 7,
                                 gender == "Female" & TruthCon == "BFL" ~ 5.25,
                                 gender == "Female" & TruthCon == "CT" ~ 3.1,
                                 gender == "Male" & TruthCon == "CT" ~ 1.0))%>%
  dplyr::mutate(tco = case_when(gender == "Male" & TruthCon == "BFL" ~ .03,
                               gender == "Female" & TruthCon == "BFL" ~ -.03,
                               gender == "Female" & TruthCon == "CT" ~ .7,
                               gender == "Male" & TruthCon == "CT" ~ -.03)) %>%
  dplyr::mutate(tin = case_when(gender == "Male" & TruthCon == "BFL" ~ .25,
                               gender == "Female" & TruthCon == "BFL" ~ -.40,
                               gender == "Female" & TruthCon == "CT" ~ .03,
                               gender == "Male" & TruthCon == "CT" ~ -.25))

df_post_hoc_SynCon
```

```
  gender TruthCon          SynCon_pair   EMM_diff         SE           p
1   Male      BFL Correct - Incorrect  0.3052083 0.13580769   p = .025*
2   Male       CT Correct - Incorrect -0.2677083 0.13580769   p = .049*
3 Female      BFL Correct - Incorrect -0.3625801 0.09778104 p < .001***
4 Female       CT Correct - Incorrect -0.9354968 0.09778104 p < .001***
         SMD ypos   tco   tin
1  0.1900799 7.00  0.03  0.25
2 -0.1667254 1.00 -0.03 -0.25
3 -0.2258104 5.25 -0.03 -0.40
4 -0.5826157 3.10  0.70  0.03
```

```r
df_emm <- E3_final_model %>%
  emmeans::emmeans(~ gender + SynCon +TruthCon ) %>%
  data.frame()

df_emm
```

```
  gender    SynCon TruthCon   emmean        SE       df   lower.CL upper.CL
1   Male   Correct      BFL 6.630729 0.2560805 20.91123 6.0980430 7.163415
2 Female   Correct      BFL 5.603566 0.1607447 21.94522 5.2701534 5.936978
3   Male Incorrect      BFL 6.325521 0.2560805 20.91123 5.7928347 6.858207
4 Female Incorrect      BFL 5.966146 0.1607447 21.94522 5.6327336 6.299558
5   Male   Correct       CT 1.406771 0.2560805 20.91123 0.8740847 1.939457
6 Female   Correct       CT 2.050280 0.1607447 21.94522 1.7168682 2.383693
7   Male Incorrect       CT 1.674479 0.2560805 20.91123 1.1417930 2.207165
8 Female Incorrect       CT 2.985777 0.1607447 21.94522 2.6523650 3.319190
```

```
bracket_span_gender <- df_emm %>%
  dplyr::group_by(SynCon, TruthCon) %>%
  dplyr::summarise(ymin = min(emmean),
                   ymax = max(emmean)) %>%
  dplyr::ungroup()

bracket_span_gender
```

```
# A tibble: 4 x 4
  SynCon    TruthCon  ymin  ymax
  <fct>     <fct>    <dbl> <dbl>
1 Correct   BFL       5.60  6.63
2 Correct   CT        1.41  2.05
3 Incorrect BFL       5.97  6.33
4 Incorrect CT        1.67  2.99
```

```
df_post_hoc_gender <- E3_final_model %>%
  emmeans::emmeans(~ gender | SynCon +TruthCon ) %>%
  pairs() %>%
  data.frame() %>%
  dplyr::mutate(d = estimate/est_SD) %>%
  dplyr::mutate(d = d %>%
                  abs() %>%
                  apa2()) %>%
  dplyr::filter(p.value < .10) %>%
  dplyr::mutate(label = glue::glue("SMD = {d}, {pformat(p.value)}")) %>%
  dplyr::left_join(bracket_span_gender, by = c("SynCon", "TruthCon")) %>%
  dplyr::rename(gender = "contrast") %>%
  dplyr::mutate(ymid = rowmeans(ymin, ymax)) %>%
  dplyr::select(SynCon, TruthCon, gender, label, ymin, ymax, ymid) %>%
  dplyr::mutate(xpos = case_when(SynCon == "Correct" ~ .8,
                                 SynCon == "Incorrect" ~ 2.2)) %>%
  dplyr::mutate(t = case_when(SynCon == "Correct" ~ +.1,
                              SynCon == "Incorrect" ~ -.1)) %>%
  dplyr::mutate(xtext = case_when(SynCon == "Correct" ~ +.7,
                                  SynCon == "Incorrect" ~ 2.4))

df_post_hoc_gender
```

```
     SynCon TruthCon        gender                   label     ymin     ymax
1   Correct      BFL Male - Female  SMD = 0.64, p = .003** 5.603566 6.630729
2   Correct       CT Male - Female   SMD = 0.40, p = .044* 1.406771 2.050280
3 Incorrect       CT Male - Female SMD = 0.82, p < .001*** 1.674479 2.985777
      ymid xpos    t xtext
1 6.117147  0.8  0.1   0.7
2 1.728526  0.8  0.1   0.7
3 2.330128  2.2 -0.1   2.4
```

```
which(is.na(df_post_hoc_gender), arr.ind = TRUE)
```

```
     row col
```

```r
label_pairwise_1v <- E3_final_model %>%
  emmeans::emmeans(~ TruthCon|SynCon) %>%
  pairs() %>%
  data.frame() %>%
  dplyr::filter(SynCon == "Correct") %>%
  dplyr::mutate(d = estimate/est_SD) %>%
  dplyr::mutate(d = d %>%
                  abs() %>%
                  apa2()) %>%
  dplyr::filter(p.value < .05) %>%
  dplyr::mutate(label = glue::glue(" d = {d}, {pformat(p.value)}")) %>%
  dplyr::select(contrast, label) %>%
  dplyr::mutate(y1 = c(4.62)) %>%
  dplyr::mutate(y2 = c(5.71)) %>%
  dplyr::mutate(x1 = c(0.8)) %>%
  dplyr::mutate(TruthCon = "Bald Faced Lies") %>%
  dplyr::mutate(ymid = furniture::rowmeans(y1, y2))

label_pairwise_1v
```

```
  contrast                  label   y1   y2  x1        TruthCon  ymid
1 BFL - CT  d = 2.73, p < .001*** 4.62 5.71 0.8 Bald Faced Lies 5.165
```

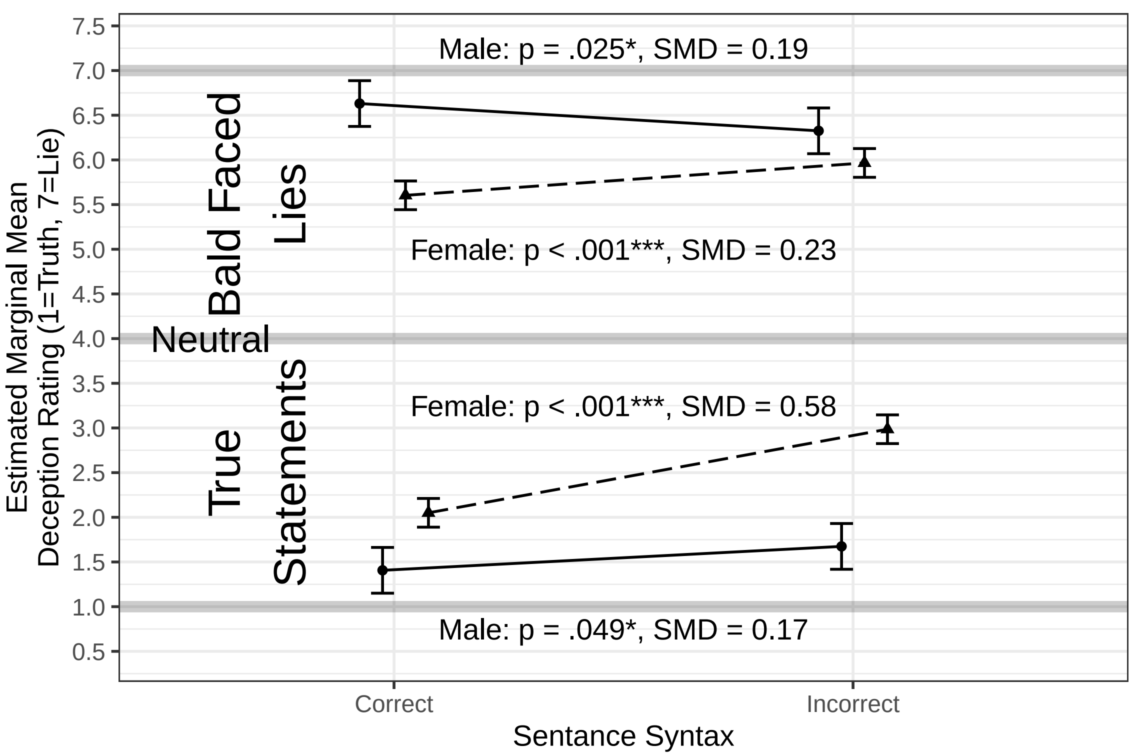
Experiment 3 Behavioral Visualizations

```
df_ref <- tibble::tribble(~gender, ~TruthCon, ~SynCon, ~cutoff,
                          "Male", "BFL", "Correct", 7,
                          "Male", "CT", "Correct", 1) %>%
  dplyr::mutate(across(c(gender, TruthCon, SynCon), factor))
```

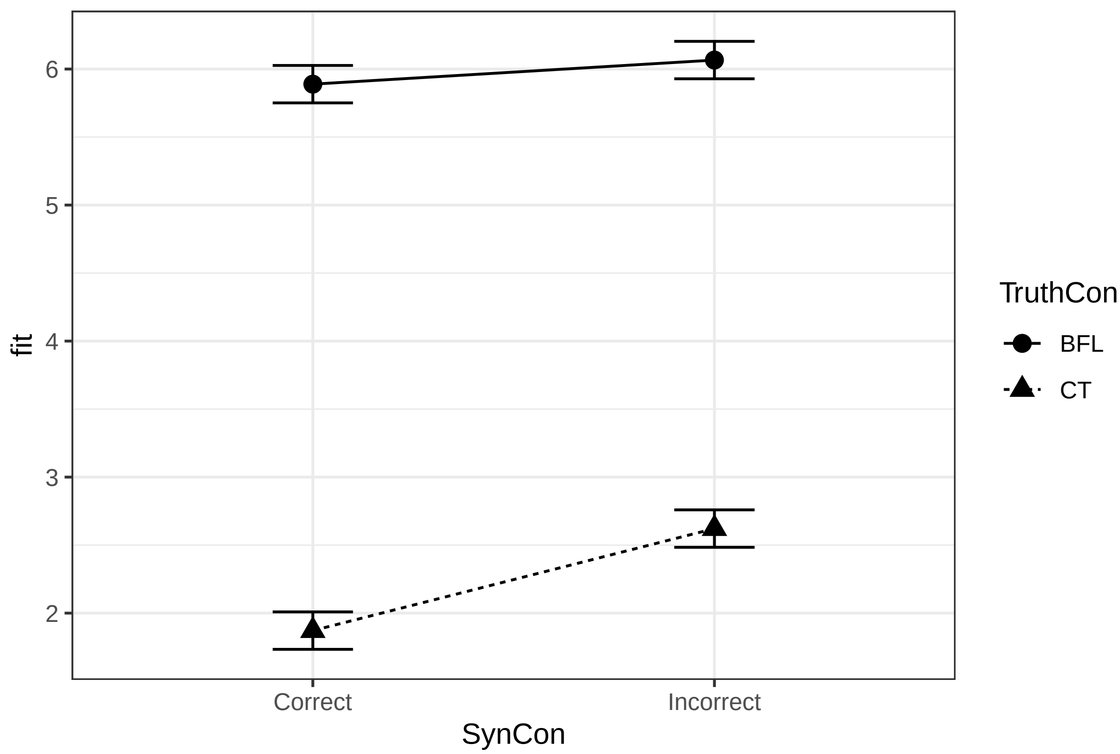
```
df_lim <- tibble::tribble(~gender, ~TruthCon, ~SynCon, ~fit,
                          "Male", "BFL", "Correct", 4.9,
                          "Male", "BFL", "Correct", 7.3,
                          "Male", "CT", "Correct", 0.5,
                          "Male", "CT", "Correct", 3.5) %>%
  dplyr::mutate(across(c(gender, TruthCon, SynCon), factor))
```

```
effects::Effect(mod = E3_final_model,
                focal.pred = c("TruthCon", "SynCon", "gender")) %>%
  data.frame() %>%
  ggplot(aes(x = SynCon,
             y = fit,
             group = interaction(TruthCon, gender),
             shape = gender)) +
  geom_hline(yintercept = c(1, 4, 7),
             alpha = .2,
             linewidth = 2) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se),
                width = .2,
                position = position_dodge(width = .2)) +
  geom_point(position = position_dodge(width = .2)) +
  geom_line(aes(linetype = gender),
            position = position_dodge(width = .2)) +
  theme_bw() +
  # facet_wrap( ~ TruthCon, scale = "free_y") +
  # facet_wrap(~ TruthCon) +
  geom_point(data = df_lim,
             aes(x = SynCon,
                 y = fit),
             color = "black",
             alpha = 0) +
  labs(x = "Sentance Syntax",
       y = "Estimated Marginal Mean\nDeception Rating (1=Truth, 7=Lie)") +
  geom_text(data = df_post_hoc_SynCon,
            aes(x = 1.5,
                y = c(7.25, 0.75, 5, 3.25),
                label = paste0(gender, ": ",
                               p, ", SMD = ",
                               round(abs(SMD), 2)))) +
  scale_linetype_manual(values = c("solid", "longdash")) +
  scale_y_continuous(breaks = .5*(0:100)) +
  theme(legend.position = "none") +
  annotate(geom = "text",
           label = "Bald Faced\nLies",
```

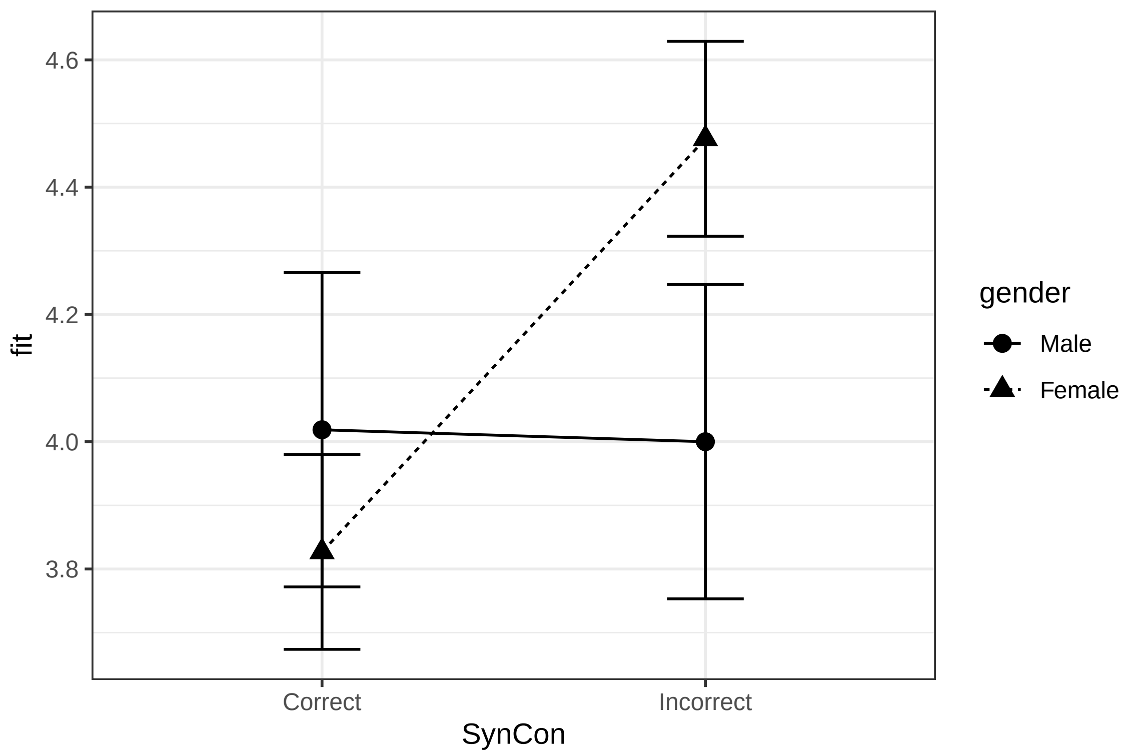
```
         x = .7,
         y = 5.5,
         cex = 6,
         angle = 90)+
annotate(geom = "text",
         label = "True\nStatements",
         x = .7,
         y = 2.5,
         cex = 6,
         angle = 90) +
annotate(geom = "text",
         label = "Neutral",
         x = .6,
         y = 4,
         cex = 5)
```



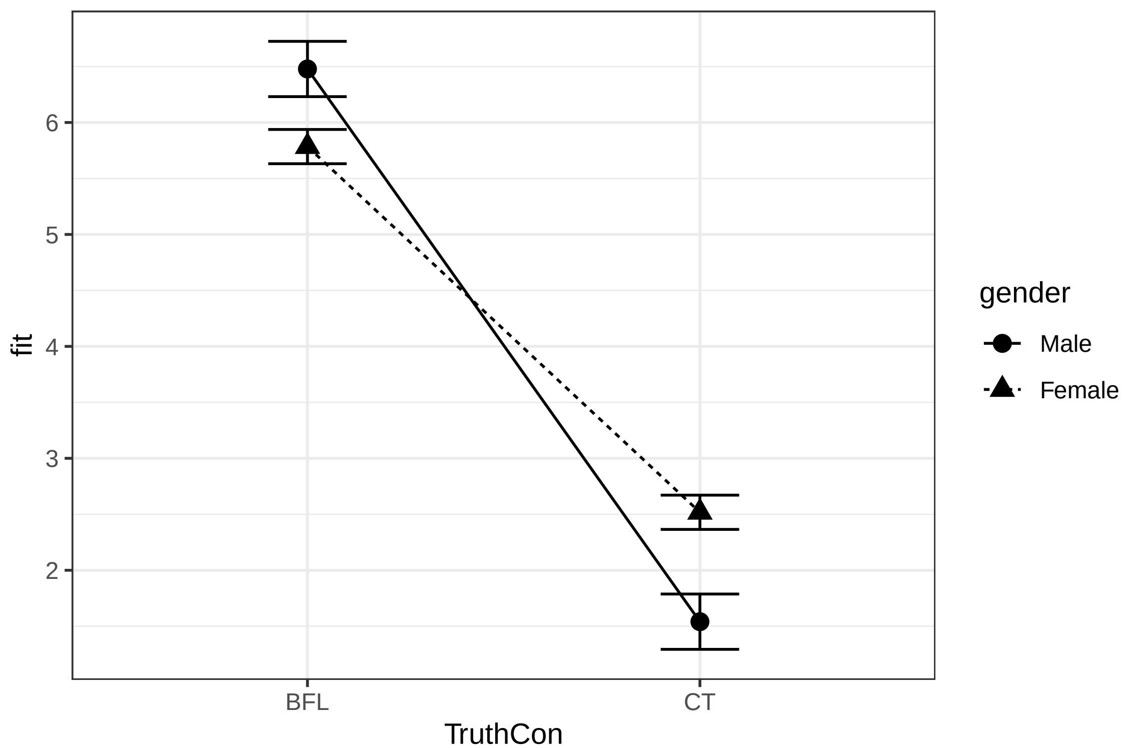
```
effects::Effect(focal.predictors = c("SynCon", "TruthCon"),
                mod = E3_final_model) %>%
  data.frame() %>%
  ggplot(aes(x = SynCon,
             y = fit,
             group = TruthCon,
             shape = TruthCon)) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se),
                width = .2) +
  geom_point(size = 3) +
  geom_line(aes(linetype = TruthCon)) +
  theme_bw()
```



```
effects::Effect(focal.predictors = c("SynCon", "gender"),
                mod = E3_final_model) %>%
  data.frame() %>%
  ggplot(aes(x = SynCon,
             y = fit,
             group = gender,
             shape = gender)) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se),
                width = .2) +
  geom_point(size = 3) +
  geom_line(aes(linetype = gender)) +
  theme_bw()
```

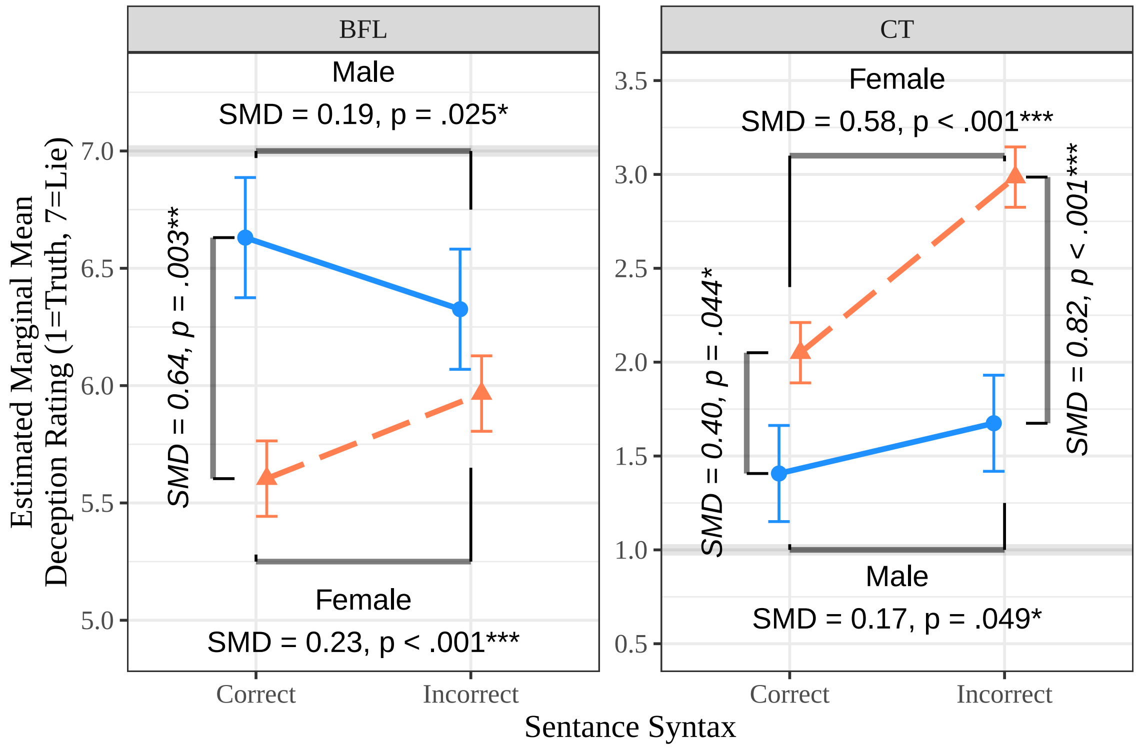


```r
effects::Effect(focal.predictors = c("TruthCon", "gender"),
                mod = E3_final_model) %>%
  data.frame() %>%
  ggplot(aes(x = TruthCon,
             y = fit,
             group = gender,
             shape = gender)) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se),
                width = .2) +
  geom_point(size = 3) +
  geom_line(aes(linetype = gender)) +
  theme_bw()
```



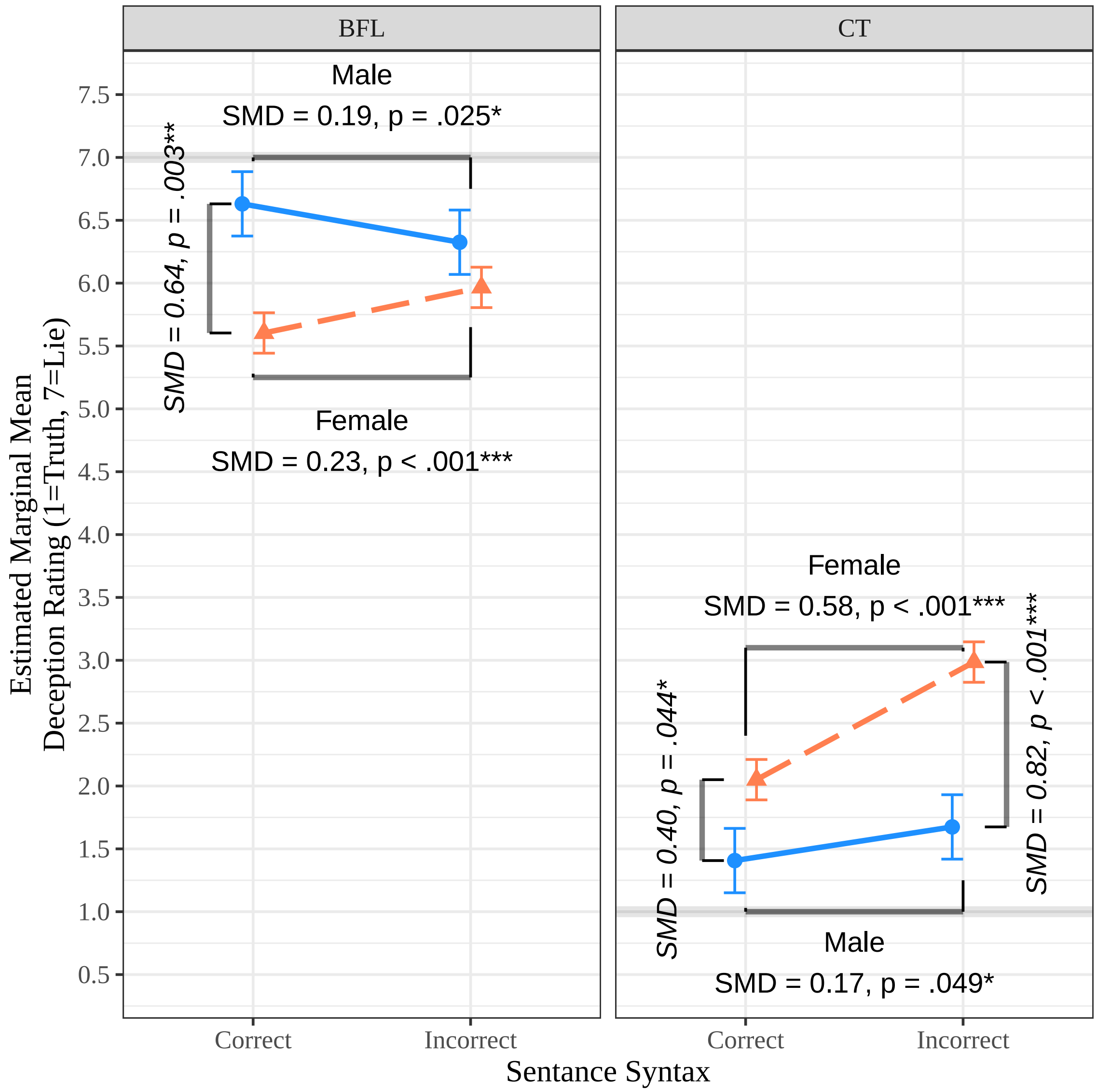
```
effects::Effect(mod = E3_final_model,
                focal.pred = c("TruthCon", "SynCon", "gender")) %>%
  data.frame() %>%
  ggplot(aes(x = SynCon,
             y = fit,
             group = gender,
             shape = gender)) +
  geom_hline(data = df_ref,
             aes(yintercept = cutoff),
             alpha = .1,
             linewidth = 2) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se,
                    color = gender),
                width = .2,
                position = position_dodge(width = .2)) +
  geom_point(aes(color = gender),
             size = 2.5,
             position = position_dodge(width = .2)) +
  geom_line(aes(linetype = gender,
                color = gender),
            linewidth = 1,
            position = position_dodge(width = .2)) +
  theme_bw() +
  facet_wrap( ~ TruthCon, scale = "free_y") +
  # facet_wrap(~ TruthCon) +
  geom_point(data = df_lim, # invisible points
             aes(x = SynCon,
                 y = fit),
             color = "black",
             alpha = 0) +
  labs(x = "Sentance Syntax",
       y = "Estimated Marginal Mean\nDeception Rating (1=Truth, 7=Lie)") +
  geom_text(data = df_post_hoc_SynCon,
            aes(x = 1.5,
                y = c(7.25, 0.75, 5, 3.4),
                label = paste0(gender,
                               "\nSMD = ",
                               round(abs(SMD), 2),
                               ", ",
                               p))) +
  scale_linetype_manual(values = c("solid", "longdash")) +
  scale_y_continuous(breaks = .5*(0:100)) +
  theme(legend.position = "none",
        text = element_text(family = "serif",
                            size =12)) +
   geom_segment(data = df_post_hoc_gender,
               aes(x = xpos, xend = xpos,
                   y = ymin, yend = ymax),
               group = 1,
               linewidth = 1,
               alpha = .5,
               color = "black",
```

```
             linetype = "solid") +
geom_segment(data = df_post_hoc_gender,
             aes(x = xpos, xend = xpos + t,
                 y = ymin, yend = ymin)) +
geom_segment(data = df_post_hoc_gender,
             aes(x = xpos, xend = xpos + t,
                 y = ymax, yend = ymax)) +
geom_text(data = df_post_hoc_gender,
         aes(label = label,
             x = xtext,
             y = ymid),
          fontface = "italic",
         nudge_x = -.065,
         angle = 90)  +
scale_color_manual(values = c("dodgerblue", "coral")) +
 geom_segment(data = df_post_hoc_SynCon,
             aes(x = 1, xend = 2,
                 y = ypos, yend = ypos),
             group = 1,
             linewidth = 1,
             alpha = .5,
             color = "black",
             linetype = "solid")  +
geom_segment(data = df_post_hoc_SynCon,
             aes(x = 1, xend = 1,
                 y = ypos, yend = ypos - tco)) +
geom_segment(data = df_post_hoc_SynCon,
             aes(x = 2, xend = 2,
                 y = ypos, yend = ypos - tin))
```


BFL
CT
Male
SMD = 0.19, p = .025*
Female
SMD = 0.23, p < .001***
SMD = 0.64, p = .003**
Female
SMD = 0.58, p < .001***
Male
SMD = 0.17, p = .049*
SMD = 0.40, p = .044*
SMD = 0.82, p < .001***
Estimated Marginal Mean
Deception Rating (1=Truth, 7=Lie)
7.0
6.5
6.0
5.5
5.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
Correct
Incorrect
Correct
Incorrect
Sentance Syntax

```
effects::Effect(mod = E3_final_model,
                focal.pred = c("TruthCon", "SynCon", "gender")) %>%
  data.frame() %>%
  ggplot(aes(x = SynCon,
             y = fit,
             group = gender,
             shape = gender)) +
  geom_hline(data = df_ref,
             aes(yintercept = cutoff),
             alpha = .1,
             linewidth = 2) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se,
                    color = gender),
                width = .2,
                position = position_dodge(width = .2)) +
  geom_point(aes(color = gender),
             size = 2.5,
             position = position_dodge(width = .2)) +
  geom_line(aes(linetype = gender,
                color = gender),
            linewidth = 1,
            position = position_dodge(width = .2)) +
  theme_bw() +
  facet_wrap( ~ TruthCon, scale = "fixed") +
  # facet_wrap(~ TruthCon) +
  geom_point(data = df_lim, # invisible points
             aes(x = SynCon,
                 y = fit),
             color = "black",
             alpha = 0) +
  labs(x = "Sentance Syntax",
       y = "Estimated Marginal Mean\nDeception Rating (1=Truth, 7=Lie)") +
  geom_text(data = df_post_hoc_SynCon,
            aes(x = 1.5,
                y = c(7.5, 0.6, 4.75, 3.6),
                label = paste0(gender,
                               "\nSMD = ",
                               round(abs(SMD), 2),
                               ", ",
                               p))) +
  scale_linetype_manual(values = c("solid", "longdash")) +
  scale_y_continuous(breaks = .5*(0:100)) +
  theme(legend.position = "none",
        text = element_text(family = "serif",
                            size =12)) +
   geom_segment(data = df_post_hoc_gender,
               aes(x = xpos, xend = xpos,
                   y = ymin, yend = ymax),
               group = 1,
               linewidth = 1,
               alpha = .5,
               color = "black",
```

```
             linetype = "solid") +
geom_segment(data = df_post_hoc_gender,
             aes(x = xpos, xend = xpos + t,
                 y = ymin, yend = ymin)) +
geom_segment(data = df_post_hoc_gender,
             aes(x = xpos, xend = xpos + t,
                 y = ymax, yend = ymax)) +
geom_text(data = df_post_hoc_gender,
         aes(label = label,
             x = xtext,
             y = ymid),
          fontface = "italic",
         nudge_x = -.065,
         angle = 90)  +
scale_color_manual(values = c("dodgerblue", "coral")) +
 geom_segment(data = df_post_hoc_SynCon,
             aes(x = 1, xend = 2,
                 y = ypos, yend = ypos),
             group = 1,
             linewidth = 1,
             alpha = .5,
             color = "black",
             linetype = "solid")  +
geom_segment(data = df_post_hoc_SynCon,
             aes(x = 1, xend = 1,
                 y = ypos, yend = ypos - tco)) +
geom_segment(data = df_post_hoc_SynCon,
             aes(x = 2, xend = 2,
                 y = ypos, yend = ypos - tin))
```


BFL
CT
Male
SMD = 0.19, p = .025*
Female
SMD = 0.23, p < .001***
SMD = 0.64, p = .003**
Female
SMD = 0.58, p < .001***
Male
SMD = 0.17, p = .049*
SMD = 0.40, p = .044*
SMD = 0.82, p < .001***
Estimated Marginal Mean
Deception Rating (1=Truth, 7=Lie)
7.5
7.0
6.5
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
Correct
Incorrect
Correct
Incorrect
Sentance Syntax

Integration of EEG Data into Behavioral Best Fit model

To integrate the Event-Related Potential (ERP) data into my analysis, I began by adopting the best fit model identified from the behavioral data as my starting point. Subsequently, I systematically incorporated control for the interaction between each ERP component and its corresponding Level 1 IV. Utilizing Likelihood Ratio Tests (LRT), I established that the model which accounted for the exploratory ERP component yielded the most compelling fit. Further scrutiny of the parameter estimates within this optimal model revealed a significant main effect of the N400 amplitude, interestingly, without it interacting with its respective Level 1 IV. Thus, I crafted a subsequent model that factored in the N400 amplitude as a main effect. This refined model was then evaluated and confirmed as the superior fit through the application of the LRT method.

```
#Controlling for ERP amplitudes
E3_bf_c4_N400 <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon +
                                  TruthCon*gender + SynCon*gender + SemCon*N400_amp_sd
                                  + (1|id_per),
                                data = data,
                                REML = FALSE)

E3_bf_c4_P600 <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon +
                                  TruthCon*gender + SynCon*gender + SynCon*P600_amp_sd
                                  + (1|id_per),
                                data = data,
                                REML = FALSE)

E3_bf_c4_Lies <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon +
                                  TruthCon*gender + SynCon*gender + TruthCon*Lies_amp_sd
                                  + (1|id_per),
                                data = data,
                                REML = FALSE)
#Models Based on Significant Main Effects and Interactions
E3_bf_me_n4_int_lies <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon +
                                         TruthCon*gender + SynCon*gender +
                                         N400_amp_sd + TruthCon*Lies_amp_sd +
                                           (1|id_per),
                                       data = data,
                                       REML = FALSE)
```

```
#LRTs controling for ERPs
anova(E3_final_model, E3_bf_c4_N400)
```

```
Data: data
Models:
E3_final_model: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender +
E3_bf_c4_N400: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender + S
               npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_final_model   10 8528.6 8586.0 -4254.3   8508.6
E3_bf_c4_N400    12 8525.3 8594.2 -4250.7   8501.3 7.2973  2    0.02603 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(E3_final_model, E3_bf_c4_P600)
```

```
Data: data
Models:
E3_final_model: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender +
E3_bf_c4_P600: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender + S
               npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_final_model   10 8528.6 8586.0 -4254.3   8508.6
E3_bf_c4_P600    12 8531.4 8600.3 -4253.7   8507.4 1.2096  2     0.5462
```

```
anova(E3_final_model, E3_bf_c4_Lies)
```

```
Data: data
Models:
E3_final_model: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender +
E3_bf_c4_Lies: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender + T
               npar    AIC  BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_final_model   10 8528.6 8586 -4254.3   8508.6
E3_bf_c4_Lies    12 8518.1 8587 -4247.0   8494.1 14.566  2   0.000687 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
texreg::knitreg(list(E3_bf_c4_N400, E3_bf_c4_P600, E3_bf_c4_Lies),
                custom.model.names = c("N400 ERP", "P600 ERP", "Exploratory ERP"),
                caption = "Experiment 2 MLM Parameter Estimates: ERP Components")
```

Table 38

Experiment 2 MLM Parameter Estimates: ERP Components

	N400 ERP	P600 ERP	Exploratory ERP
(Intercept)	6.46^{***}	6.46^{***}	6.44^{***}
	(0.24)	(0.25)	(0.24)
SemConDisfluent	0.37^{***}	0.38^{***}	0.37^{***}
	(0.06)	(0.06)	(0.06)
TruthConCT	-5.22^{***}	-5.22^{***}	-5.16^{***}
	(0.14)	(0.14)	(0.14)
SynConIncorrect	-0.31^{*}	-0.33^{*}	-0.30^{*}
	(0.14)	(0.14)	(0.14)
genderFemale	-1.05^{***}	-1.05^{***}	-1.02^{***}
	(0.28)	(0.28)	(0.28)
N400_amp_sd	-0.10^{*}		
	(0.04)		
TruthConCT:SynConIncorrect	0.57^{***}	0.57^{***}	0.54^{***}
	(0.13)	(0.13)	(0.13)
TruthConCT:genderFemale	1.67^{***}	1.67^{***}	1.63^{***}
	(0.14)	(0.14)	(0.14)
SynConIncorrect:genderFemale	0.67^{***}	0.69^{***}	0.66^{***}
	(0.14)	(0.14)	(0.14)
SemConDisfluent:N400_amp_sd	0.02		
	(0.06)		
P600_amp_sd		0.05	
		(0.05)	
SynConIncorrect:P600_amp_sd		-0.06	
		(0.07)	
Lies_amp_sd			0.03
			(0.05)
TruthConCT:Lies_amp_sd			-0.21^{**}
			(0.06)
AIC	8525.33	8531.41	8518.06
BIC	8594.24	8600.32	8586.97
Log Likelihood	-4250.66	-4253.71	-4247.03
Num. obs.	2304	2304	2304
Num. groups: id_per	18	18	18
Var: id_per (Intercept)	0.23	0.24	0.23
Var: Residual	2.30	2.30	2.29

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

```
anova(E3_bf_c4_N400, E3_bf_c4_Lies, E3_bf_me_n4_int_lies)
```

```
Data: data
Models:
E3_bf_c4_N400: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender + S
E3_bf_c4_Lies: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gender + T
E3_bf_me_n4_int_lies: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender + SynCon * gen
                     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
E3_bf_c4_N400          12 8525.3 8594.2 -4250.7   8501.3
E3_bf_c4_Lies          12 8518.1 8587.0 -4247.0   8494.1 7.2689  0
E3_bf_me_n4_int_lies   13 8512.8 8587.5 -4243.4   8486.8 7.2459  1   0.007106

E3_bf_c4_N400
E3_bf_c4_Lies
E3_bf_me_n4_int_lies **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

EEG Integrated Final Model and Parameter Estimates

```r
ERP_final <- lmerTest::lmer(decept_rate ~ SemCon +  TruthCon*SynCon +
                              TruthCon*gender + SynCon*gender +
                              N400_amp_sd + TruthCon*Lies_amp_sd + (1|id_per),
                            data = data,
                            REML = TRUE)
summary(ERP_final)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: decept_rate ~ SemCon + TruthCon * SynCon + TruthCon * gender +
    SynCon * gender + N400_amp_sd + TruthCon * Lies_amp_sd +      (1 | id_per)
   Data: data

REML criterion at convergence: 8521.1

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.8022 -0.5307  0.0757  0.5280  3.7441

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.2482   0.4982
 Residual             2.2919   1.5139
Number of obs: 2304, groups:  id_per, 18

Fixed effects:
                               Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                     6.46242    0.24998   21.99799  25.852  < 2e-16
SemConDisfluent                 0.35437    0.06341 2277.30115   5.588 2.57e-08
TruthConCT                     -5.16109    0.13632 2277.19888 -37.860  < 2e-16
SynConIncorrect                -0.30404    0.13535 2277.00781  -2.246  0.02478
genderFemale                   -1.03530    0.28942   20.61862  -3.577  0.00182
N400_amp_sd                    -0.08744    0.03268 2290.04514  -2.675  0.00752
Lies_amp_sd                     0.02693    0.04582 2292.93191   0.588  0.55674
TruthConCT:SynConIncorrect      0.53635    0.12659 2277.04805   4.237 2.36e-05
TruthConCT:genderFemale         1.63074    0.14164 2277.04344  11.513  < 2e-16
SynConIncorrect:genderFemale    0.66373    0.14104 2277.13971   4.706 2.68e-06
TruthConCT:Lies_amp_sd         -0.20992    0.06455 2281.18367  -3.252  0.00116

(Intercept)                  ***
SemConDisfluent              ***
TruthConCT                   ***
SynConIncorrect              *
genderFemale                 **
N400_amp_sd                  **
Lies_amp_sd
TruthConCT:SynConIncorrect   ***
TruthConCT:genderFemale      ***
SynConIncorrect:genderFemale ***
TruthConCT:Lies_amp_sd       **
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) SmCnDs TrtCCT SynCnI gndrFm N400__ Ls_mp_ TCCT:S TCCT:F
SemCnDsflnt -0.129
TruthConCT  -0.269 -0.007
SynCnIncrrc -0.272  0.001  0.218
genderFemal -0.836  0.002  0.184  0.184
N400_amp_sd -0.036  0.088 -0.004  0.022  0.026
Lies_amp_sd -0.024 -0.008  0.053  0.013  0.034  0.016
TrthCCT:SCI  0.127  0.004 -0.471 -0.466 -0.002  0.001 -0.047
TrthCnCT:gF  0.204  0.004 -0.753 -0.002 -0.245  0.001 -0.089  0.008
SynCnIncr:F  0.202  0.000  0.000 -0.750 -0.242 -0.007  0.049 -0.001 -0.003
TrthCCT:L__  0.013  0.045 -0.119 -0.020 -0.026 -0.010 -0.646  0.082  0.102
            SyCI:F
SemCnDsflnt
TruthConCT
SynCnIncrrc
genderFemal
N400_amp_sd
Lies_amp_sd
TrthCCT:SCI
TrthCnCT:gF
SynCnIncr:F
TrthCCT:L__ -0.016
```

Follow-up Tests

Pooled Standard Deviation

```
ERP_final %>%
  VarCorr() %>%
  data.frame() %>%
  dplyr::summarise(tot_var = sum(vcov)) %>%
  dplyr::pull(tot_var) %>%
  sqrt()
```

```
[1] 1.593777
```

Labeling Significant Only Pairwise Tests

```
df_SVP_ss <- interactions::sim_slopes(model = ERP_final,
                         pred = Lies_amp_sd,
                         modx = TruthCon) %>%
  broom::tidy() %>%
  dplyr::mutate(TruthCon = modx.value,
                label = paste0("b = ",
                              round(as.numeric(estimate), 2),
                              "\n95% CI [",
                              round(as.numeric(conf.low), 2),
                              ", ",
                              round(as.numeric(conf.high), 2),
                              "]\n",
                              pformat(as.numeric(p.value)))) %>%
  dplyr::select(TruthCon, label)

df_SVP_ss
```

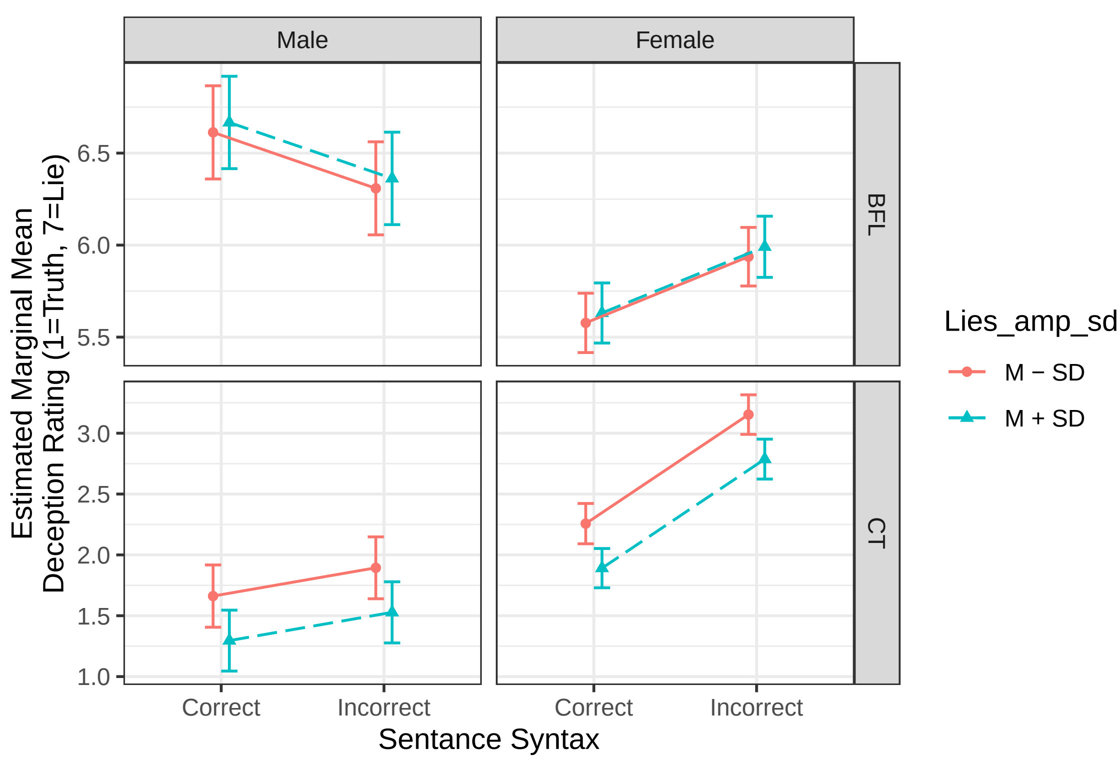
```
# A tibble: 2 x 2
  TruthCon label
  <chr>    <chr>
1 CT       "b = -0.18\n95% CI [-0.28, -0.09]\np < .001***"
2 BFL      "b = 0.03\n95% CI [-0.06, 0.12]\np = .557"
```

```
filtered_df_ss <- df_SVP_ss %>%
  filter(TruthCon =="CT")
filtered_df_ss
```

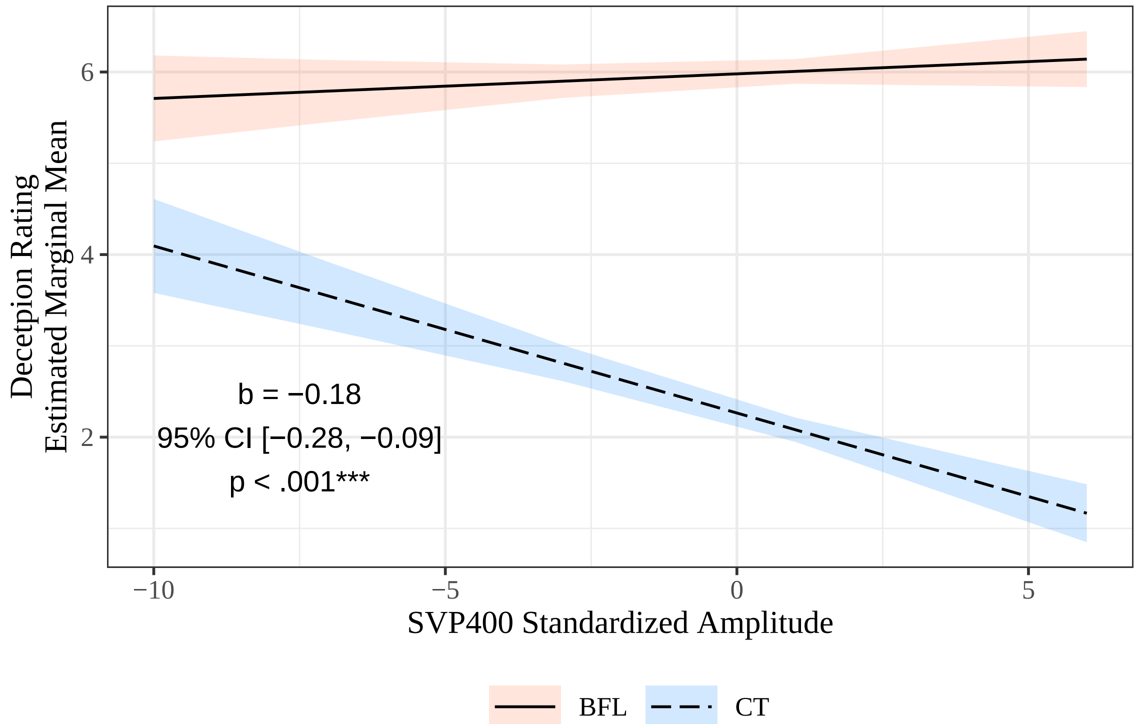
```
# A tibble: 1 x 2
  TruthCon label
  <chr>    <chr>
1 CT       "b = -0.18\n95% CI [-0.28, -0.09]\np < .001***"
```

Experiment 3 EEG Integrated Visualizations

```
effects::Effect(mod = ERP_final,
                focal.pred = c("TruthCon", "SynCon", "gender","Lies_amp_sd"),
                xlevels = list(Lies_amp_sd = c(-1,  1))) %>%
  data.frame() %>%
  dplyr::mutate(Lies_amp_sd = factor(Lies_amp_sd,
                                     labels = c("M - SD", "M + SD"))) %>%
  ggplot(aes(x = SynCon,
             y = fit,
             group = interaction(Lies_amp_sd, TruthCon, gender),
             shape = Lies_amp_sd,
             color = Lies_amp_sd)) +
  geom_errorbar(aes(ymin = fit - se,
                    ymax = fit + se),
                width = .2,
                position = position_dodge(width = .2)) +
  geom_point(position = position_dodge(width = .2)) +
  geom_line(aes(linetype = Lies_amp_sd),
            position = position_dodge(width = .2)) +
  theme_bw() +
  facet_grid(TruthCon ~ gender, scale = "free_y") +

  labs(x = "Sentance Syntax",
       y = "Estimated Marginal Mean\nDeception Rating (1=Truth, 7=Lie)") +
  scale_linetype_manual(values = c("solid", "longdash", "dotted")) +
  scale_y_continuous(breaks = .5*(0:100))
```



```
fig_SVP_ss <- effects::Effect(focal.predictors = c("TruthCon", "Lies_amp_sd"),
                              mod = ERP_final) %>%
  data.frame() %>%
  ggplot(aes(x = Lies_amp_sd,
             y = fit,
             group = TruthCon,
             shape = TruthCon))+
  geom_ribbon(aes(ymin = fit-se,
                  ymax = fit+se,
                  fill = TruthCon),
              alpha = .2) +
  geom_line(aes(linetype = TruthCon)) +
  theme_bw() +
  labs(x = "SVP400 Standardized Amplitude",
       y = "Decetpion Rating\nEstimated Marginal Mean",
       color = NULL,
       fill = NULL,
       linetype = NULL) +
  geom_text(data = filtered_df_ss,
            aes(label = label,
                x = -7.5,
                y = 2),
            inherit.aes = FALSE,
            size = 4) +
  scale_linetype_manual(values = c("solid", "longdash")) +
  theme(legend.position = "bottom",
        legend.key.width = unit(1, "cm"),
        text = element_text(family = "serif",
                            size = 12)) +
  scale_color_manual(values = c("BFL" = "coral",
                               "CT" = "dodgerblue")) +
  scale_fill_manual(values = c("BFL" = "coral",
                              "CT" = "dodgerblue"))

fig_SVP_ss
```


Decetpion Rating
Estimated Marginal Mean
6
4
2
b = −0.18
95% CI [−0.28, −0.09]
p < .001***
−10
−5
0
5
SVP400 Standardized Amplitude
BFL
CT

EEG/ERP Model Building

Visualizations for ERP differences and topographical heat maps were created using MatLab and BrainVision.

N400 Model

```
#Null Model
null_pd_n400_re <- lmerTest::lmer(N400_amp ~ 1 + (1|id_per),
                                  data = data,
                                  REML = TRUE)
null_pd_n400_ml <- lmerTest::lmer(N400_amp ~ 1 + (1|id_per),
                                  data = data,
                                  REML = FALSE)
#Predictive Model
sem_n400 <- lmerTest::lmer(N400_amp ~ SemCon + (1|id_per),
                                  data = data,
                                  REML = FALSE)
sem_n400_re <- lmerTest::lmer(N400_amp ~ SemCon + (1|id_per),
                                  data = data,
                                  REML = TRUE)
```

```
performance::icc(null_pd_n400_re) %>%
  pander::pander(caption = "N400 Interclass Correlation: Participant Difference Only")
```

Table 39
N400 Interclass Correlation: Participant Difference Only

ICC_adjusted	ICC_conditional	ICC_unadjusted
0.059	0.059	0.059

```
anova(null_pd_n400_re, sem_n400)
```

```
Data: data
Models:
null_pd_n400_re: N400_amp ~ 1 + (1 | id_per)
sem_n400: N400_amp ~ SemCon + (1 | id_per)
                npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
null_pd_n400_re    3 13321 13338 -6657.4    13315
sem_n400           4 13305 13328 -6648.6    13297 17.753  1  2.515e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(sem_n400_re)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: N400_amp ~ SemCon + (1 | id_per)
   Data: data

REML criterion at convergence: 13299.5

Scaled residuals:
    Min      1Q  Median      3Q     Max
-8.5122 -0.5897  0.0104  0.5698  5.1458

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept)  1.174   1.084
 Residual             18.487   4.300
Number of obs: 2304, groups:  id_per, 18

Fixed effects:
                 Estimate Std. Error        df t value Pr(>|t|)
(Intercept)        0.4212     0.2851   20.9266   1.477    0.154
SemConDisfluent   -0.7561     0.1792 2285.0000  -4.221 2.53e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr)
SemCnDsflnt -0.314
```

P600 Model

```
#Null Model
null_pd_p600_re <- lmerTest::lmer(P600_amp ~ 1 + (1|id_per),
                                data = data,
                                REML = TRUE)
null_pd_p600_ml <- lmerTest::lmer(P600_amp ~ 1 + (1|id_per),
                                data = data,
                                REML = FALSE)
#Predictive Model
syn_p600 <- lmerTest::lmer(P600_amp ~ SynCon + (1|id_per),
                                data = data,
                                REML = FALSE)
syn_p600_re <- lmerTest::lmer(P600_amp ~ SynCon + (1|id_per),
                                data = data,
                                REML = TRUE)
```

```
performance::icc(null_pd_p600_re) %>%
  pander::pander(caption = "N400 Interclass Correlation: Participant Difference Only")
```

Table 40

N400 Interclass Correlation: Participant Difference Only

ICC_adjusted	ICC_conditional	ICC_unadjusted
0.068	0.068	0.068

```
anova(null_pd_p600_re, syn_p600)
```

```
Data: data
Models:
null_pd_p600_re: P600_amp ~ 1 + (1 | id_per)
syn_p600: P600_amp ~ SynCon + (1 | id_per)
                npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
null_pd_p600_re    3 14385 14402 -7189.5    14379
syn_p600           4 14369 14392 -7180.4    14361 18.216  1  1.972e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(syn_p600_re)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: P600_amp ~ SynCon + (1 | id_per)
   Data: data

REML criterion at convergence: 14362.1

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.8355 -0.5777  0.0195  0.5958 10.5018

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept)  2.158   1.469
 Residual             29.301   5.413
Number of obs: 2304, groups:  id_per, 18

Fixed effects:
                 Estimate Std. Error        df t value Pr(>|t|)
(Intercept)        0.9436     0.3812   20.4155   2.475   0.0222 *
SynConIncorrect    0.9643     0.2255 2285.0000   4.276 1.98e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr)
SynCnIncrrc -0.296
```

Exploratory ERP Model

```r
#Null Models
null_pd_lies_re <- lmerTest::lmer(Lies_amp ~ 1 + (1|id_per),
                                  data = data %>%
                                    dplyr::mutate(Lies_amp_sd = scale(Lies_amp)),
                                  REML = TRUE)
null_pd_lies_ml <- lmerTest::lmer(Lies_amp ~ 1 + (1|id_per),
                                  data = data %>%
                                    dplyr::mutate(Lies_amp_sd = scale(Lies_amp)),
                                  REML = FALSE)
#Predictive Models
lies_ml <- lmerTest::lmer(Lies_amp_sd ~ TruthCon + (1|id_per),
                                  data = data %>%
                                    dplyr::mutate(Lies_amp_sd = scale(Lies_amp)),
                                  REML = FALSE)
lies_re <- lmerTest::lmer(Lies_amp_sd ~ TruthCon + (1|id_per),
                                  data = data %>%
                                    dplyr::mutate(Lies_amp_sd = scale(Lies_amp)),
                                  REML = TRUE)
```

```r
performance::icc(null_pd_lies_re ) %>%
  pander::pander(caption = "N400 Interclass Correlation: Participant Difference
                Only")
```

Table 41

N400 Interclass Correlation: Participant Difference Only

ICC_adjusted	ICC_conditional	ICC_unadjusted
0.181	0.181	0.181

```r
anova(null_pd_lies_re, lies_ml)
```

```
Data: data %>% dplyr::mutate(Lies_amp_sd = scale(Lies_amp))
Models:
null_pd_lies_re: Lies_amp ~ 1 + (1 | id_per)
lies_ml: Lies_amp_sd ~ TruthCon + (1 | id_per)
                npar     AIC     BIC  logLik deviance Chisq Df Pr(>Chisq)
null_pd_lies_re    3 13677.1 13694.4 -6835.6  13671.1
lies_ml            4  6144.1  6167.1 -3068.0   6136.1  7535  1  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(lies_re)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: Lies_amp_sd ~ TruthCon + (1 | id_per)
   Data: data %>% dplyr::mutate(Lies_amp_sd = scale(Lies_amp))

REML criterion at convergence: 6143.6

Scaled residuals:
     Min       1Q   Median       3Q      Max
-11.8622  -0.5772   0.0095   0.6010   6.1312

Random effects:
 Groups   Name        Variance Std.Dev.
 id_per   (Intercept) 0.1828   0.4276
 Residual             0.8185   0.9047
Number of obs: 2304, groups:  id_per, 18

Fixed effects:
             Estimate Std. Error        df t value Pr(>|t|)
(Intercept)   -0.0952     0.1042   18.1683  -0.913    0.373
TruthConCT     0.1904     0.0377 2285.0000   5.051 4.75e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
           (Intr)
TruthConCT -0.181
```

```r
sessionInfo()
```

```
R version 4.3.2 (2023-10-31 ucrt)
Platform: x86_64-w64-mingw32/x64 (64-bit)
Running under: Windows 11 x64 (build 22631)

Matrix products: default


locale:
[1] LC_COLLATE=English_United States.utf8
[2] LC_CTYPE=English_United States.utf8
[3] LC_MONETARY=English_United States.utf8
[4] LC_NUMERIC=C
[5] LC_TIME=English_United States.utf8

time zone: America/Denver
tzcode source: internal

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] magick_2.8.3       gt_0.10.1          MOTE_1.0.2         pBrackets_1.0.1
 [5] finalfit_1.0.7     ggpubr_0.6.0       emmeans_1.9.0      rstatix_0.7.2
 [9] viridis_0.6.4      viridisLite_0.4.2  sjstats_0.18.2     HLMdiag_0.5.0
[13] interactions_1.1.5 performance_0.10.8 optimx_2023-10.21  lmerTest_3.1-3
[17] lme4_1.1-35.1      Matrix_1.6-4       nlme_3.1-163       car_3.1-2
[21] carData_3.0-5      psych_2.3.12       gridExtra_2.3      texreg_1.39.3
[25] stargazer_5.2.3    furniture_1.9.14   pander_0.6.5       readxl_1.4.3
[29] lubridate_1.9.3    forcats_1.0.0      stringr_1.5.1      dplyr_1.1.4
[33] purrr_1.0.2        readr_2.1.4        tidyr_1.3.0        tibble_3.2.1
[37] ggplot2_3.4.4      tidyverse_2.0.0

loaded via a namespace (and not attached):
 [1] rstudioapi_0.15.0   shape_1.4.6         magrittr_2.0.3
 [4] estimability_1.4.1  jomo_2.7-6          farver_2.1.1
 [7] nloptr_2.0.3        rmarkdown_2.25      ragg_1.2.7
[10] vctrs_0.6.5         minqa_1.2.6         janitor_2.2.0
[13] htmltools_0.5.7     survey_4.2-1        broom_1.0.5
[16] cellranger_1.1.0    sjmisc_2.8.9        mitml_0.4-5
[19] pracma_2.4.4        pbkrtest_0.5.2      plyr_1.8.9
[22] lifecycle_1.0.4     iterators_1.0.14    pkgconfig_2.0.3
[25] sjlabelled_1.2.0    R6_2.5.1            fastmap_1.1.1
[28] snakecase_0.11.1    digest_0.6.33       numDeriv_2016.8-1.1
[31] colorspace_2.1-0    reshape_0.8.9       diagonals_6.4.0
[34] textshaping_0.3.7   labeling_0.4.3      fansi_1.0.6
[37] effects_4.2-2       timechange_0.2.0    httr_1.4.7
[40] abind_1.4-5         mgcv_1.9-0          compiler_4.3.2
[43] withr_2.5.2         backports_1.4.1     DBI_1.2.0
[46] ggsignif_0.6.4      pan_1.9             MASS_7.3-60
[49] tools_4.3.2         nnet_7.3-19         glue_1.6.2
[52] grid_4.3.2          reshape2_1.4.4      generics_0.1.3
```

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[55] gtable_0.3.4       MBESS_4.9.3        tzdb_0.4.0
[58] hms_1.1.3          xml2_1.3.6         utf8_1.2.4
[61] foreach_1.5.2      pillar_1.9.0       mitools_2.4
[64] splines_4.3.2      lattice_0.21-9     survival_3.5-7
[67] tidyselect_1.2.0   knitr_1.45         xfun_0.41
[70] stringi_1.8.3      rematch_2.0.0      yaml_2.3.8
[73] boot_1.3-28.1      evaluate_0.23      codetools_0.2-19
[76] cli_3.6.2          rpart_4.1.21       systemfonts_1.0.5
[79] xtable_1.8-4       munsell_0.5.0      modelr_0.1.11
[82] Rcpp_1.0.11        coda_0.19-4.1      parallel_4.3.2
[85] bayestestR_0.13.1  glmnet_4.1-8       mvtnorm_1.2-4
[88] scales_1.3.0       ez_4.4-0           insight_0.19.7
[91] crayon_1.5.2       rlang_1.1.2        mnormt_2.1.1
[94] mice_3.16.0        jtools_2.2.2
```

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Academic History

Utah State University **Logan, UT**
Ph.D. in Brain and Cognition *May 2024*

- Dissertation: ***Online deception: The impact of language in text-based deception detection***
  Faculty Advisor: Dr. Chris Warren

Angelo State University **San Angelo, TX**
Master of Science, Applied Psychology *Aug 2019*

- Thesis: ***Perjury: Establishing a better understanding of the forgotten crime***
  Faculty Advisor: Dr. Drew Curtis

Southern Utah University **Cedar City, UT**
Bachelor of Science, Psychology and Criminal Justice *April 2017*

- 3.6, Magna Cum Laude

Publications and Presentations

***Crank, S**. & Curtis, D. A. (2020). And nothing but the truth: An exploration of perjury. *Journal of Police and Criminal Psychology.*

***Crank, S**. (2019). *Perjury: Establishing a better understanding of the forgotten crime* (Master's Thesis). Angelo State University, San Angelo, TX.

***Crank, S**. (2018). Male perception of physical attractiveness and tendency for mate guarding. *Angelo State University Social Sciences Research Journal, 4*

Avila, S. (2022, May). *The Power of Language: A Continued Exploration of the Perception of Deception.* Poster Presentation at Association for Psychological Sciences conference, Chicago, IL.

***Crank, S.** & Curtis, D. (2019, April). *Perjury: Establishing a better understanding of the forgotten crime.* Poster Presented at Southwest Psychological Association conference, Albuquerque, NM.

Jones, B., ***Crank, S.**, & Kreitler, C. (2019, April). *Male perception of attractiveness and tendency toward mate guarding.* Poster Presented at Southwest Psychological Association conference, Albuquerque, NM.

Professional Experience

Graduate Assistantships **Utah State University and Angelo State University**
Graduate Instructor *Fall 2023, Spring 2023, Fall 2022, Summer 2020*

- Instructed online and in-person courses in cognitive psychology, general psychology, and applied behavior analysis by developing and delivering a comprehensive curriculum, creating and implementing engaging lesson plans

*Former Last Name

and assignments, utilizing various teaching methods to foster interactive learning, and maintaining consistent communication with students.
- Implemented laboratory sessions focusing on practical applications of ABA principles and research methodologies. Collaborated with faculty members. Facilitated hands-on learning experiences by guiding students through experimental procedures and data analysis.

Catalyst Project *Summer 2023*
- Skilled in the sophisticated processing of EEG data, including filtering, artifact removal, and baseline correction, ensuring high-quality and accurate neurological analysis.
- Created efficient EEG data preprocessing pipelines using BrainVision, enhancing reliability and analysis speed.
- Generated clear and insightful visualizations of EEG data, effectively communicating complex research findings.

Research Assistant, *Dr. Chris Warren* *Summer 2022, Spring 2020, Fall 2019*
- Efficiently conducted experiments and research in adherence to established protocols, ensuring accuracy and consistency in data collection.
- Diligently reviewed various resources to gather relevant information, contributing to comprehensive research analysis.
- Prepared laboratory equipment and effectively managed participant involvement in research studies.

Teaching Assistant *Spring 2024, Spring & Fall 2020-2022, Spring & Fall 2017-2019*
- Evaluated assignments and papers for general psychology and research methods while developing comprehensive syllabi and classroom materials and facilitating group discussions.
- Regularly attended training sessions and professional meetings to stay abreast of educational trends and collaborate with colleagues.
- Provided targeted tutoring and mentorship to students requiring additional help and effectively taught and presented materials, reinforcing key concepts and facilitating academic success.

Additional Research Experience

Role of neuromodulation in reactive balance control **Logan, UT**
Utah State University, *Dr. Chris Warren & Dr. Dave Bolton* *Sept 2019-Present*
- Learning EEG methodology
- Establishing an understanding of cognitive neuroscience paradigms

Psychophysiological Markers of Detecting Deception in Dating Profiles **Logan, UT**
Utah State University, *Dr. Chris Warren and Ariel Snowden* *Aug 2021 – May 2023*
- Development of a unique neurocognitive paradigm
- Collaborative study utilizing eye-tracking methods

Egocentrism, language, and successful deception **Logan, UT**
Utah State University, *Dr. Chris Warren* *Aug 2020- Fall 2022*
- Development of novel theory in deception research

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Understanding the relationship between gender and student engagement **San Angelo, TX**

Angelo State University, *Dr. Steffany Homolka* *March 2018-May 2019*

- Assisted with the development of group dynamic
- Established a leadership role within research

Honors, Affiliations, & Volunteer

Volunteer providing language support and cultural guidance *2020-Present*
Student of the Year *2019*
Court Appointed Children's Advocate *2018-2019*
Outstanding Scholar in Psychology *2017*
Psi Chi (Vice President 2018-2019) *2015-Present*

References

Available upon request

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