Cognitive Load-Oriented Deception Detection Based on Memory-Response Conflict

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Abstract

Deception detection has long constituted a significant research issue in psychology. Grounded in the cognitive perspective of deception theory, researchers have proposed a cognitive load approach to deception detection. By employing the Concealed Information Test as a lie detection paradigm and manipulating cognitive load to influence the memory-response conflict resolution process during deceptive responding, this approach investigates the impact of increased cognitive load on deception detection, aiming to better elucidate the cognitive mechanisms underlying deception detection. Building upon this foundation, the study examines behavioral and physiological indicators of deception detection based on memory-response conflict in both general populations and criminal suspects, and utilizes machine learning methods to model and predict individual deceptive behaviors based on the obtained behavioral and physiological indicators. The research findings will serve deception detection applications in judicial, security, and interpersonal communication domains.

Full Text

Preamble

Deception Detection Based on Memory-Response Conflict: A Cognitive Load Approach

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Abstract

Deception detection has long been a central research topic in psychology. Grounded in the cognitive perspective of deception theory, researchers have proposed a cognitive-load approach to deception detection. Using the Concealed Information Test (CIT) paradigm, this project manipulates cognitive load to influence the memory-response conflict resolution process during deceptive responding, examining how increased cognitive load affects deception detection to better illuminate its underlying cognitive mechanisms. Building upon this foundation, the study investigates behavioral and physiological indicators of memory-response conflict-based deception detection in both non-criminal and criminal populations, subsequently employing machine learning methods to model and predict individual deceptive behavior based on these indicators. The findings will inform deception detection practices in judicial, security, and interpersonal contexts.

Keywords: deception detection; cognitive load; memory-response conflict; interfering task; machine learning

1. Problem Statement

Deception is defined as the deliberate use of verbal or nonverbal information to induce false beliefs in others, typically to obtain benefits or avoid losses, when the deceiver knows the truth (Bai et al., 2019; Cui et al., 2013; Zhang & Zhang, 2008; Abe, 2009, 2011). Malicious deception often leads to severe consequences, making timely and effective deception detection crucial for reducing errors. Deception detection has consistently been a significant research focus in psychology, attracting widespread attention from scholars.

Early deception detection research primarily sought deception cues (physiological and behavioral differences) based on differential emotional arousal between liars and truth-tellers (Vrij, Granhag, & Porter, 2010). However, these cues have proven unreliable (DePaulo et al., 2003; Sporer & Schwandt, 2006, 2007). Consequently, researchers have advocated shifting detection approaches for more effective lie identification. Grounded in the cognitive perspective of deception theory—namely that deception entails higher cognitive load and consumes more cognitive resources (Suchotzki et al., 2017; Gamer, 2014; Meijer & Verschuere, 2017; Spence et al., 2001; Zuckerman et al., 1981)—the cognitive-load approach to deception detection has been proposed (Vrij, Fisher, Mann, & Leal, 2006). This approach posits that since deception inherently demands greater cognitive load, increasing the cognitive demands of lying/truth-telling disproportionately affects deceivers, thereby amplifying physiological and behavioral differences between liars and truth-tellers that can serve as deception cues.

Under the cognitive-load approach, researchers have predominantly used observational methods to identify deception cues (e.g., facial expressions, posture, vocal tone, linguistic content). A meta-analysis by Vrij, Fisher, and Blank (2017) found this method could achieve a 71% deception detection rate. However, other researchers have questioned this meta-analysis on methodological grounds, suggesting the results are less optimistic (Levine, Blair, & Carpenter, 2018), and the identified cues still suffer from insufficient reliability and analytical difficulties (Liang et al., 2014).

Over recent decades, memory detection research has significantly influenced deception detection, prompting researchers to shift perspectives by testing recognition of critical information to identify deception (Ben-Shakhar, 2012). When individuals (e.g., criminal suspects) possess critical information (e.g., crime-related details), recognizing this information elicits distinct physiological and psychological responses compared to irrelevant information. For innocent individuals, responses to both information types are similar. Deception is inferred by comparing differential reactions to critical versus irrelevant information. Additionally, when individuals falsely respond to recognized critical information (responding "haven' t seen" to something seen, or "don' t remember" to something remembered), a memory-response conflict arises. Resolving this conflict requires inhibiting truthful information and automatic truthful responses while converting them to deceptive ones, processes that consume substantial cognitive resources (Christ et al., 2009; Gamer & Berti, 2010; Hu, Wu, & Fu, 2011; Kubo & Nittono, 2009; Spence et al., 2001). The cognitive-load approach thus raises a key question: Can increasing cognitive load impact deceivers' conflict monitoring and response inhibition processes, thereby amplifying differences between deceivers and truth-tellers and improving detection rates? Can this method yield reliable, ecologically valid deception detection indicators? Can these indicators predict individual deceptive behavior?

Current research on these questions remains limited and yields inconsistent results (Verschuere et al., 2018). This project aims to address these issues.

The Concealed Information Test (CIT) is a widely used deception detection paradigm that essentially detects memory traces (Ben-Shakhar & Elaad, 2003). In laboratory settings, participants first complete a mock crime phase before undergoing the CIT. The test includes three stimulus types: (1) Probe stimuli—crime-related information known only to the "guilty" participant and authorities; (2) Irrelevant stimuli—unrelated information unrecognizable to both guilty and innocent participants; and (3) Target stimuli—also irrelevant but requiring a specific response different from probes and irrelevants to maintain participant attention. While all participants make identical behavioral responses ("no") to probes and irrelevants, probes hold specific significance for guilty participants, eliciting memory-response conflict during false recognition and consuming more cognitive resources. This project employs the CIT with interfering tasks to increase cognitive load (Vrij et al., 2006), systematically examining whether increased cognitive load improves detection accuracy based on memory-response conflict. Using both non-criminal and criminal populations, the project investigates behavioral and physiological indicators of memory-response conflict-based deception detection and employs machine learning to predict deceptive behavior.

2.1 Effects of Interfering Tasks on Memory-Response Conflict-Based Deception Detection

When individuals falsely respond to true memories, they must first retrieve and maintain truthful information in working memory (Debey, Houwer, & Verschuere, 2014) while simultaneously inhibiting truthful responses and converting them to deceptive ones (Debey, Liefooghe, De Houwer, & Verschuere, 2015). These three executive function components—working memory, response inhibition, and task switching—make deception more cognitively demanding (Christ et al., 2009; Gamer & Berti, 2010; Hu et al., 2011; Kubo & Nittono, 2009; Spence et al., 2001). Researchers therefore typically add concurrent tasks that interfere with these executive functions during the CIT to increase cognitive load and examine whether such interference amplifies behavioral and physiological differences between deceivers and truth-tellers, thereby improving detection rates.

Ambach, Stark, Peper, and Vaitl (2008) added a Go/No-go interfering task to a polygraph-based CIT to examine whether response inhibition interference facilitates deception detection. Recording reaction time (RT) and physiological measures (skin conductance, respiration, heart rate), they found that response inhibition interference did not increase differences between probe and irrelevant stimuli across measures and failed to facilitate detection. Subsequently, Ambach, Stark, and Vaitl (2011) introduced an n-back interfering task to a polygraph-based CIT to examine working memory interference effects. While working memory interference enhanced skin conductance differences between probe and irrelevant stimuli, it reduced differences in respiration and heart rate, yet still failed to facilitate detection.

Some studies have identified RT as an effective memory detection indicator (Gamer, 2011; Rosenfeld, 2011). However, polygraph-based CITs focus on physiological measures without restricting response time, rendering RT measures insensitive. Researchers have thus further investigated these questions using RT-based CITs. Visu-Petra, Varga, Miclea, and Visu-Petra (2013) examined whether interfering tasks facilitate detection using working memory interference (recalling the last word of each of the previous three items) and task-switching interference (pressing once for bold items, twice for italicized items). Results showed both interference types increased RT differences between deceivers and truth-tellers, but the insufficient task difficulty prevented these differences from significantly improving detection. Hu, Evans, Wu, Lee, and Fu (2013) examined dot-probe interference effects, which primarily involve task switching, and found that interference increased RT differences and facilitated detection.

Previous research has revealed differential relationships between executive function components and deception ability: response inhibition and task-switching abilities positively correlate with deception speed and accuracy, while working memory capacity negatively correlates with deception speed (Visu-Petra, Miclea, & Visu-Petra, 2012). This suggests different interference types may have varying effects on deception detection. While task-switching interference appears promising, the effects of response inhibition and working memory interference require further investigation. Additionally, Visu-Petra et al. (2013) found task-switching interference failed to facilitate detection, possibly due to insufficient difficulty (93% accuracy), suggesting task difficulty may moderate detection outcomes.

In summary, this project will systematically examine whether increasing cognitive load facilitates memory-response conflict-based deception detection by implementing interfering tasks of different natures and difficulties within the CIT paradigm.

2.2 Multi-Modal Deception Detection: Reaction Time and ERP Measures

As noted, RT may be an ideal behavioral measure for examining cognitive load effects on deception detection. RT is also widely recognized as an effective deception detection indicator (Seymour & Kerlin, 2008; Verschuere, Rosenfeld, et al., 2009; Verschuere & De Houwer, 2011; Verschuere & Kleinberg, 2016; Visu-Petra, Buş, & Miclea, 2011). Seymour, Seifert, Shafto, and Mosmann (2000) compared RTs to crime-relevant, irrelevant, and target information, achieving 89% and 100% discrimination rates for guilty and innocent participants, respectively. A recent meta-analysis of 114 studies by Suchotzki et al. (2017) found that lying takes longer than truth-telling, further supporting RT as a deception detection tool.

Autonomic nervous system responses (e.g., skin conductance, respiration, heart rate) have traditionally served as physiological deception indicators. However, since neural activity and brain activation more directly reflect cognitive and emotional changes, researchers have proposed using central nervous system measures (e.g., ERP, fMRI) instead (Rosenfeld, Soskins, Bosh, & Ryan, 2004). ERP technology offers similar accuracy to fMRI while being more economical and convenient (Rosenfeld et al., 2008) and has been widely adopted (Meijer, Selle, Elber, & Ben Shakhar, 2014). The P300 component, which signals "recognition," is commonly used in deception detection—when participants recognize concealed crime-related information, P300 is elicited. This project therefore focuses on ERP measures, particularly the P300 component.

Many researchers advocate combining multiple measures for deception detection (Ambach et al., 2010; Bhutta et al., 2015; Gamer, Verschuere, Crombez, & Vossel, 2008; Gronau, Ben-Shakhar, & Cohen, 2005; Hu, Pornpattananangkul, & Rosenfeld, 2013). Most studies combining behavioral and physiological measures find superior detection compared to single measures (Gronau et al., 2005; Hu & Rosenfeld, 2012; Rosenfeld et al., 2004; Vincent & Furedy, 1992). This project will therefore examine the effectiveness of combining RT and ERP measures for memory-response conflict-based deception detection.

2.3 Machine Learning for Predicting Individual Deceptive Behavior: Current Status and Trends

A persistent research focus in cognitive neuroscience involves using machine learning to decode brain states from neural activation patterns (Haxby, 2012). Davatzikos et al. (2005) first applied Support Vector Machines (SVM) to deception detection, distinguishing brain activation patterns between deceptive and truthful responses with over 90% accuracy. Subsequent studies using SVM to classify EEG signals from deceptive versus truthful responses achieved similarly high accuracy rates (Gao et al., 2010; Zhao et al., 2010; Simbolon et al., 2015). Comparisons of SVM, Linear Discriminant Analysis (LDA), k-Nearest Neighbor (KNN), and Back Propagation Neural Network (BPNN) for classifying deception-related EEG signals yielded accuracies of 74.5%, 79.4%, 97.9%, and 89%, respectively (Haider et al., 2018). This project will employ machine learning methods to explore and validate the effectiveness of obtained indicators for predicting individual deceptive behavior.

3. Research Framework

Under the cognitive-load approach, this project primarily employs the Concealed Information Test paradigm for deception detection research. First, the study systematically investigates how increased cognitive load affects memory-response conflict-based deception detection by implementing interfering tasks of different natures and difficulties. Second, using both non-criminal and criminal populations, the project examines behavioral and physiological indicators (RT and ERP) of memory-response conflict-based deception detection, assessing the discriminative power of combined measures. Finally, machine learning methods will be used to predict individual deceptive behavior based on the obtained RT and ERP indicators.

[Figure 1: see original paper]

3.1 Study 1: Effects of Interfering Task Nature and Difficulty on Memory-Response Conflict-Based Deception Detection

Study 1 adds interfering tasks to the CIT to increase cognitive load, examining how increased cognitive load affects memory-response conflict-based deception detection and how different task natures and difficulties produce differential effects.

Experiment 1 investigates the effects of varying-difficulty response inhibition interference on memory-response conflict-based deception detection. Response inhibition—the ability to suppress inappropriate or currently unnecessary behavioral responses—is crucial for flexible, goal-directed behavior (Aron, Robbins, & Poldrack, 2004; Booth et al., 2004; Diamond, 2013). The Go/No-go task (Trommer, Hoeppner, Lorber, & Armstrong, 1988) is commonly used in response inhibition research, typically involving high-frequency stimuli (e.g., letter X) requiring a response and low-frequency stimuli (e.g., letter O) requiring response withholding. Errors on low-frequency stimuli indicate inhibition difficulties. Task difficulty can be manipulated by varying the ratio of high- to low-frequency stimuli (Thorell et al., 2009). Following previous research (Ciesielski, Harris, & Cofer, 2004), this experiment will use a Go/No-go interfering task with high:low stimulus ratios of 3:1 and 1:3 to examine differential difficulty effects.

Procedure: Participants are randomly assigned to guilty or innocent groups. Guilty participants complete six phases: mock crime, crime detail recall, target learning, no-interference CIT, simple-interference CIT, and difficult-interference CIT. (1) Mock crime: Participants enter an unlocked laboratory to steal a yellow disc containing confidential information. They move a chair blocking the door, retrieve a key from a bookshelf near a notebook, use it to open a drawer containing a music card with the disc inside, and steal it. (2) Crime detail recall: Participants return to the testing room and answer questions about crime details to ensure clear memory. (3) Target learning: Participants memorize five words as CIT target stimuli, requiring "yes" responses during the CIT while responding "no" to all other stimuli. (4) No-interference CIT: This includes three stimulus types—five probes (laboratory, disc, chair, notebook, music card), five targets (library, USB drive, table, calculator, tape recorder), and 20 irrelevants (words matching probes in length and category). All stimuli appear randomly four times. Each trial presents a fixation cross (500–750 ms), then a stimulus (300 ms), followed by a 1000 ms blank screen. Participants respond as quickly as possible whether they have seen each stimulus ("yes" for targets, "no" for others). For innocent participants, "no" responses to probes are truthful; for guilty participants, they are deceptive. All participants respond truthfully to irrelevants. (5) Simple-interference CIT: After the fixation cross, letters X or O appear (100–250 ms). Participants press the spacebar for X but not for O, with an X:O ratio of 1:3. After the letter disappears, the CIT stimulus appears (300 ms) with the same response requirements as phase (4), followed by a 1000 ms blank screen. (6) Difficult-interference CIT: Identical to phase (5) except the X:O ratio is 3:1.

Innocent participants are told they are helping researchers retrieve a disc from the laboratory and undergo the same detail testing and experimental tasks. The order of the three CIT conditions is counterbalanced across participants. Given that callous-unemotional traits correlate with violent crime (Xiao et al., 2014), all participants complete the Callous-Unemotional Traits Scale after the experimental tasks.

Data Analysis: Groups are compared on gender and age to ensure homogeneity. Three-way ANOVAs (Group: guilty vs. innocent × Stimulus Type: probe vs. irrelevant) are conducted for each CIT condition on RT and accuracy, with callous-unemotional trait scores as covariates. Classification accuracy, hit rate, and correct rejection rate are calculated via regression using mean RT, RT variance, and error rates. These three metrics are converted to z-scores and averaged to create a composite z-score for each condition. Signal detection theory is used to calculate discriminability for guilty and innocent participants under each condition, with Z-tests comparing discriminability across conditions.

Experiment 2 investigates varying-difficulty working memory interference effects. Working memory is a crucial executive function component, with prefrontal cortex activation increasing in scope and intensity with task difficulty (Baddeley & Hitch, 1974). Working memory comprises the phonological loop, visuospatial sketchpad, and central executive, which can be divided into verbal and visuospatial working memory. This experiment examines both types.

Experiment 2a uses a letter delayed-matching task to examine verbal working memory interference. After a fixation cross (500–750 ms), uppercase letters appear (300–500 ms) for participants to memorize (4 letters in the simple condition, 8 in the difficult condition). Following letter disappearance, a CIT stimulus appears (300 ms) with a 1000 ms blank screen, requiring participants to respond whether they have seen it. After responding, a lowercase letter appears, requiring participants to judge whether it matches any previously presented uppercase letters (ignoring case).

Experiment 2b uses a spatial position delayed-matching task to examine visuospatial working memory interference. After a fixation cross (500–750 ms), a 15$×$15 cm grid with 16 cells appears (300–500 ms). In the simple condition, one black square appears in any cell; in the difficult condition, five black squares appear in five random positions. Participants must memorize the location(s). After the grid disappears, a CIT stimulus appears (300 ms) with a 1000 ms blank screen, followed by a grid with black squares requiring participants to judge whether the positions match the previously shown configuration.

Experiment 3 investigates varying-difficulty task-switching interference effects. Task switching is a key component of cognitive flexibility, requiring individuals to recognize inappropriate cognitive sets, disengage from them, and adopt new sets to coordinate behavior with environmental demands (Woodward, Ruff, & Ngan, 2006). Switching between tasks A and B incurs a "switch cost" (Monsell, 2003). Following previous research (Wang & Guo, 2008), participants perform odd/even classification on colored target digits.

Procedure: Identical to Experiment 1 except for phases (5) and (6). (5) Simple-interference CIT: After fixation, target and distractor digits appear (300–500 ms). Participants judge whether a target digit of a specific color is even, while ignoring a differently colored distractor digit appearing above or below the target. Target and distractor digits always differ in parity. Colors are randomly selected from red, green, yellow, and blue; digits range from 0–9. The target color switches every 15 trials. After digit disappearance, a CIT stimulus appears (300 ms) with a 1000 ms blank screen. (6) Difficult-interference CIT: Identical to (5) except the interference task includes both digit and letter judgments, requiring participants to determine whether target letters are vowels. Digit and letter judgments appear randomly, with target digits and letters sharing one color and distractors sharing another.

3.2 Study 2: Reaction Time and ERP Indicators of Memory-Response Conflict-Based Deception Detection Under Cognitive Load

The autobiographical Implicit Association Test (aIAT) is a recently developed method for detecting crime-related memories, with research showing that combining aIAT with CIT improves detection rates (Sartori et al., 2008). Hu and Rosenfeld (2012) first combined aIAT and CIT, recording RT and ERP indicators to assess their combined discriminative power. This study adopts this combined approach, collecting RT and ERP measures and using signal detection theory to evaluate combined indicator effectiveness at the group level. Following Hu et al. (2013), a dot-probe interfering task is implemented to examine indicator effectiveness under cognitive load.

Experiment 4a uses university students to examine RT and ERP discriminative power in non-criminal populations. Since most laboratory deception research uses mock crime scenarios with non-criminals, its ecological validity and applicability to field settings and forensic practice have been questioned (Liu et al., 2018). Fu (2011) first applied ERP deception detection to 31 actual criminal suspects, using case outcomes to validate results, finding lower accuracy than laboratory studies. Therefore, Experiment 4b uses actual criminal suspects and real crime scene materials to enhance ecological validity and examine indicator effectiveness in criminal populations, promoting application in criminal investigation.

Experiment 4a Procedure: Participants are randomly assigned to guilty or innocent groups. Guilty participants receive mock crime instructions: "Imagine you are a thief. There is something valuable in a small box in the behavioral laboratory. Go steal it." Participants find and steal a ring from a desk drawer, carrying it in their pocket. Innocent participants simply tour the laboratory and retrieve an article.

All participants first complete the EEG experiment, then the aIAT. The interfering task follows Hu et al. (2013), requiring a dot-probe task (judging whether two dots are horizontally or vertically arranged).

Following Rosenfeld et al. (2008), the EEG procedure is: fixation cross (500–700 ms), two dots (300–500 ms) requiring horizontal/vertical judgment (right-hand mouse button press), then experimental stimulus (300 ms) requiring left-hand keypress response. Stimuli include one probe (ring) and eight irrelevants (article, necklace, hairpin, watch, bracelet, earrings, bangle, hat), with "article" representing the innocent group' s action. Each probe and irrelevant repeats randomly 50 times (450 total trials). After stimulus response, one of five number strings (11111, 22222, 33333, 44444, or 55555) appears (300 ms), requiring right-hand mouse response (left-click for target 11111, right-click for others).

The aIAT comprises five blocks: (1) Classify true sentences as "F" and false sentences as "J" (20 trials); (2) Classify crime-related sentences as "F" and crime-unrelated sentences as "J" (20 trials); (3) Classify true OR crime-related sentences as "F" and false OR crime-unrelated sentences as "J" (60 trials—congruent for guilty, incongruent for innocent); (4) Reverse responses from block 2 (40 trials); (5) Classify true OR crime-unrelated sentences as "F" and false OR crime-related sentences as "J" (60 trials—incongruent for guilty, congruent for innocent). Each trial presents fixation (500–700 ms), two dots (300–500 ms) for orientation judgment, then a sentence (1000 ms) for classification.

Data Analysis: Groups are compared on gender and age. EEG analysis involves Group × Stimulus Type ANOVAs on RT and P300 amplitude, with discriminability calculated via signal detection theory. aIAT analysis uses D-scores (positive = association between crime-related and true sentences; negative = association between crime-unrelated and true sentences). D-scores are compared between groups, with discriminability calculated via signal detection theory.

Experiment 4b recruits 30 incarcerated criminal suspects without physiological or psychiatric disorders, meeting criteria: complete crime scene information available; confessed crimes allowing result validation; all attempted homicide cases with serious penalties. EEG stimuli are crime tools from relevant and irrelevant crime scenes. aIAT stimuli are crime-detail sentences concerning tools, traces, body, and scene overview.

3.3 Study 3: Predicting Individual Deceptive Behavior

Machine learning methods are widely applied in text analysis, speech recognition, face recognition, and neuroimaging data analysis. This study will employ commonly used algorithms in neuroimaging analysis—SVM, LDA, KNN, and BPNN—to explore effective prediction of individual deceptive behavior by combining classifier strengths. Data from Studies 1 and 2 (RT and ERP data) will be analyzed.

ERP data reflects neuronal activity comprising specific oscillatory components. Waveform changes accompanying cognitive state shifts also involve frequency characteristics, meaning ERP data contains rich temporal and frequency domain information. This component focuses on selecting and extracting appropriate ERP temporal and frequency features for deception prediction, combining different feature selection/extraction methods to identify the most effective predictive features.

4. Theoretical Framework

The cognitive mechanism underlying deception detection in this project is that deceivers experience memory-response conflict when falsely responding to probes. Increasing cognitive load during conflict resolution makes resolution more difficult, increasing RT and decreasing accuracy while manifesting in neurophysiological changes. By manipulating cognitive load to amplify differences between deceivers and truth-tellers, deception detection is enhanced. The theoretical framework is illustrated in Figure 2 [Figure 2: see original paper].

Figure 2. Cognitive Load-Based Deception Detection Principles

First, during CIT, deceivers' responses to probes involve memory-response conflict. This cognitive-load approach differs from emotion-based deception theories. Traditional detection assumes deception produces specific emotions (e.g., fear of discovery) and elevated physiological arousal when key questions are asked. However, as detailed in the National Research Council report (2003), this assumption lacks theoretical foundation—deceivers do not necessarily show increased arousal, while truth-tellers may show elevated arousal due to anxiety. The cognitive-load approach proposes that when deceivers falsely respond to existing true memories (probes), memory-response conflict arises. Resolving this conflict requires executive functions like response inhibition and consumes cognitive resources. Truth-tellers' responses to probes involve no conflict. This project manipulates/increases cognitive load to examine differential effects on deceivers versus truth-tellers and on detection outcomes.

Second, "secondary tasks" increase cognitive load during CIT. Information processing theory posits that human cognitive capacity is limited—individuals have finite, specific cognitive resources available for task execution at any given time. Performing multiple tasks simultaneously requires resource allocation across tasks, creating resource competition. When fewer resources are allocated to a specific task, performance becomes more difficult and declines. Researchers typically increase cognitive load by having participants perform multiple concurrent tasks and measuring performance (Eysenck & Eysenck, 1979). Vrij et al. (2006, 2008; Vrij, Mann, Leal, & Fisher, 2010) increased cognitive load during interrogation by requiring reverse-order recall or maintaining eye contact, making lying more difficult and revealing more deception cues. In the highly controlled, closed-question CIT paradigm, cognitive interference tasks are more suitable because their clear cognitive processes, quantifiable operations, and well-understood mechanisms allow detailed investigation of how increased cognitive load affects deception and its underlying cognitive mechanisms. Task complexity also affects resource demands—more complex tasks require more resources. Since the CIT requires executive function involvement, this project implements interfering tasks related to response inhibition, working memory, and task switching at varying difficulty levels to increase cognitive load.

Third, increased cognitive load differentially affects deceivers' and truth-tellers' response processes. In the CIT, deceivers experience memory-response conflict when responding to probes, requiring longer resolution time, while truthful responses to irrelevants involve no conflict and require less time. Thus, deceivers show RT differences between probes and irrelevants. Truth-tellers make truthful responses to both stimulus types, requiring minimal time and showing no significant RT differences.

When interfering tasks increase cognitive load, they consume resources needed for conflict resolution in deceivers, making probe responses more difficult (increased RT). Since truthful responses to irrelevants require fewer resources, interference has minimal impact. Thus, increased cognitive load amplifies deceivers' RT differences between probes and irrelevants. For truth-tellers, interference similarly affects both stimulus types, so cognitive load does not increase their RT differences. Consequently, increased cognitive load magnifies behavioral differences between deceivers and truth-tellers, facilitating detection.

Interference effects on RT should also manifest in EEG indicators, particularly P300. Research shows deceivers exhibit larger P300 amplitudes for probes than irrelevants, while truth-tellers show no significant P300 differences (Mertens & Allen, 2008). P300 amplitude relates to cognitive effort—greater effort produces larger amplitudes. Increased cognitive load forces deceivers to expend more time and effort for correct probe responses, increasing probe-elicited P300 amplitude and amplifying P300 differences between probes and irrelevants, thereby increasing differences between deceivers and truth-tellers.

The CIT requires suppressing automated "yes" responses to probes while explicitly making "no" responses, demanding response inhibition. Studies show CIT variants requiring more response inhibition (e.g., concealed information oddball paradigm) achieve more stable detection (Verschuere & Ben-Shakhar, 2011). Thus, response inhibition is a crucial CIT component. When secondary tasks also require response inhibition, they interfere with probe responses. Since the CIT involves response switching between targets and probes, task-switching secondary tasks also interfere with "correct responses." Working memory demands in the CIT are minimal (only one target stimulus must be remembered), so working memory interference may have limited effect. This project therefore hypothesizes that response inhibition and task-switching interference tasks will yield better detection outcomes in the CIT.

In summary, whether cognitive-load-based deception detection improves outcomes requires further investigation, which must first understand the underlying cognitive processes and mechanisms (Blandón-Gitlin et al., 2014). This project systematically examines how interfering tasks of different natures and difficulties affect memory-response conflict-based deception detection, with results contributing to understanding the cognitive processes underlying the cognitive-load approach and addressing whether and how it improves detection rates. The research will also help identify appropriate deception detection indicators for automatic lie detection applications.

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