Fraud Susceptibility Across Adulthood: Age, Context, and the Role of Individual Differences

by

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Abstract

As rates of fraudulent crime rise globally, understanding fraud susceptibility (FS) is paramount to public interest and safety. Mixed findings exist regarding (a) the effect of older age on FS behaviours and (b) the processes that underlie different behavioural aspects of decision-based susceptibility.

Using a mixed ANOVA design with within- and between-subjects factors, we examined relationships between age and decision-based FS behaviours in a community-dwelling sample of younger adults (n = 76, age 17-35, M_{age} = 20.34, SD = 3.51) and older adults (n = 46, age 59-96, M_{age} = 74.35, SD = 8.79) on a novel experimental task using real-world stimuli. We employed signal detection theory (SDT), between-subjects (Age Group) ANOVAs and regression analysis to investigate susceptibility as a function of age (young vs. old) and individual differences (neurocognition including, Theory of Mind [ToM], interpersonal trust) while concurrently examining the influence of contextual decision-making factors (deliberation time, decision confidence) on performance.

Contrary to our predictions, older adults were significantly less likely to participate in fraudulent offers, $F[1,120] = 4.86$, $p = .029$, $\eta^2 = .04$, and demonstrated stronger ability to detect fraudulent stimuli, $F[1,120] = 10.33$, $p = .002$, $\eta^2 = .08$ than younger adults. While they were also significantly better at discriminating between stimuli types, $F(1,120) = 6.42$, $p = .01$, $\eta^2 = .05$, this performance was accompanied by inflated response bias (i.e., a tendency towards classifying all stimuli as fraudulent/unsafe). Consistent with our predictions, regression modelling suggested that context (deliberation time), ToM, and trust are strong predictors of FS outcomes while other neurocognitive skills are not. Contrary to our predictions, associations between FS and age were not qualified by confidence, which was less relevant to discrimination accuracy than other contextual and social cognitive skills across age groups.

In the first study to examine ToM and FS in aging, we demonstrated that older adults are not more susceptible to fraud than younger adults. Further, deliberation time and some socially-based cognitive skills portended FS on an ecologically-valid task. Our findings refute the notion that there is an age-related vulnerability to fraud and suggest that contextual and social decision-making factors appear to be more critical in FS than are other age-sensitive neurocognitive resources.

Keywords: fraud susceptibility; social cognition; theory of mind; aging; neuropsychological ability; scams; phishing; signal detection theory

Dedication

This is for my parents.

To my Mom, Cecilia, who believes in me in a way only a mother can. Thank you Mom for your butter tarts and peach cobbler, your intelligence, your infectious laugh, and your electric optimism. You remind me to never take things too seriously and I cherish our adventures together. You are my hero and my best friend.

To my Dad, Tim, who taught me about integrity, patience, thinking outside the box, and strength of character. Thank you Dad for your hugs. They get me through so much. Thank you as well for your expert proofreading, your life insights, and your steadfast faith in my ability to do this. You instilled confidence in me when I had none. Dad, you'll always be one of the good guys.

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On a personal note, I would like to thank my loved ones who have been my safe harbour over the course of my doctoral studies. To Mom and Dad: Thank you for all of your love which is truly too vast to capture with words. Your sacrifices have made my experiences possible, and your unconditional belief in me has made all the difference. To my strong and beautiful sisters Kate, Ali, and Emily: Thank you for inspiring me in your own pursuits and dreams, and for never forgetting about your youngest sis in the process. You are my crew for life and I love you. To their partners Fernando, Marc, and Nick: I've been blessed with the best bonus brothers and am thankful for your presence in my life. To my precious girl gang of nieces Gabriella Kay, Isabella Rose, and Evelyn Celeste: Thank you for giving me one of the utmost honors of my life, becoming your Aunt Lolo! It has been the absolute highlight of my time in graduate school. And finally to my best friend and husband Gurdeep Gill: Thank you for keeping me laughing, safe, well-fed, and always guessing. You are the love of my life, all ways, always. We did it!

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FS	fraud susceptibility
C-ToM	cognitive theory of mind
A-ToM	affective theory of mind
dlPFC	dorsolateral prefrontal cortex
vmPFC	ventromedial prefrontal cortex
SDT	signal detection theory

Chapter 1. Introduction

The COVID-19 global pandemic triggered a disproportionate increase in reported annual frauds in Canada between March 2020 and 2021, leaving in its wake approximately 43,000 victims and an estimated $110 million in losses (Canadian Anti-Fraud Centre, 2021). Discouragingly, these events mirror a broader and ongoing trend of rising scam victimization rates in North America (FTC, 2021) and globally (Competition Bureau, 2018). This is a particularly sobering notion considering that less than 5% of victims report fraud-related crime (Statistics Canada, 2020). As technology continues to influence our everyday lives, fraud exposure has increased in sophistication (Pinkser & McFarland, 2010; Anderson, 2013) and frequency (Button & Cross, 2017); highly effective deceptive advertising increasingly targets online platforms (Anderson, 2013), widening access to potential victims (Button & Cross, 2017). Fraud victimization has devastating social and economic consequences, and fraudulent crimes target particularly vulnerable groups (e.g., older adults) that may be differentially impacted by these consequences. As such, at its core fraud is also a social issue that has received heightened attention in recent years given the upward trend of fraudulent crime rates, and associated psychological consequences including loss of independence, financial hardship, depression, anxiety, and stigma/shame (Lichtenberg et al., 2016; Burnes et al., 2017) that have been documented particularly amongst older adults (Lichtenberg, Sugarman, Paulson, Ficker, and Rahman-Filipak, 2016).

While fraudulent exploitation is considered a specific public health problem of older adulthood (Ebner et al., 2020), victimization rates are steadily rising across all age groups (Competition Bureau, 2020), underscoring its societal relevance. The identification of broad demographic characteristics such as older age helps to guide broader policy and public health initiatives but offers only marginal insight into individual risk factors. It is important to clarify whether old age represents a particularly *vulnerable* period for fraud, given that older adults may be attractive targets for scammers due to assumptions regarding wealth and access (e.g., financial stability, accumulated retirement savings, well-established credit; Ebner et al., 2020). Older adults also report rising rates of Internet usage (Perrin & Duggan, 2015) and increased comfort navigating the Internet and online banking (Smith, 2014), and awareness campaigns tend to cater to an older adult audience (Norris et al., 2019). Clarity regarding at-risk groups is also needed given emerging longitudinal evidence that decreased scam awareness may be a preclinical sign of pathologic cognitive aging (e.g., dementia; see Boyle et al., 2019) or cerebrovascular pathology (specifically infarcts: see Kapasi et al., 2022) and may represent a behavioural harbinger of Alzheimer's disease (AD; Kapasi et al., 2021). Thus, understanding how fraud susceptibility (FS) is expressed in both younger and older age groups is a central priority. Further, determining whether decision-making in the FS context maps onto decision-making more generally (e.g., regarding healthcare decisions) holds important clinical implications for the aging population.

Thus, to better inform both clinical and community decisions regarding fraud risk, our project aims to inform a theoretical framework of FS that describes the interplay between age, individual differences, and contextual processes that underlie vulnerabilities.

1.1. Mechanisms of FS

Theoretically, pinpointing fraud mechanisms is an imprecise science, but current conjecture suggests that nonoptimal *decision-making* may account for fraud victimization amongst healthy, cognitively intact individuals (Lighthall et al., 2020). Decision-making (i.e., a set of cognitive, affective, and context-based appraisals used to arrive at a conclusion to inform behaviour; see Spreng et al., 2016) is a complex and multifactorial skill that shapes the quality of our experiences across the lifespan, and is fundamental for judgment and independence. Successful fraud tactics exploit errors/biases in judgment during the decision-making process (e.g., see Fischer, Lea, & Evans, 2013, for review), and target a variety of cognitive, affective, and motivational resources inherent to sound decision-making. Fraud is also a *social* transaction (Workman, 2008) and neuroimaging studies have lent strong support for a neuroanatomical profile of FS that specifically implicates *social cognitive processes* such as theory of mind (ToM; see Spreng, Karlawish, & Marson, 2016 for review).

ToM is a social cognitive skillset essential for navigating the social world by identifying, understanding, and predicting others' mental states, emotions, and intentions (see Premack & Woodruff, 1978). ToM skills may be particularly relevant to FS because they recruit both cognitive and affective components (Shamay-Tsoory et al., 2010) which map onto System 1/System 2 processing styles (Stanovich, 1999) during decision-making (Lieberman, 2007). Affective or “hot” ToM (A-ToM) and cognitive or “cold” ToM (C-ToM) represent distinct, neuroanatomically differentiated domains (Shamay-Tsoory, 2007) that functionally and structurally align with System 1/System 2 processing theories (see Liberman, 2007a; 2007b), creating an explanatory link to illustrate how seemingly capable, cognitively intact individuals may be persuaded into exploitative situations. ToM skills are also relevant to real-world contexts (Fett et al., 2011) and have been widely studied across the lifespan and in a variety of everyday decision-making circumstances (e.g, social cooperation/sharing; moral dilemmas; identification of lying). Emerging research on phishing scams suggest that people who rely on rational (i.e., cold, slower, deliberate, rational, cognitive-based, System 2) social processing strategies tend to make more accurate judgments and report lower trust in the legitimacy of a fraudulent email (Jones et al., 2019; Kelley et al., 2023); conversely, those who employ more intuitive (i.e., hot, faster, automatic, affective-based, System 1) strategies tend to make less accurate judgments and rate their trust in the legitimacy as higher (Yan & Gozu, 2012; Harrison, Vishwanath, & Rao, 2016; Shang et al., 2023). System 1 routes allow for rapid decision-making, with less time recruited for information processing, making it the default response type in decision-making scenarios. In contrast, System 2 requires suppression of this initial intuitive response, allowing consideration of future consequences and weighing of options.

As people age, there is evidence that individuals may employ different strategies in their decision-making, offering several theoretical possibilities to explain disparities regarding age effects in current empirical work; for example, individual differences in neurocognition (e.g., reduced working memory capacity, preserved affective ToM) might affect the likelihood of resorting to System 1 processing (Markovits et al., 2002).

1.1.1. Decision-Making in Normal Aging

Cognitive Factors. Aging yields selectively greater declines in functions supported by the frontal lobe (e.g., working memory, attention, processing speed; Salthouse et al., 2009) because this region sustains relatively greater deterioration during the natural aging process (i.e., the *frontal aging hypothesis;* West, 1996; MacPherson & Cox, 2017). Dorsolateral regions and their associated neurocognitive functions (e.g., executive functions) are more vulnerable to age-related decline than other frontal lobe regions, such as the ventromedial prefrontal cortex and its associated neurocognitive functions (e.g., social decision-making, affective processing; MacPherson, Phillips, & Della Sala, 2002; Lighthall et al., 2020). By extension of the frontal lobe hypothesis, cognitive aging literature suggests that while aging causes selective declines in “fluid cognitive abilities” (i.e., deliberative functions; frontal executive functioning; Horn & Cattell, 1967; Salthouse, 2004; Schaie & Willis, 2002), there is relative preservation and even growth in “crystallized cognitive abilities” (i.e., knowledge). Scam avoidance may involve the recruitment of fluid cognitive abilities (Wood et al., 2016; Walzak & Thornton, 2022) and complex, higher-order cognitive functions such as reasoning, judgment, and sensitivity to deception that are more likely to decline with age (Mata et al., 2011; Burnes et al., 2017; Oliveira et al., 2017;Boyle et al., 2012; James, Boyle, & Bennett, 2014; Thornton & Dumke, 2005).

Affective Factors. In tandem with cognitive changes, aging is associated with socioemotional and motivational changes including an increased preference for processing positive over negative information during decision-making (“positivity bias”; Reed & Carstensen, 2012), prioritization of social/emotional goals over knowledge acquisition (Carstensen et al., 1999; Carstensen, 2006), and stronger trust in others (Castle et al., 2012; Van Lange, 2015). Normal aging is also associated with other gains including the maintenance of affective skills (“affective resiliency”; Lighthall et al., 2021) including the preservation of affective ToM relative to cognitive ToM (Wang & Su, 2013; Bottiroli et al., 2016; Baksh et al., 2018). These shifts can lead to better emotional regulation (Kryla-Lighthall & Mather, 2009; Scheibe & Carstensen, 2009) and selective processing of affective information (“affective enhancement”; Peters et al., 2007), both of which are relevant to decision-making in ambiguous contexts (Spreng et al., 2016). Older adults also rely moreso on affective/intuitive processing (e.g., System 1 automatic processes and heuristics; Stanovich, 1999), which stay relatively intact in late life, and less so on deliberative abilities that involve heavy working memory demands (e.g., System 2), which are more sensitive to age-related declines. Compellingly, emerging evidence shows that in ambiguous contexts, decisions that recruit deliberative processing demonstrate more age effects than those that are more experiential (Huang, Wood, Berger, & Hanoch, 2015).

Contextual Factors. A class of contemporary theories propose that age-related changes in decision-making are influenced by the *interplay* between context, physiological and psychological factors. Built around the widely adopted notion that normal aging involves 1) the emergence of some deficits, in tandem with 2) the development of new skills and strengths, these theories emphasize the importance of "fit" between older adults' abilities and goals with the context in predicting decision behaviour (Frazier, Lighthall, Horta, Perez, & Ebner, 2019; Hess, 2015; Li et al., 2013; Yoon et al., 2009). For example, the affect-integration-motivation framework (AIM; Samanez-Larkin & Knutson, 2015) illustrates how brain aging, preserved crystallized abilities, and age-related shifts in affective goals may collectively influence decision behaviours in a context-relevant way. Emphasis on contextual factors has also been highlighted in psychological theories within the fraud-specific domain (see Lichtenberg's 2016 person-centred model of fraud victimization).

1.2. The Predictive Role of Age in FS

Older adults are disproportionately represented in fraud research (Acierno et al., 2010; Scheibe et al., 2014; Wood & Lichtenberg, 2017), and based on theoretical perspectives from cognitive aging, we can extrapolate that (a) older adults will be more likely to show deficits when optimal decision-making strongly relies on fluid cognitive abilities, (b) preserved crystallized and socioemotional abilities may be recruited for compensatory gain to allow for maintained or enhanced decision-making performance, and (c) age differences in decision processing are more likely to be observed when choices evoke strong arousal.

Some evidence from empirical work supports the contention of increased age-related vulnerability in FS; older adults demonstrate decreased decision-making capacity and reduced sensitivity to deception cues on some behavioural fraud tasks (Denburg et al., 2007; Asp et al., 2012; Castle et al., 2012; Ruffman, Murray, Halberstaft, & Vater, 2012; Ross, Grossman, & Schryer, 2014; Wood, Liu, Hanoch, & Estevez-Cores, 2016). Older age is also associated with poorer discrimination between legitimate and fraudulent emails in some studies (i.e., excess suspiciousness for safe emails and excess credibility for unsafe emails; Grilli et al., 2021) as well as lower awareness of online frauds (Oliveria et al., 2017). Age-related cognitive declines in numeracy (Anderson, 2013), episodic memory and verbal fluency (Ebner et al., 2020), and executive functions (Wood et al., 2016; Wood et al., 2014) have been linked to increased FS in older adults. In the broader literature on deception detection, older age has been linked with reduced emotional recognition of facial expressions in truthful/deceptive vignettes (Stanley & Blanchard-Fields, 2008) and poorer performance on veracity judgment tasks (Ruffman et al., 2012). Older adults also show own-age biases (i.e., tendency to believe same-age deceptors; Slessor et al., 2014) and poorer ability to detect lies in social settings (Sweeney & Ceci, 2014) compared to younger counterparts.

Further, neuroimaging studies of FS profiles in community-dwelling older adults suggest that age is associated with specific neuroanatomical changes in areas relevant for detecting fraud (and social cognitive processing more generally; see Frazier, 2019), including cortical thinning of grey matter (anterior insula and posterior superior temporal gyrus; Spreng et al., 2017; mid-temporal regions; Han et al., 2016c), reduced white matter integrity in right temporal and parietal regions (Lamar et al., 2020), and decreased functional activation in the vmPFC during consumer decision-making (e.g., Koestner, Hedgcock, Halfmann, & Denburg, 2016; Asp et al., 2012). Frontal regions involved in deception/cooperation detection have also been associated with other cognitive functions that tend to decline with age, including executive control (Christ et al., 2009), flexibility and verbal fluency (Calso, Besnard, & Allain, 2020) and cognitive theory of mind (El Haj, Antoine, & Nadrino, 2017).

However, empirical research has failed to reliably model older age itself as a robust predictor of increased FS (Ebner et al., 2020; Lin et al., 2019; Oliveira et al., 2017; Sarno, Lewis, & Neider, 2020), with some studies even reporting an age *advantage* amongst older adults on performance-based fraud/phishing tasks (Gavett et al., 2017; Mueller, Wood, Hanoch, Huang, & Reed, 2020; O’Connor et al., 2021) and on self-report surveys (Lichtenberg et al., 2016; Ross et al., 2014; Wood et al., 2015). Older age is not associated with an overall shift in perception of email safety (i.e., perceiving all phishing emails as generally safe; Grilli et al., 2021, O’Connor et al., 2021) and older adults are less susceptible to persuasion tactics in investment scams than younger adults (see Mueller et al., 2020). Identified age differences may also simply reflect differences in sampling methodology (e.g., social/behaviourally-based tasks vs. cognitive -based tasks), which may recruit different decision-making strategies that complement or interfere with age differences (see Canfield et al., 2016).

Taken together, current approaches focused exclusively on the impact of older age and associated cognitive changes on decision-making are likely too narrow. Emphasis on age-related assumptions in fraud research also distract from potential protective factors in later life (e.g., experience; Lichtenberg et al., 2015; emotional intelligence; Mueller et al., 2020; affective resilience; Lighthall et al., 2021) and reinforce the old-age stereotype of cognitive fragility that contributes to underreporting of fraud crimes (Norris et al., 2019). Further, they distract from identifying, and thus informing, other potentially at-risk groups (e.g., younger adults).

1.3. Individual Differences in FS

Age aside, other demographic variables including race, socioeconomic status, education, gender, and household size have been identified as correlates of FS in population-based studies (Beach et al., 2010; Peterson et al., 2014) and in empirical work (Halevi et al., 2015; Sheng et al., 2010; Oliveira et al., 2017; Ebner et al., 2020; Nolte et al., 2021). Further, dominant theoretical orientations in current cognitive aging fraud literature (e.g., Lichtenberg's person-centred model, 2016) emphasize the role of the individual amongst an interplay of traits and contextual factors relevant to aging. In support, a growing empirical literature suggests that individual differences (i.e., traits) largely determine who is defrauded (e.g., see Button et al., 2016; Judges et al., 2017; Norris et al., 2019). However, these demographic differences have not materialized in other studies with large sample sizes (see Norris et al., 2019), and identified gender differences may be largely confounded by gender-related personality differences (e.g., risk-seeking; Borghans et al., 2009). Thus, in our current study, we chose to investigate age as a predictor and other demographic variables as potential covariates.

Neurocognitive variables including reduced executive functioning (Wood et al., 2014; Gavett et al., 2017), global cognition (Cole & Shastry, 2009; Lichtenberg et al.; Kleitman et al., 2018), and decision-making capacity (Boyle et al., 2012; Lichtenberg et al., 2013; James et al., 2014) have been identified as predictors of FS. Other studies have cited skills including numeracy (Cokely et al., in press; Wood, Liu, Hanoch, & Estevez-Cores 2015; Kleitman et al., 2018) and semantic memory (Wood et al., 2014) as being relevant to FS in older adults in particular. Potential FS-cognition relationships may also vary with age; for example, Ebner et al. (2020) found that in middle-old participants (age 75-89), poorer short-term episodic memory was associated with greater FS (i.e., worse deceit detection), and that poorer verbal fluency was associated with reduced awareness of potential fraud risks in both young adults and middle-old age groups only. This study failed to substantiate the contribution of other previously identified neurocognitive processes in both young and old age groups (e.g., numeracy; executive functions, memory; Anderson, 2013; Wood et al., 2016). Thus, we opted to include individual neurocognitive skills in our models as well as a global cognitive composite variable to test these relationships.

While ToM has been implicated in assessing cooperation and reciprocity in others (Trivers, 1971) as well as detecting intentional deception (Byrne, 1988), this skill has not been formally studied in the FS context to date. ToM impairments are linked to increased willingness to tolerate risky financial or medical decisions in real-world settings (Rogalsky, Vidal, Li, & Damasio, 2012), and natural variations in ToM may underlie the ability to detect deception in observed dyads (Sylwester at al., 2012). In a study on judgment and detection of guilty suspects, participants who were trained to explicitly use their ToM/mentalizing skills when interviewing suspects demonstrated better discrimination accuracy (Granhag & Hartwig, 2008). In another study on detection of co-operators vs. defectors in video clips based on the Prisoner's Dilemma, lower A-ToM hindered participants from identifying people with deceptive intentions (Sylwester et al., 2012). More generally, there is evidence to support that fraud-related decision-making outcomes are heavily influenced by differences in social cognitive processing; better C-ToM supported more accurate deception detection, but not truth detection, on a task identifying truth-tellers and liars in real-life scenarios (Stewart, Wright, & Atherson, 2019), and poorer overall ToM predicted lower performance on a task of social deception and cooperation (Calso et al., 2019, 2020). To date, we are aware of no studies that have employed relevant multivariate models to examine ToM skills in predicting FS outcomes; as such, we opted to include both C-ToM and A-ToM in order to clarify the direction and strength of these potential associations. Please see Appendix B: Literature Review for additional commentary on the theoretical links between ToM and FS.

Finally, trust has been cited by the FTC (2007) as a primary driver of FS that may be linked to the age-related positivity bias (i.e., socioemotional selectivity theory; Carstensen, 1999; Kircanski et al., 2018). In tandem with the alteration of neurocognitive and socioemotional processes as we age, older adults tend to exhibit greater trust toward strangers (Castle et al., 2012; Li & Fung, 2013; Poulin & Hasse, 2015). Paired with the fact that older adults also demonstrate poorer accuracy in deceit detection in *some* studies (Oliveria et al., 2017; Ruffman et al., 2012; Tehan & Blanchard-Fields, 2008), current conjecture is that excessive trust must be a primary factor in age-related fraud vulnerability (e.g., see Titus & Gover, 2001, Kirchheimer, 2011). Higher trust is also associated with higher rates of deception in text-based online chat (Friend & Fox Hamilton, 2016). Some studies have failed to provide robust evidence for the popular assumption that excessive trust underlies fraud victimization (Garg & Camp, 2012; Judges et al., 2017; Shao et al., 2019), with still others proposing that more trusting individuals are actually *better* at differentiating trustworthy from untrustworthy solicitations (Carter & Weber, 2010). We opted to include interpersonal trust in our study to clarify its role in FS amongst younger and older adults.

1.4. Contextual Factors

1.4.1. Decision Confidence

In the decision-making context, confidence is a belief about the validity of our own thoughts, knowledge, or performance and relies on a subjective feeling (Luttrell et al., 2013). Further, confidence is encoded within decision-making circuits (Grimaldi et al., 2015) and is thus an important predictor of decision-making in real-world contexts. This metacognitive process has been more recently included in some FS models to examine correspondence with detection accuracy (e.g., higher confidence is associated with better detection; see Iuga et al., 2016; Griffin & Brenner, 2014). Wang, Li and Rao (2016) found that on-task confidence predicted phishing detection accuracy even after controlling for self-efficacy, and Canfield et al. (2019) reported a significant positive association between on-task confidence and discrimination ability. To address the potential domain-specificity of this relationship, Kleitman et al. (2018) also included external confidence judgments (e.g., self-report of one's overall confidence as a trait) in FS modelling, but this variable failed to predict significant variance beyond on-task confidence in FS outcomes. Amongst older adults in particular, there is some evidence to suggest that on-task confidence may actually inflate with age relative to actual performance (Gamble, Boyle, Yu, & Bennett, 2014), though findings are mixed (see Plinkse & Mutter, 1996; Iuga et al., 2016) and higher confidence generally appears to predict lower FS across age groups (Canfield et al., 2016; O'Connor et al., 2021).

1.4.2. Deliberation Time

Given that deliberation time (i.e., reaction speed) is frequently used as a proxy for depth of processing and also tends to increase with age, some researchers posit that slower deliberation time is associated with higher accuracy on deceit detection tasks due to the recruitment of deliberative processing (i.e., System 2 processing; see Iuga, 2016; Sarno et al., 2020). However, other studies have challenged these findings by showing that reliance on *intuitive/heuristic* and *automatic* "gist" reasoning actually leads to lower FS and less risk-taking overall (Wang et al., 2012; White, Wood, Hanoch et al., 2017; Nolte et al., 2022; see also Reyna & Brainerd, 1995) and that a cautious and deliberative approach, for older adults in particular, may come at the cost of classification speed without significantly improving accuracy on fraud detection (Sarno et al., 2020). While it is an important contextual variable, it remains unclear how deliberation time interfaces with age and FS outcomes.

In sum, social abilities are critical to the independent functioning of adults in our society, and deficits in socially-relevant skills may be a central feature of successful exploitation (Wood et al., 2015) along with other factors such as context. As interest in the clinical value of social cognitive abilities grows (e.g., DSM-V diagnostic considerations for MCI; Luck et al., 2017; incorporation of social variables into validated scales of persuasion/scam compliance; Modic & Lea, 2018), examining how ToM in particular relates to FS holds promise in contributing to our understanding of these issues. While there is clear overlap between ToM skills and decision-making correlates, no studies have empirically addressed the potential implications of these declines in healthy older adults, nor have they drawn comparison to younger age groups. ToM may hold greater ecological validity than traditional neurocognitive abilities in predicting practical outcomes (e.g., Bernstein, Thornton, & Sommerville, 2011; Sandoz et al., 2014), and this project aims to provide an introductory examination of links between ToM and FS in adulthood while concurrently examining age, context, and other relevant individual difference factors.

Chapter 2. The Current Study

Using advertisements and offers derived from real-world social contexts, we investigated the associations between age and FS outcomes and determined the extent to which relevant contextual factors and individual differences underlie these relationships across adulthood. We quantify FS behaviour in terms of participants' 1) purchase intention (likelihood of participating in fraudulent offers), 2) deceit detection (ability to discern the credulity of the offer/product), 3) discrimination accuracy (ability to distinguish fraudulent from legitimate stimuli), and 4) response bias (likelihood of responding in an overly cautious or overly liberal style).

This project extends the current body of literature on individual differences in FS by examining context-relevant factors (e.g., on-task confidence, deliberation time) and social cognitive variables (ToM) which have been rarely investigated in conjunction with a comprehensive set of commonly studied variables (e.g., demographics, traditional neurocognitive variables, trust; see Shao et al., 2019). By using an ecologically-valid task, a broad set of predictors, and comparison age groups, we aim to build upon previous empirical work that employed limited measurement methods (e.g., self-report or population-based data; Lichtenberg et al., 2015; Burnes et al., 2017), assessed only older adults (Denburg et al., 2007; Grilli et al., 2021; Han et al., 2016; Koestner et al., 2016; Lamar et al., 2020; Spreng et al., 2017; White, Wood, & Hanoch, 2017) or younger adults (Hakim et al., 2020; Iuga et al., 2016; Jones et al., 2018; Kleitman et al., 2018), used single-modality media (e.g., online phishing: Ebner et al., 2020; Gavett et al., 2017; Lin et al., 2019; Oliveira et al., 2017; Sarno et al., 2020), or analyzed a small set of predictors (e.g., Modic & Lea, 2018; Mueller et al., 2020) or select FS outcomes (e.g., behavioural response to fraudulent stimuli only). Further, the application of signal detection theory (SDT; Green & Swets, 1988) to our experimental task builds upon previous SDT-informed approaches in fraud research (e.g., Canfield et al., 2015, 2016; Grilli et al., 2021, Jones et al., 2019) complementing behavioural outcomes and setting an important benchmark for future investigations. Inclusion of these variables also holds important implications for informing theory in fraud literature and for designing counter-measures to combat fraud in everyday life. Together, our task and design provide a contemporary, theoretically-informed, and multidimensional framework for concurrently studying age differences and candidate predictors in the context of fraud. Please see

Appendix A for additional commentary on background, definitions, and measurement in fraud literature.

2.1. Experimental Task of FS

To address the well-known measurement limitations in fraud literature including use of a single modality and limited ecological validity (see Appendix A.1.2 for more detail) we designed our FS measure, the Everyday Social Decisions task (ESD), to evaluate real-world behaviours and optimize ecological validity. The ESD is a novel laboratory-based measure designed with several decision-making FS outcomes that lend themselves to a variety of analyses and theoretical models. By incorporating designs from neuroanatomical deceit detection research, social decision-making/judgment perspectives, and cognitive aging/individual differences approaches, we attempted to broaden current understanding of the elements of decision-based FS.

We derived both legitimate (i.e., safe, no intent to mislead) and fraudulent (i.e., unsafe, misleading) scenarios from publicly available sources (e.g., mass mailing lists, authentic transcripts of telemarketing scams, YouTube commercials, advertisements on popular social media websites such as Facebook). As illustrated in Figure 2.1, the stimuli were diverse in nature and included content such as banking, media (e.g., Netflix), shopping, and charity donations. We judged stimuli for inclusion according to criteria developed by the Federal Trade Commission (as published in FTC Decisions, 2013) in determining whether each scenario met classification as false/unsafe advertising, in line with current task development conventions in fraud literature (see Wood et al., 2016; Jones et al., 2019). Where possible, scenarios were directly replicated from documented cases (e.g., from sample phishing phone call scripts released by the RCMP and the Government of Canada to raise public awareness). Please see Appendix D for additional details on the development of the ESD including pilot trials and stimuli selection.

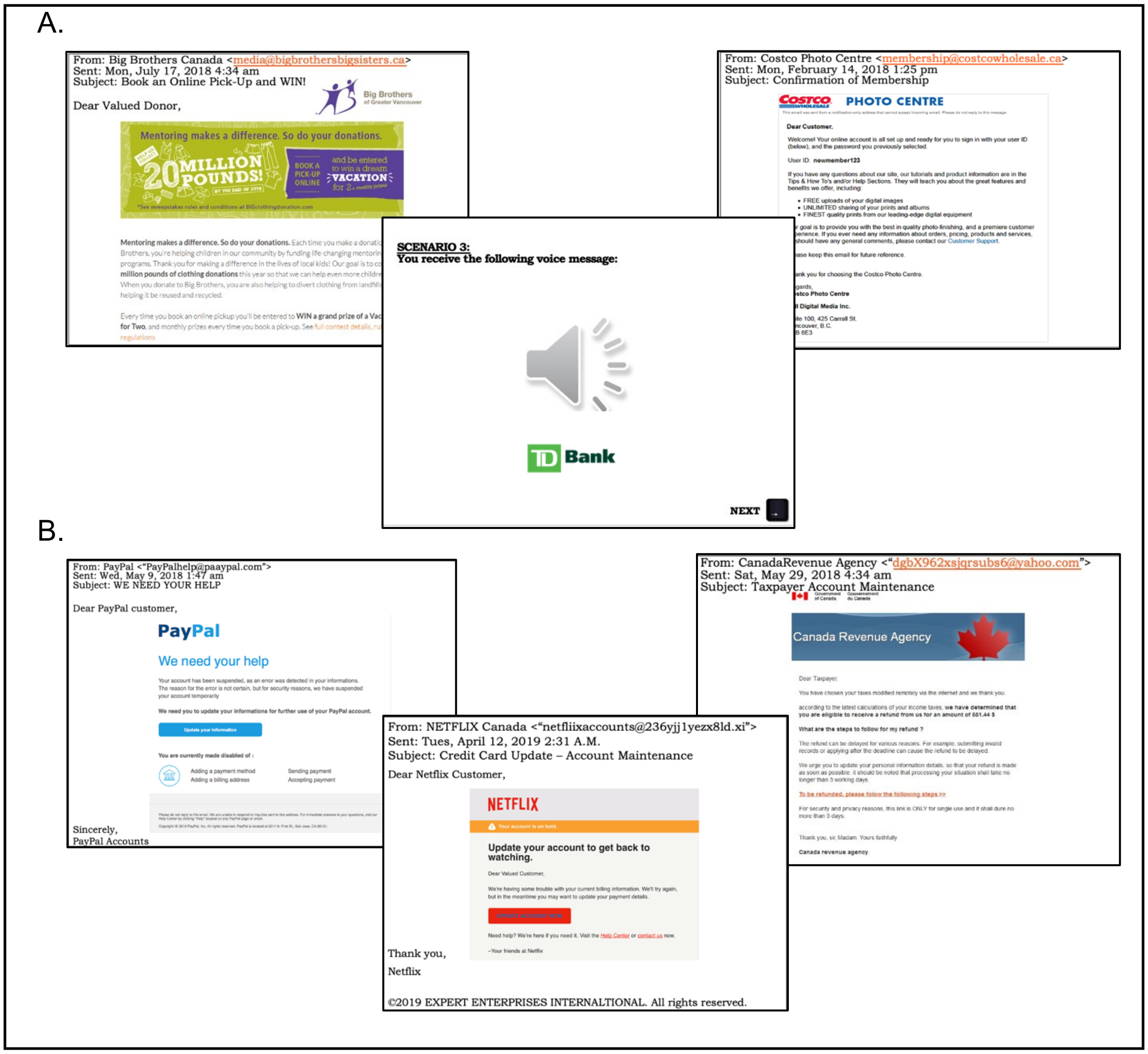

Figure 2.1. Example stimuli: (A) legitimate media; (B) fraudulent media

2.2. Discrimination Paradigm

Adults are regularly required to navigate incoming legitimate and fraudulent propositions and actively determine which to respond to and which to delete/report. While engaging with fraudulent requests has clear consequences, interpreting legitimate requests as fraudulent can also have consequences. For example, deleting legitimate emails (interpreted as fraudulent) about privacy and security of banking information can leave one susceptible to identity fraud and may have serious personal consequences for one's online accounts and credibility. Importantly, by including both legitimate and fraudulent advertisements, we were able to capture a richer estimate of decision-making that includes one's ability to discriminate *between* offer types (i.e., discrimination paradigm; see Asp et al., 2012). Inclusion of legitimate scenarios also allowed us to replicate recent approaches that have used SDT (Green & Swets, 1966) to calculate FS behaviours free of response bias influence (e.g., Jones et al., 2018; Sarno et al., 2020; Grilli et al., 2021; O'Connor et al., 2021). Importantly, SDT has been validated as a viable approach to assess FS (with an equal-variance assumption[1]; see Martin et al., 2018) and yields measures that are superior to more intuitive metrics that confound an individual's bias and accuracy (Martin et al., 2018). By including a diverse set of ad types including television commercials and telemarketing voice messages, we also aimed to extend previous work in the exclusive email phishing modality (e.g., Lin et al., 2019; Ebner et al., 2020; Hakim et al., 2020; Grilli et al., 2021). Please see Chapter 3: Methods for additional details on task development and scales.

2.2.1. Primary outcomes

Several cognitive processes were incorporated into our measurement of FS that reflect dual-system reasoning theories (i.e., System 1/System 2 processing; Stanovich, 1999) mapping onto decision-making under uncertainty and further supported by neuroanatomical correlates (Denburg, 2007; Asp et al., 2012). Please see Chapter 3 and Appendix D, 1.10.3 – 1.10.4 for additional details on scoring.

Purchase Intention. We measured purchase intention (or *salience/motivation*) as a consumer behaviour variable to capture the "buy-in," or likelihood that an individual will purchase or participate in an offer. Purchase intention was measured by asking participants to supply intention judgments on a variety of advertisements and messages/offers that they viewed; how likely were they to purchase the product or participate in the offer? Were they interested in or motivated by the messages? For each advertisement or message/offer, participants were asked "Assuming you are _____ (e.g., context specific to item, such as *a Netflix subscriber),* how likely are you to ____ (e.g., context specific to item, such as *click the link to update your account information*; *purchase the product*; *return the call to update your banking credentials*)" and responded

[1] According to a validation study by Martin, Dube, and Coovert (2018), FS primarily reflects temporally stable discriminative characteristics of observers. Therefore, equal-variance signal detection theory (EVSDT)-based metrics are appropriate for both modelling and measuring FS without the need for parameter estimation or model comparison using unequal-variance SDT (UVSDT).

on a Likert scale ranging from 1 (*Not at all Likely*) to 7 (*Very Likely*; possible score range = 5-35 for legitimate and fraudulent offers respectively). The purchase intention variable is a behavioural outcome that captures affective framing prior to specific queries about the legitimacy of the offer/item (Kircanski et al., 2018) and reflects associated vmPFC activation during decision-making. For example, high purchase intentions for misleading products are related to faulty decision-making and reduced ability to detect fraud (Denburg et al., 2007). Further, an individual's purchase intention for misleading products has been shown to be influenced by affective factors (e.g., framing with positive or negative affect; Kircanski et al., 2018), and is related to increased brain activity in the vmPFC during fraud-related decision-making (i.e., ToM-overlapping circuits; Asp et al., 2012; Koestner, Hedgcock, Halfmann, & Denburg, 2016).

Deceit Detection & Discrimination. We measured deceit detection (or *credulity/suspiciousness*), which describes a person's ability to accurately discern the deceptive nature of an advertisement. We explicitly asked participants to supply legitimacy judgments on whether they believed the stimuli to be misleading. For each advertisement or message/offer, participants were asked "Based on your evaluation, how likely is the _____ 's (e.g., context specific to item, such as *caller; sender of email; company selling the product)* intent to mislead you?" and responded on a Likert scale ranging from 1 (*Not at all Likely*) to 7 (*Very Likely*; possible score range = 5-35 for legitimate and fraudulent offers respectively). Deceit detection has been utilized across a number of studies to investigate judgment and decision-making within deceptive-advertising paradigms in both younger and older adults. Applying SDT to deceit detection scores, we derived a metric of discrimination accuracy (or *sensitivity;* ability to differentiate between legitimate and fraudulent stimuli). For the purposes of this project, discrimination analyses are defined by how well one can detect the *presence* of a fraudulent offer (i.e., the signal) and *absence* of a fraudulent offer. Performance can be categorized into four response types: (1) hits (correctly classifying fraudulent offers as unsafe); (2) correct rejections (correctly classifying legitimate offers as safe); (3) misses (incorrectly classifying fraudulent offers as safe, i.e., missing the signal when it was present), and (4) false alarms (incorrectly classifying the legitimate offer as unsafe, i.e., detecting the signal when it was not present).

Response Bias. In line with recent SDT-based approaches, we derived a complementary and non-redundant response bias outcome (a tendency to perceive all stimuli as safe or unsafe) based on hit rate and false alarm rate (Green & Swets, 1988). Standardized false alarm rate was calculated by dividing the number of false alarms by the total number of legitimate stimuli, and standardized hit rate was calculated by dividing the number of hits by the total number of fraudulent stimuli. Recent investigations have identified the importance of quantifying response bias in FS modelling, though findings are mixed regarding the hypothesis that age leads to a more cautious approach (O'Connor et al., 2021; Sarno et al., 2020) in identifying and classifying fraudulent information. For the purposes of this project, response bias (ß) values further from zero indicate greater bias in one's responding (0-1: liberal responders; >1: conservative responders; Green & Swets, 1988). Given recent assertion that the liberal and conservative bounds of other response bias metrics are more balanced than ß (Sarno et al., 2022), we supplemented our calculations with Response criterion (c) scores (<0: liberal responders; >0: conservative responders, 0: unbiased. See Appendix D for calculations).

2.2.2. Decision-making Factors

We also included a number of other complementary key dimensions of decision-making that have been understudied in FS models to date: deliberation time and decision confidence (a subjective, retrospective rating). They are two of the most often-used performance measures in cognitive and decision sciences (Pleskac & Busemeyer, 2010; Tversky & Kahneman, 1974) and have been used in recent FS work (Yu, Boyle, Mottolla, 2020; O'Connor et al., 2021).

2.3. Project Scope

For the purposes of the present project and to inform future theoretical models, we aimed to explore the impact of previously neglected variables within-subjects on a social decision-making FS task. Broadly, our project was guided by the overarching goal of determining whether older age truly represents a unique period of increased vulnerability relative to other variables in the fraud context. Adopting a person-centered approach (see Lichtenberg, 2016) and employing our newly developed ESD task, the present project represents an important extension of previous work in fraud research. We aimed to address previous measurement limitations by using an ecologically valid paradigm with outcomes that lend themselves to SDT-based analytic approaches, thus offering a richer picture of decision-making performance. Using contemporary cognitive/affective ToM distinctions, we also aimed to delineate the effects of various social cognitive contributors to inform more accurate susceptibility risk profiles and future interventions. Finally, we aimed to extend previous work on individual differences in FS by modelling a diverse set of theorized predictors across young and older adult age groups, while controlling for a comprehensive set of relevant variables and demographic covariates previously linked with FS (Figure 2.1). Given the limited knowledge on factors contributing to fraud risk, especially amongst younger adults, the present study integrated several theories (frontal lobe theory on aging; West, 1996; compensatory theories; Samanez-Larkin & Knutson, 2015; Park & Reuter-Lorenz, 2009; individual differences; Wood et al., 2015; Ebner et al., 2020; dual-processing; Stanovich, 1999) in a conceptual framework to guide our hypotheses. Figure 2.2. illustrates the conceptual model developed for the present study, including the ESD design and primary variables of interest.

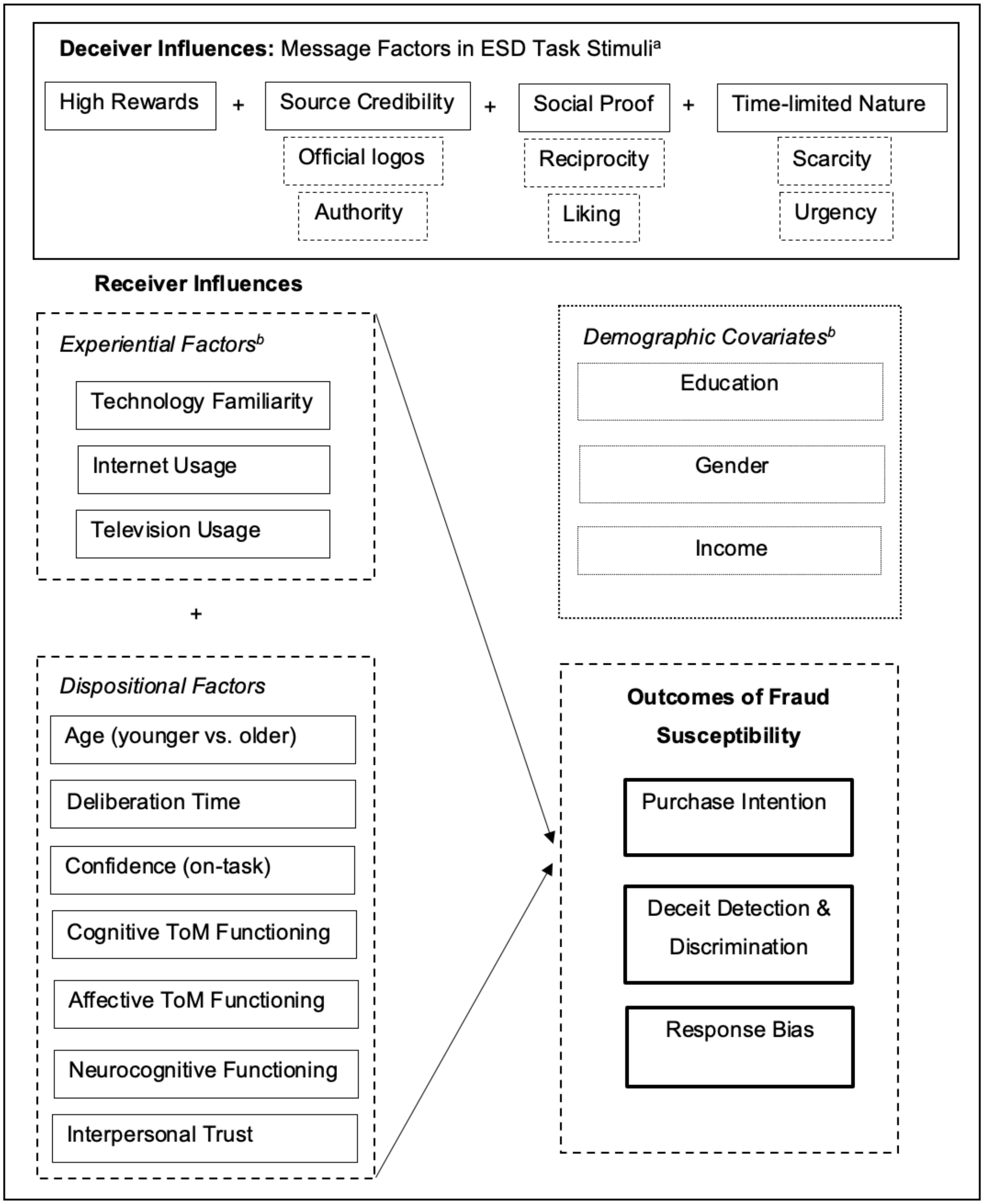

Figure 2.2. Conceptual model of FS developed for the current study

[a] The presented message factors are considered *motivation triggers* which were fixed and not manipulated in present study; variables are potential targets for future research.

[b] With an aim to optimize modelling, only experiential factors and demographic covariates correlated with FS outcomes at *r* >.30 were included in final models due to limited theoretical foundations and empirical support for their inclusion.

2.3.1. Study Objectives and Hypotheses

Please refer to Table 2.1 for summary of hypotheses and their associated statistical tests described below.

Objective 1: FS Response Patterns. We first conducted an analysis of FS response patterns within age groups on the novel ESD task using bivariate correlations. Guided by research on FS task characteristics (e.g., O'Connor et al., 2021; Sarno et al., 2020) and relationships between decision-making components (Asp et al., 2012; Lighthall, 2020), we hypothesized that **(1.a)** higher purchase intention for a given fraudulent offer/product would be associated with poorer deceit detection, and that **(1.b)** higher confidence would relate to lower purchase intention and stronger deceit detection. Based on System 1/System 2 distinctions (Stanovich, 1999), we also hypothesized that **(1.c)** longer deliberation time would be associated with stronger deceit detection (i.e., longer deliberation time is associated with more deliberative and thus accurate processing), and quicker deliberation time would be associated with higher purchase intention for fraudulent items.

Objective 2: Age Differences in FS. We then evaluated age effects using between-subjects ANOVAs to determine group differences in FS parameters, verified for robustness using SDT-derived metrics. We hypothesized that **(2.a)** more accurate deceit detection and stronger discrimination would favor younger adults, given population-based evidence suggesting that older adults are overrepresented in fraud cases and specific findings demonstrating poorer decision-making with age, especially in ambiguous or "risky" situations (Denburg et al., 2007; Rogalsky et al., 2012; Bauer et al., 2013; Yeh, 2013; Rolison et al., 2017).

However as discussed, competing models (frontal lobe theory; Craik, 1986; West, 1996; Salthouse, 2011 vs. socioemotional theory; Carstensen, 1999; STAC; Park & Reuter-Lorenz, 2009; AIM; Samanez-Larkin et al., 2015) and more recent empirical work posit that older adults may exhibit equivalent or better decision-making due to compensatory mechanisms including life experience (Yu, Mottolla, et al., 2022), stronger emotional regulation (Ebner et al., 2020), and relatively spared emotional processing (Mueller et al., 2020). Further, there is evidence to suggest that age group performance will be related to individual differences in ToM and processing of behaviourally-based vs.

information-based details (see Objective 3). Given these mixed age effects in similar novel lab-based judgment tasks (see Ebner et al., 2020; Gamble et al., 2014), we hypothesized **(2.b)** older adults would exhibit lower purchase intentions (e.g., involving intuitive, affective-based reasoning) for fraudulent offers.

With respect to response bias, guided by previous findings (Grilli et al., 2020; Sarno et al., 2020; O'Connor et al., 2021) we expected **(2.c)** younger adults' classifications of offers to be less biased (i.e., their categorizations more evenly distributed across offer types) compared to older adults. We specifically hypothesized that **(2.c.i)** when older age is associated with poorer deceit detection, there would be an age-related response bias toward judging all stimuli as legitimate/safe. Conversely, **(2.c.ii)** when age is associated with better deceit detection, there would be a potential age-related response bias toward judging all stimuli as fraudulent/unsafe.

Objective 3: Predictors and Modifiers of FS. Another study aim was to employ an array of social cognitive tasks that overlap with decision-making and may have better utility in predicting everyday outcomes than age and traditional cognitive measures. As supported by current theoretical conjecture, both ToM domains could plausibly aid in fraud detection; A-ToM skills could enable individuals to perceive and decode emotional states (e.g., guilt) involved in deceptive messaging, and C-ToM could support individuals in reasoning about the deceptors' true intentions and underlying mental states. Reduced ToM in both domains may impair an individual's capacity to accurately predict behaviours and make sound judgments, thus increasing their risk of making poor decisions and heightening susceptibility to fraud and other vulnerabilities in the social world.

We hypothesized the possibility of a ToM double dissociation with respect to FS outcomes - such that A-ToM was expected to predict affective-based purchase intentions, while C-ToM was expected to predict deliberative-based discrimination - beyond the effects of context (confidence, deliberation time), other relevant individual differences (neurocognition, trust) and demographic covariates.

Purchase Intention (Model A). Given the affective-based task demands of consumer decision-making that elicit System 1 processing (see Asp et al., 2012), we predicted that **(3.a)** stronger A-ToM performance (which is somewhat resilient to age-related decline; Wood et al., 2015) would emerge as a predictor of purchase intention, beyond the effects of age and neurocognition. We also hypothesized that **(3.b)** while age would be less relevant to purchase intentions, stronger neurocognitive functioning (executive functions, semantic memory, numeracy, processing speed) would predict lower purchase intentions for fraudulent items, given evidence that decisions facilitated by System 1 processing demonstrate inverse (or sometimes nonexistent) associations with cognitive ability (Markovits, Doyon, & Simoneau, 2002; Stanovich & West, 1997; Stanovich, 2011). Finally, we predicted that **(3.c)** other contextual and social variables (specifically higher confidence, longer deliberation time, and lower trust) would also be associated with more optimal (i.e., lower) purchase intentions for fraudulent items, with **(3.d)** no age interactions across groups.

Discrimination (Model B). For the detection-based discrimination outcome which encourages participants to evoke deliberate reasoning, we anticipated that **(3.e)** stronger C-ToM performance (which has been robustly linked to cognition; Walzak & Thornton, 2018) would predict an individual's ability to correctly discern legitimate vs. fraudulent stimuli above and beyond age and neurocognition. Given that deceit detection is a discrete component of the larger mentalizing system (Spreng et al., 2017), there is also evidence that differentiating between stimuli requires the integration of context and other individual differences (e.g., neurocognition, trust; Grilli et al., 2021; Shao et al., 2019). As such, we expected that **(3.f)** higher interpersonal trust would be associated with weaker discrimination across age groups, with **(3.g)** age moderating significant associations between discrimination and C-ToM and neurocognition (i.e., a stronger effect of these variables in the younger adult group), and confidence (i.e., a stronger effect of confidence in the older adult group). This is supported by evidence that cognitive ability is strongly correlated with System 2 processing (Evans & Stanovich, 2013) and individuals with higher cognitive ability tend to demonstrate fewer belief biases (Stanovich, 2011). Higher confidence has also been shown to facilitate more accurate discrimination in some studies (O'Connor et al., 2022), particularly when task demands exceed individual processing ability (e.g., on deliberative reasoning tasks or with advancing age; see Gamble, Boyle, and Yu, 2015).

Response Bias (Model C). Informed by recent empirical work (Grilli et al., 2021, O'Connor et al., 2021), we hypothesized that **(3.h)** reduced confidence, poorer C-ToM and A-ToM, and lower trust would emerge as unique predictors of inflated response bias (i.e., a tendency to classify all stimuli as unsafe/fraudulent), **(3.i)** specifically in the older adult group, with no associations in younger adults. Response bias appears less relevant in younger adulthood, while older adults have shown a propensity to employing a “high suspicion” strategy (O’Connor et al., 2021) and age is associated with an increased tendency to judge stimuli as unsafe (Butavicius, Taib, & Han, 2022; Grilli et al., 2021, Sarno et al., 2020).

Table 2.1 Summary of hypotheses

Hypothesis	Variable(s) of interest	Statistical Test / Coefficients	Rationale
Objective 1: ESD Task (Whole Sample)		**Bivariate correlations / Pearson & Point-biserial coefficients**	
1.a) ↑ purchase intention correlated with ↓ deceit detection	Purchase Intention; Deceit Detection		Preference for a specific offer or product elicits System 1 processing and strongly influences consumer decision-making (Asp et al., 2012; Denburg et al., 2017).
1.b) ↑ confidence correlated with ↓ purchase intention & ↑ deceit detection	On-task Confidence		Higher confidence is associated with better deliberative decision-making (Iuga et al., 2016) and higher detection accuracy on phishing tasks (Wang, Li, & Rao, 2016; Canfield et al., 2016; Kleitman et al., 2018)
1.c) ↑ deliberation time correlated with ↓ purchase intention & ↑ deceit detection	Deliberation Time		Longer deliberation time is a proxy for System 2 reasoning (Stanovich, 1999) which is associated with better FS-based decision-making (Iuga, 2016; Sarno et al., 2020)
Objective 2: Age Differences		**One-way between-subjects ANOVAs / F**	
2.a) ↑ deceit detection & ↑ discrimination favouring younger adults	Age Group; Deceit Detection; Discrimination		Evidence from population-based studies (Lichtenberg et al., 2016; Han et al., 2017) and empirical work suggest that older adults are overrepresented in fraud cases and demonstrate poorer decision-making with age, especially in ambiguous or “risky” situations (Denburg et al., 2007; Rogalsky et al., 2012; Bauer et al., 2013; Yeh, 2013; Rolison et al., 2017).
2.b) ↓ purchase intention favouring older adults	Age Group; Purchase Intention		Older adults exhibit equivalent (or better) decision-making on similar lab-based judgment tasks that involve intuitive, affective-based reasoning (e.g., Ebner et al., 2020; Gramble et al., 2014)

			as age may be a proxy for compensatory mechanisms including life experience (Yu, Mottolla, et al., 2022), stronger emotional regulation (Ebner et al., 2020), and relatively spared emotional processing (Mueller et al., 2020).
2.c) response bias associated with older adults *i) if older age associated with ↓ deceit detection, ↑ response bias (i.e., bias toward judging all stimuli as legitimate/safe)* *ii) if older age associated with ↑ deceit detection, ↓ response bias (i.e., bias toward judging all stimuli as fraudulent/unsafe)*	Age Group; Response Bias		Relative to younger age groups, older age is associated with inflated response bias on similar lab-based judgment tasks (e.g., “high suspicion strategy”; Grilli et al., 2020; Sarno et al., 2020; O’Connor et al., 2021)
Objective 3: Predictors & Modifiers		**Hierarchical multiple linear regressions / β & R^2**	
Model A	Outcome: Purchase Intention		
3.a) A-ToM is a predictor beyond effects of age and neurocognition			
3.b) Age not relevant, neurocognition not relevant or inversely associated			
3.c) Other predictors: ↑ confidence & deliberation, ↓ trust = ↓ purchase intention			

3.d) No age interactions		Given the affective-based task demands (i.e., eliciting System 1 processing; Asp et al., 2012), theoretical conjecture suggests that age and traditional neurocognitive skills are less relevant to purchase intentions (Markovits, Doyon, & Simoneau, 2002; Stanovich & West, 1997; Stanovich, 2011). There is also evidence that regardless of age, contextual and social factors including confidence, deliberation time, and trust are relevant to affective-based decisions (Canfield et al., 2016; Kleitman et al., 2018; O'Connor et al., 2021; Iuga, 2016; Sarno et al., 2020). The role of A-ToM is yet to be explored in this context, though is relevant to System 1 processing (Shamay-Tsoory et al, 2006; Lieberman, 2007) and is hypothesized to predict outcome.
Model B	Outcome: Discrimination	
3.e) C-ToM is a predictor beyond effects of age and neurocognition		
3.f) ↑trust = ↓discrimination		

3.g) Younger adults: ↑ deliberation time, ↑ C-ToM & ↑ neurocognition = ↑ discrimination Older adults: ↑confidence = ↑ discrimination			Given the deliberative reasoning-based elements of discrimination (i.e., eliciting System 2 processing) and that deceit detection is a component of the mentalizing system (Spreng et al., 2017), there is evidence that individual differences in neurocognition and trust are relevant (Grilli et al., 2021, Shao et al., 2019). The role of C-ToM is yet to be explored in this context, though it is relevant to System 2 processing (Lieberman, 2007) and robustly linked to traditional neurocognition (Walzak & Thornton, 2018) and is hypothesized to predict outcome. Age interactions are hypothesized for C-ToM, neurocognition, and confidence, given that deliberative decisions show more age affects than those that are experiential (Huang et al., 2015), and these skills are particularly sensitive to aging. Higher confidence has also been shown to facilitate more accurate discrimination (O'Connor et al., 2022), particularly when task demands exceed individual processing ability (e.g., on deliberative reasoning tasks or with advancing age; see Gamble, Boyle, and Yu, 2015). Further, deliberation time may be less relevant for older adults, as some evidence suggests that they sacrifice speed without significantly improving accuracy on similar fraud detection tasks (Sarno et al., 2020).
Model C	Outcome: Response Bias		

3.h & i) Older adults: ↓C-ToM, A-ToM, confidence, & trust = ↑ response bias (i.e., lower score; more cautious approach)		Response bias appears less relevant in younger adulthood, while older adults have shown a propensity to employing a "high suspicion" strategy (O'Connor et al., 2021) and age is associated with an increased tendency to judge stimuli as unsafe (Butavicius, Taib, & Han, 2022; Grilli et al., 2020, Sarno et al., 2020).

Chapter 3. Methods

3.1. Participants

3.1.1. Recruitment

We recruited two independent samples (N = 125) of healthy, community-dwelling adults living in the Lower Mainland, BC, Canada: 78 young (range = 17-35, M_{age} = 20.34, SD = 3.51) and 47 older adults (range = 59-96, M_{age} = 74.33, SD = 8.83). Please see Figure 1 for details on the recruitment process, including participants who completed the initial pre-screening process but were excluded at intake due to not meeting inclusion/exclusion criteria described below, and those who dropped out prior to testing. While older adults were sampled from the full range of later life (i.e., normal distribution from age 59-96), the younger adult sample's chronological age distribution was highly positively skewed ($Median_{\text{age}}$ = 19.00, IQR = 3). Figures 3.1 and 3.2 depict the age distribution in our sample stratified by age group. The young adult sample comprised undergraduate students enrolled at Simon Fraser University (SFU) who were primarily recruited through the university-based research participation system and via community events such as the SFU Undergraduate Psychology Research Fair. Older participants were community residing and recruited using advertisements placed in local newspapers, free online volunteer postings (Craigslist, Facebook), and flyers posted at various community locations such as libraries and recreation centres. The Cognitive Aging Lab also hosted seminars on aging and cognition at local venues for additional recruitment purposes. Participants completed a 3-hour test battery individually administered by a trained graduate student and were compensated with $20 cash honorarium or equivalent course credit for participation.

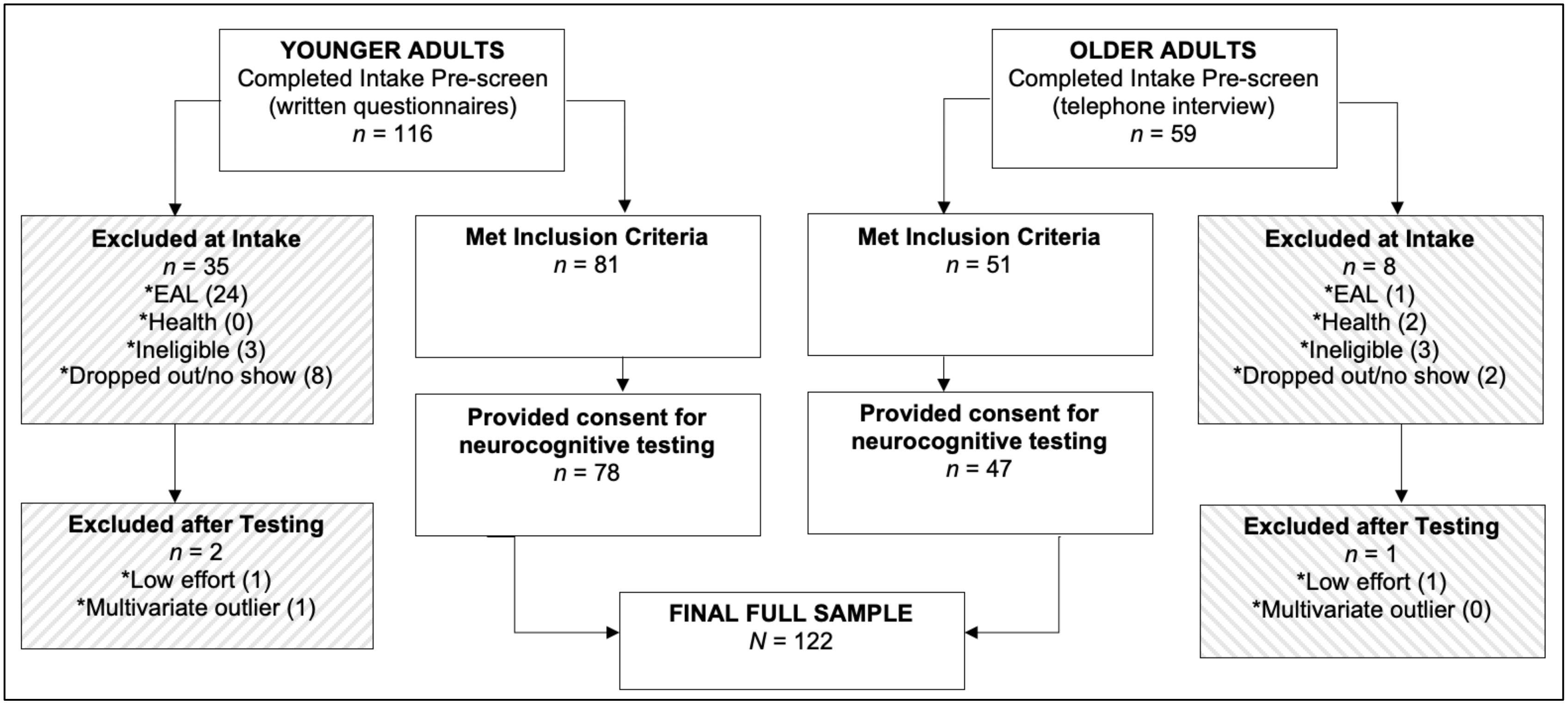

Figure 3.1 Recruitment flow chart

Note: EAL = participants who indicated on an acculturation questionnaire less than 3 out of 4 preferences as "English" for speaking, reading, writing, and thinking; Health = sensory impairment, diagnosed cognitive impairment, color-blindness, diagnosis of major psychotic illness, concurrent disorder affecting the CNS, neurodegenerative disease, and history of major stroke or head injury with >15 minutes LOC; Ineligible = participants who did not meet study criteria for other inclusion/exclusion reasons (e.g., falling outside age ranges of 17-35 and 60+ at month of testing); Dropped out/no show = participants who signed up for the study and completed intake but did not show up for testing appointment.

3.1.2. Inclusion & Exclusion Criteria

All participants met the following inclusion criteria: (a) ability to independently provide informed consent, (b) English fluency (as determined by an acculturation measure developed within our lab that examines language preferences; Thornton et al., 2007), (c) a minimum Grade 6 education to ensure that reading level was adequate for questionnaire completion, and (d) no impairments in vision, hearing, or other sensory/motor functions that could interfere with testing. To ensure adequate vision for task completion, participants were screened for visual acuity with a set lower limit of 20/50 in both eyes (corrected; Yeung et al., 2015).

In addition, exclusion criteria included: a) a self-reported history of dementia or MCI diagnosed by a physician, (b) color-blindness (for Stroop test), (c) diagnosis of a major psychotic illness (e.g., schizophrenia), (d) any concurrent major illness with known central nervous system effects (e.g., brain cancer, organ failure), (e) major neurological illness (e.g., Parkinson's disease, Huntington's disease, Multiple Sclerosis), (f) history of major stroke, and (g) history of major head injury (defined by a loss of consciousness > 15 minutes; i.e., moderate TBI). The SFU Research Ethics Board approved all study protocol (Ethics Certificate # 20200023).

Global cognitive status was screened in all participants in the older adult sample using the Mini Mental Status Examination (MMSE; Folstein, Folstein, & McHugh, 1975). All participants scoring < 26/30 were excluded from analyses, based on conservative cut-offs recommended by current assessment standards to control for probability of undiagnosed cognitive impairment and dementia screening (Bour et al., 2010; Erdodi et al., 2020).

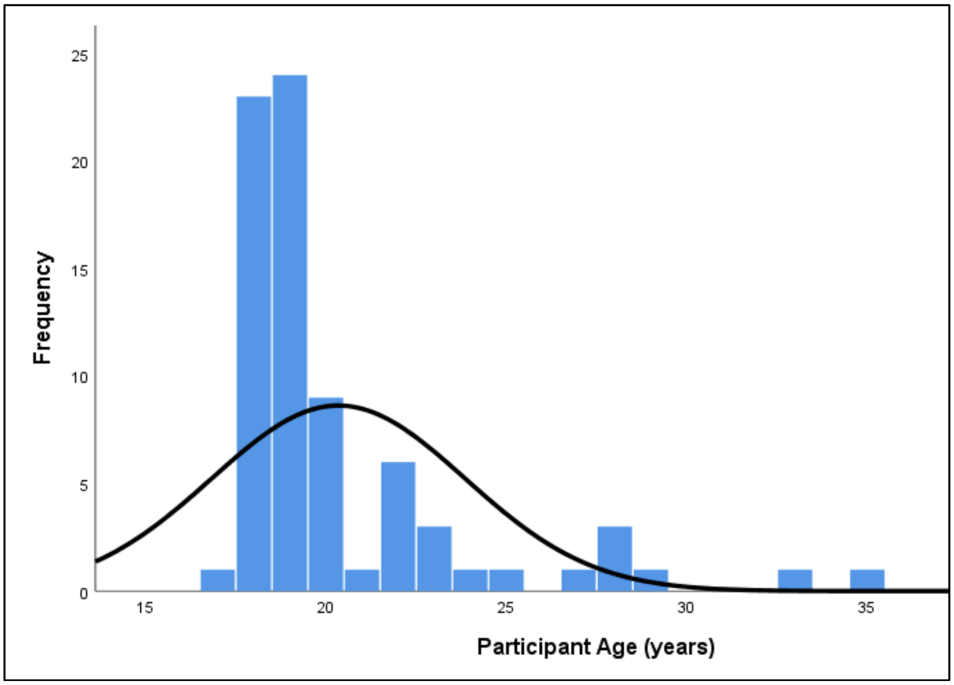

Figure 3.2. **Chronological age distribution for the younger adult sample (*n* = 76)**

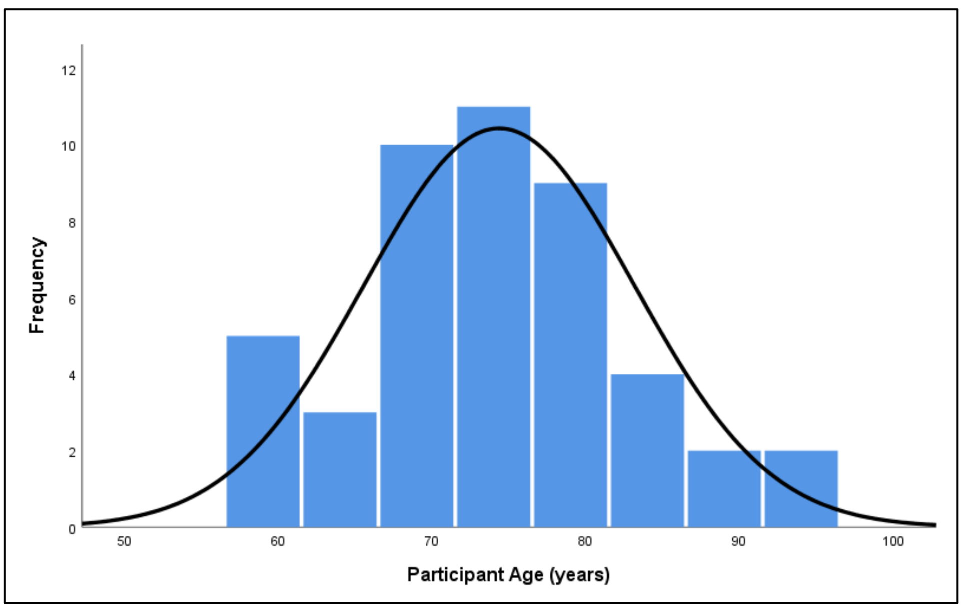

Figure 3.3. **Chronological age distribution for the older adult sample (*n* = 46)**

3.2. Assessment Procedure

After obtaining informed consent, we tested all participants individually on a 3-hour battery that assessed standard neurocognitive functions, ToM, and FS. A trained graduate student conducted all testing under the supervision of Dr. Wendy Loken Thornton. Testing was conducted in quiet rooms at the SFU Burnaby or SFU Surrey campuses or a rented community location (e.g., Ocean Park Library) depending on participants' travel preferences. Prior to the testing session, participants completed questionnaires assessing background demographics, medical history, technology familiarity and usage, self-ratings of current depressive and anxiety symptoms, social functioning, and interpersonal trust. We standardized the administration order of our test battery given that blood pressure readings were also collected for concurrent projects; at the start of each session, we measured participants' resting blood pressure prior to any neurocognitive testing. We then administered the performance measures.

Importantly, participants were not informed about the nature of the project and specific study goals (i.e., the focus on fraud) prior to participation. Rather, they were told that they would be completing a variety of questionnaires on health and wellbeing as well as some laboratory-based neuropsychological and decision-making tasks. Participants were fully informed about the specific study goals during the debriefing session following participation and were given the option to rescind their data if they desired. Participants were also educated about the prevalence of fraudulent exploitation and examples of common fraud crimes in Canada. Finally, they were given a take-home educational resource developed by the Government of Canada and the Canadian Anti-Fraud Centre (*The Little Black of Scams, 2nd Edition – 2018)* to increase preventative awareness.

3.3. Materials

3.3.1. Questionnaire Protocol

We administered a self-report questionnaire addressing participant demographics (age, sex, gender, ethnicity, education, income, employment status), lifestyle behaviours (e.g., technology familiarity, estimated weekly television and Internet exposure, alcohol/tobacco use), and history of medical illness and treatment. This measure was developed in our lab and is used routinely to screen exclusionary criteria and identify medical diagnoses (Yeung & Thornton, 2017). We were specifically interested in obtaining information about current diagnoses of neurological conditions known to affect the central nervous system and history of significant stroke or head injury with loss of consciousness (as per exclusion criteria above). Further, given the rising prevalence of comorbid chronic illnesses among older adults, responses from this measure aided in characterizing our sample and estimating generalizability to the general population (see Appendix F, Table F.1).

3.3.2. Neurocognitive Protocol

Participants completed a series of neurocognitive tests to collect information about neurocognitive functioning across a number of key domains: executive functions, working memory and auditory attention (Delis-Kaplan Executive Function System [D-KEFS] Color-Word Interference subtest, Wechsler Adult Intelligence Scale – Third Edition [WAIS-III] Letter-Number Sequencing subtest, Backwards Digit Span subtest), numeracy (WAIS-III Arithmetic subtest – untimed), processing speed (WAIS-III Coding subtest), and semantic memory (Kaufman Brief Intelligence Test – Second Edition [KBIT-2] Verbal Knowledge subtest). Please see Appendix D for additional information regarding administration and scoring for these tests.

3.3.3. Social Cognitive Protocol

Adopting a multi-dimensional approach which has been employed in other studies (e.g., see Fischer et al., 2017), we included separate measures to assess both C-ToM and A-ToM. All participants completed the Strange Stories test (C-ToM; Happé, 1994; Happé et al., 1998) and the Reading the Mind in the Eyes test – Revised Version (A-ToM; Baron-Cohen et al., 2001). A subset of participants (N = 94) also completed the Edinburgh Social Cognition Test (ESCoT; Baksh et al., 2018), a contemporary ToM measure combining both cognitive and affective components which was published during the initial data collection phase and subsequently incorporated into the battery. Importantly, unlike legacy ToM measures which tend to be confounded by neurocognitive skills (e.g., processing speed, executive functioning; Happe et al., 1995; Rakoczy et al., 2012), the ESCoT appears to measure domain-specific aspects of social cognition (i.e., cognitive and affective ToM) with minimal overlap (Baksh et al., 2018).

Please see Appendix D for additional information on the nature and psychometric properties of these measures.

To assess levels of self-reported trust amongst our samples, we used the Trust Scale developed by the World Values Survey (Inglehart et al., 2012). This measure is a 7-item questionnaire used to assess general trust outlook as well as subjective trustworthiness in everyday settings. Participants were asked *“Do you believe that others are generally trustworthy?”* and then asked to rate their level of trust with various groups (e.g,, family, people you meet for the first time; 1 – *trust completely* to 4 – *do not trust at all*). Scores were reverse-coded for ease of interpretation and alignment with other measures, with higher scores indicating higher trust. The Trust Scale has been used widely in large, population-based research conducted by the World Values Survey and is considered a robust measure of subjective interpersonal trust (Fleisher, 2017).

3.3.4. Everyday Social Decisions (ESD) Task

We used the computer-based ESD task developed in our lab to assess behavioural domains of FS elicited during the decision-making process. The task is self-paced, but participants were instructed to briefly consider and respond as quickly as possible in Part A (Purchase Intention; Figure 3.4) to elicit System 1 processing by capturing initial judgments and discouraging contemplation. First, participants were asked to make intention judgments about whether they would participate in each of the 10 scenarios, indicating their decision on a 7-point Likert scale where *1 = not at all likely to participate* and *7 = very likely to participate*. Responses were summed separately for legitimate and fraudulent subscales to determine likelihood of participation in the respective offers. Deliberation time was recorded in seconds.

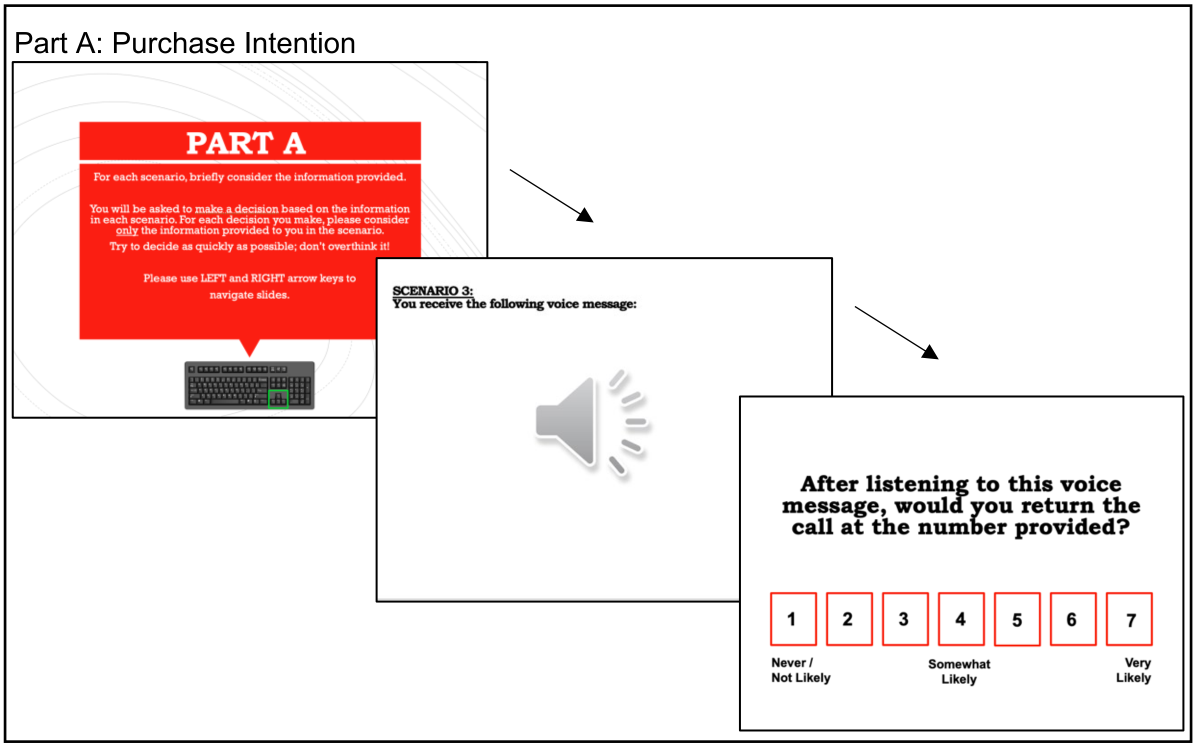

Figure 3.4. **Example trial sequence with mouse click or arrow keys (*Purchase Intention*)**

Part B (Deceit Detection; Figure 3.5) assessed participants' ability to detect fraudulent advertising. Participants were asked to *carefully review* the original 10 scenarios in the same order of presentation as in Part A. After each scenario, participants were prompted to respond to two questions rating their perception about the author's intent on a 7-point Likert scale. The first question asked, "*Based on your evaluation, how likely is the [author's/caller's/company's] intent to mislead?*", with legitimacy rating responses falling on a 7-point Likert scale where *1 = not at all likely* and *7 = very likely*. Deliberation time was recorded in seconds. A follow-up question asked, "*How confident are you in your judgment about this [author's/caller's/company's] intent?*", where *1 = not at all confident* and *7 = very confident*. Confidence rating scores were simply summed for the legitimate and fraudulent subscales, with higher scores indicating stronger decision confidence.

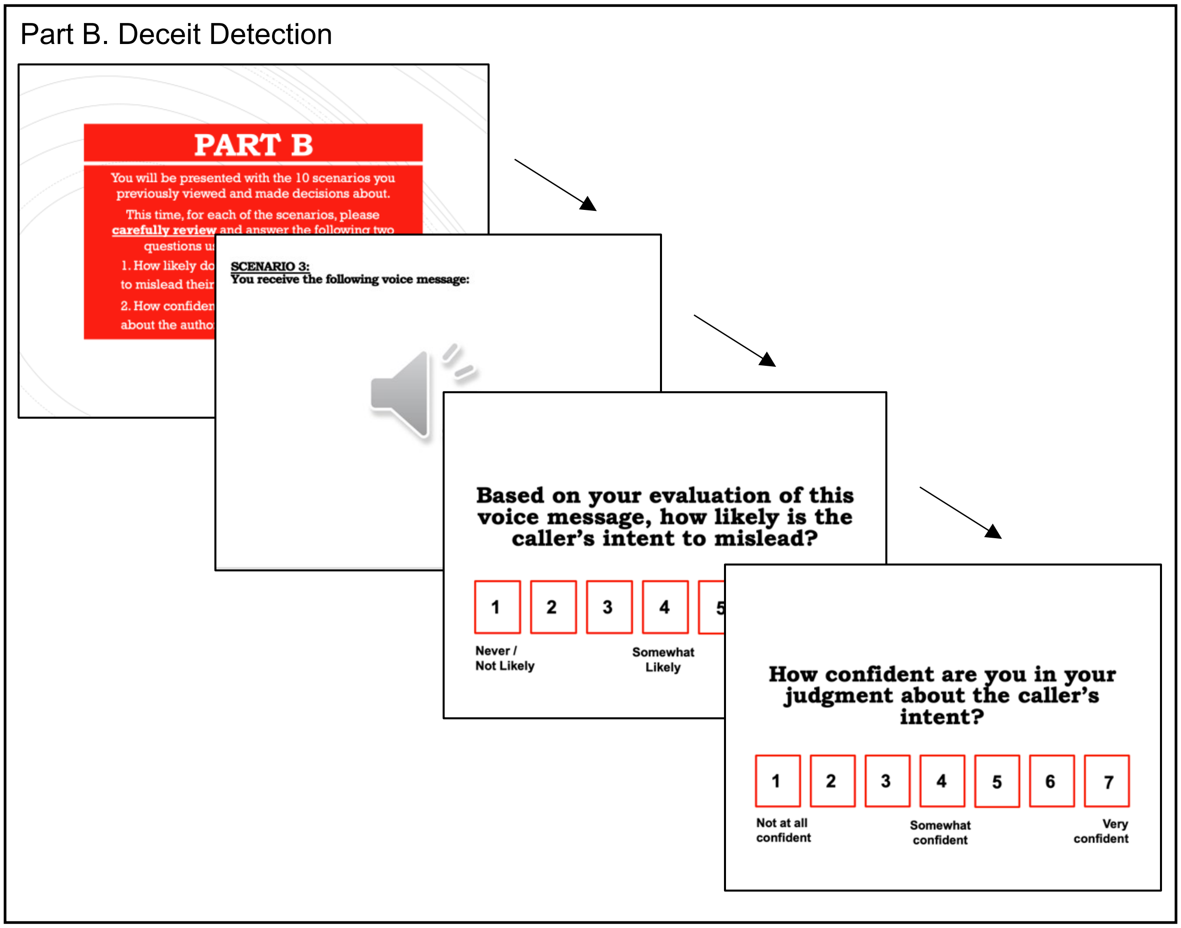

Figure 3.5. **Example trial sequence with mouse click (*Deceit Detection*)**

Using scale-based responses, area under the curve (AUC) values were calculated using a receiver operating characteristic (ROC) curve to identify any participants ineffectively using or misusing the scale (as per methodology in Jones et al., 2018). Purchase intention and deceit detection scores were then derived from the scale-based responses for the fraudulent items (i.e., raw sum of one's hits and misses). Note that while <u>lower</u> purchase intention scores suggest <u>optimal</u> performance (i.e., reduced likelihood of purchasing a fraudulent product), <u>higher</u> deceit detection scores indicate <u>stronger</u> ability (i.e., better accuracy in identifying fraudulent offers). Scale-based responses were also dichotomized (1-3: incorrect/0, 4-7: correct/1; inverse for legitimate stimuli) to derive an overall accuracy score, with higher scores indicating greater accuracy. Discrimination scores (*d'*) were derived from subtracting one's standardized false alarm rate from their standardized hit rate[2], with higher scores indicating greater

[2] Standardized false alarm rate = number of false alarms divided by the total number of legitimate stimuli; standardized hit rate = number of hits divided by the total number of fraudulent stimuli

accuracy in discriminating between legitimate and fraudulent stimuli. A measure of response bias (ß) was also calculated, with values farther from 1 indicating greater bias in one's responding; values < 1 indicate a bias toward rating all stimuli as unsafe/fraudulent, and values > 1 indicate a bias toward rating all stimuli as safe/legitimate. The formulas for these measures are outlined in Stanislaw & Todorov (1999), and we used an adjustment for extreme hit rate/false alarm rate values as outlined in Macmillan & Kaplan (1985). See Appendix D for additional details about the ESD subscales, SDT, and supplementary Criterion C response bias metric.

3.4. Summary

Table 3.1. Summary of study measures by conceptual domain

Domain/subdomain	Measure(s)	Acronym	Study Variable
Demographics			
Age	Age Group (*younger: age 17-35 / older: age 60+)*	-	Age Group
Neurocognitive Function			
Response inhibition	DKEFS Color-Word Trial 3 Score	*DKEFS CW*	Global Cognition
Working memory	WAIS-III Letter Number Sequencing	*WAIS LN*	
Auditory attention	WAIS-III Backwards Digit Span	*WAIS DS*	
Numeracy	WAIS-III Arithmetic (*untimed*)	*WAIS AR*	
Processing speed	WAIS-III Coding	*WAIS PS*	
Semantic memory	*KBIT-2* Verbal Knowledge	*KBIT VK*	
Contextual Factors			
On-task confidence	Everyday Social Decisions Task, C	*ESD-C*	Confidence
Deliberation time	Everyday Social Decisions Task, DT	*ESD-RT*	Deliberation Time
Social Cognitive Function			
Cognitive Theory of Mind	Strange Stories	*Stories*	Cognitive ToM
	Edinburgh Social Cognition Test – Cognitive ToM Subscale	*ESCoT-C*	
Affective Theory of Mind	Reading the Mind in the Eyes Test	*RMET*	Affective ToM
	Edinburgh Social Cognition Test – Affective ToM Subscale	*ESCoT-A*	
Interpersonal Trust	Trust Scale	*Trust Scale*	Trust
Fraud Susceptibility Outcome			
Behavioural FS	Everyday Social Decisions Task, A	*ESD-A*	Purchase Intention
Detection Accuracy FS	Everyday Social Decisions Task, B	*ESD-B*	Deceit Detection
Discrimination	SDT-derived score	*d'*	Discrimination
Response Bias	SDT-derived score	ß	Response Bias

Note. The study variables *Global Cognition, Cognitive ToM* and *Affective ToM* represent z-score derived composite sums based on the measures listed in their respective domains.

Chapter 4. Analytic Strategy

4.1. Initial Analyses: Cleaning & Screening

All primary analyses were conducted with SPSS v27.0 (IBM Corp, 2021), and the multiple imputation procedure was computed using the ‘mice’ package in *R* (van Buuren, 2021). Age group was dummy coded (younger adults: 0; older adults: 1). Of note, due to sample size restraints related to limited recruitment during the COVID-19 pandemic, we opted to treat the younger and older age adults as subgroups rather than a continuous age variable which would result in truncated range. This approach allowed us to maximize power in analytic models. Further, the selected age groups align with conventions in fraud-related cognitive aging research when analyzing disparate age groups (i.e., age 18-35 and age 60+; see Lin et al., 2019; Ebner et al., 2020) and map on to our understanding of age-related cognitive changes across the lifespan (e.g., exponential declines beginning around age 60; Salthouse, 2009). We inspected the data for fit between the distributions of variables of interest and the assumptions of multiple linear regression (see Appendix C). Prior to primary analyses, data were prepared by 1) conducting reliability analyses on ToM measures, 2) using inter-relationships between ToM measures to impute missing data on the ESCoT measure, and 3) reducing data to address psychometric limitations and maximize power. We conducted analyses on the full data set with a final $N = 122$.

4.1.1. Reliability Analyses

Given the historically weak psychometric properties of the legacy ToM measures (e.g., Soderstrand & Almkvist, 2012; Fischer et al., 2016; Baksh et al., 2018), we examined item-level properties of the RMET, Strange Stories, and the contemporary ESCoT measures to ensure that individual items reflected the same construct as their total scores. Six items were deleted from the RMET and one item from Strange Stories because they demonstrated poor response variability or very low item-total correlations (i.e., $r < .10$; Meyers et al., 2013; comparable to published estimates e.g., Fischer et al., 2916). As presented in Table 4.1, despite being comparable to recently published data (e.g., Calso et al., 2019; 2020), our reliability estimates for the legacy ToM measures were lower than recommended for psychometric standards (Koo & Li, 2016). The contemporary ToM measures showed improved psychometric properties and were deemed appropriate for inclusion without item-level analysis.

Table 4.1. Psychometric properties of legacy and contemporary theory of mind measures

Test	Possible score range	Actual score range	Original Internal consistency ICC [95% CI]	Original Interpretation	Revised ICC [95% CI]	Revised Interpretation
RMET	0 - 28	10 -26	.62 [.52, .71]	Moderate	.65 [.56, .73]	Moderate
STORIES	0 - 14	3 - 12	.46 [.30, .59]	Unacceptable	.61 [.38, .64]	Moderate
ESCoT C-ToM	0 - 30	11 - 30	.85 [.64, .91]	Good	N/A	
ESCoT A-ToM	0 - 30	6 - 30	.87 [.69, .93]	Good	N/A	

Note. We present internal consistency as the intraclass correlation coefficient, $ICC_{(3,1)}$, for mixed effects models (average measures), which is equal to Cronbach's α in a two-way mixed effects design.

4.1.2. Multiple Imputation

The contemporary ToM measure, the ESCoT, was added into the standard battery mid-data collection due to evidence of promising psychometric properties in initial test development and validation (Baksh et al., 2018). Thus, out of the total study pool, 28 study participants did not complete the ESCoT as they participated in an earlier phase of the study before this measure was incorporated into the standard battery. We conducted a Missing Values Analysis (MVA) and determined that the pattern of missing data (22.9%) was not missing completely at random; Little's test of MCAR, $X^2(94) = 8.9$, $p = .003$ (Little, 1998). Considering missing data mechanisms, we divided the sample into those with data on the ESCoT ($n = 94$) vs. those without ($n = 28$) and tested mean differences in demographics, neurocognitive and social cognitive performance, and FS behaviours. We concluded that no systematic differences existed between participants with and without this data, with the exception of time of testing, and thus the patterns of missing data were deemed missing at random (MAR)[3]. We employed multiple imputation analysis using Bayesian linear regression to impute the missing scores on the ESCoT ($n = 28$). The imputation model included all variables to be used in later analysis models, including the legacy ToM measures. We generated $m = 23$ imputed data sets, which we

[3] Under the assumption that the missing data mechanism is MAR or MCAR, the pooled estimates generated in multiple imputation approaches are considered unbiased and have correct standard errors (Rubin, 2004).

then applied the analysis models to[4]. Model estimates were pooled across the imputed sets using Rubin's rules (Rubin, 2004) to produce final values on ESCoT-C and ESCoT-A.

4.1.3. Data Reduction

Based on theoretical associations among constructs in neuropsychological and cognitive aging literature, we created z-score composite variables for the ToM and neurocognitive measures. This approach allowed us to reduce the number of independent variables in the models in a meaningful way while addressing the psychometric limitations of the legacy ToM measures.

Theory of Mind data. We created composite ToM measures by converting original raw score data into z-scores ($Z = (x – M)/SD$), where x is the participant's raw score and *M* and *SD* are estimated from the single group, i.e., the pooled sample; (Andrade, 2021). Note that z-score distributions have a *M* of 0 and an *SD* of 1. The z-scores were then summed to create composite C-ToM (Stories & ESCoT-C) and A-ToM (RMET & ESCoT-A) variables. The z-score composites had good univariate properties, thus stabilizing influences of skewness in the data. We also compared model results using z-score composites with logarithmic and square root transformed data, but no meaningful differences were observed; thus we retained the z-score composites for all analyses as this provided the most parsimonious interpretation of results. Table 4.2 presents inter-test correlations between ToM measures for the full sample. The generally low inter-test associations we observed are consistent with recent published estimates (e.g., Baksh et al., 2018).

[4] A rule of thumb in multiple imputation is to set the number of imputations (*m*) equal to the percentage of missing observations in the data set (van Buuren, 2012). Choosing a larger *m* results in greater power (i.e., smaller confidence intervals) in hypothesis testing, and the only cost for using a larger *m* is computation time. Given that 22.9% of the data was deemed MAR, we selected an $m = 23$ for the imputed data sets.

Table 4.2. **Correlation matrix for theory of mind variables**

	1	2	3	4	5	6
			Full Sample, N = 122			
1. RMET	-	.32**	.80***	.27**	.23*	.24*
2. ESCOT A-ToM		-	.75***	.17	.56***	.28*
3. Affective ToM			-	.21*	.21*	.49***
4. STORIES				-	.34**	.76***
5. ESCOT C-ToM					-	.79***
6. Cognitive ToM						-

Note. Cognitive ToM and Affective ToM reflect the composite z-score variables. For all variables higher scores indicate better performance.
*p < .05, **p < .01, ***p < .001.

Neurocognitive data. Table 4.3 presents inter-correlations between the individual neurocognitive variables. The executive functioning measures displayed low to moderate correlations (|.23 < r < .53|) and most neurocognitive abilities displayed significant associations in the full sample. Although theoretical rationale strongly suggests that neurocognitive abilities represent separate constructs with differential associations to age and brain morphology, mapping precise relationships between FS and specific neurocognitive abilities was not our aim in this study. Rather, we created composite *Fluid Cognition* and *Crystallized Cognition* scores as well as a *Global Cognition* score which allowed for the statistical control of all cognitive skills distinct from ToM. This approach gave us the ability to capture a comprehensive, multi-domain estimate of neurocognitive functioning for each individual while meaningfully reducing the number of variables in our models. It also allowed us to capitalize on the theoretical and empirical associations between neurocognitive abilities, in line with robust standards in current cognitive aging research (e.g., see global cognition z-score approach in the RUSH Memory and Aging Project; Han et al., 2021; Wilson et al., 2015b). Performance scores on each neurocognitive measure were z-score transformed[5], as per the approach outlined above, and the composites were calculated by summing and averaging the z-scores across all tests. These composites were used to index neurocognitive functioning in all subsequent analyses.

[5] Please see Appendix F, Table 1 for mean scores by age group across the individual neurocognitive measures; as expected and consistent with theory (e.g., Salthouse, 2009) and past research (see Fischer et al., 2016; Walzak & Thornton, 2018; Baksh et al., 2018), younger adults outperformed older adults on most tasks with the exception of semantic knowledge, $r(120) = .53$, 95% CI [.40, .64].

Table 4.3. **Intercorrelations between neurocognitive abilities and global cognition**

	1	2	3	4	5	6	7	8
Full Sample, N = 122								
1. DKEFS CW	-	-.37***	-.31**	-.23**	-.43***	.29**	.37**	.22*
2. WAIS LN		-	.53***	.33**	.42***	-.03	.67***	.53**
3. WAIS DS			-	.25*	.53***	-.21*	.54***	.44**
4. WAIS AR				-	.33***	-.25**	.29**	.37***
5. WAIS PS					-	-.29**	.44**	.52***
6. Crystallized Cog.						-	.25*	.32**
7. Fluid Cog.							-	.70***
8. Global Cognition								-

Note. DKEFS CW = DKEFS Color/Word Trial 3 Inhibition score (seconds); *WAIS LN* = WAIS-III Letter/Number Sequencing working memory subtest (range: 0-21); *WAIS DS* = WAIS=III Backwards Digit Span auditory attention subtest (range: 0-15); *WAIS AR* = WAIS-III Arithmetic numeracy subtest (untimed; range: 0-22); *WAIS PS* = WAIS-III Digit Symbol Coding processing speed subtest; *Crystallized Cognition* = z-score of KBIT-II Verbal Knowledge semantic memory subtest (range: 0-60); *Fluid Cognition* = z-score sum of DKEFS CW, WAIS LN, WAIS DS, WAIS AR, and WAIS PS; *Global Cognition* = z-score sum of all neurocognitive measures (Crystallized + Fluid Cognition).
[a]Response Inhibition scores represent a timed measure, with higher scores indicating slower performance.
**p* < .05, ** *p* < .01, ***p < .001.

4.1.4. Assumption Screening and Ceiling Effects

Table 4.4 presents descriptive statistics for all study measures. Standardized estimates for skew and kurtosis were within acceptable ranges for all independent variables in the younger adult sample (i.e., standardized values < |3.29|; Curran, West, & Finch, 1996; with adjustment for small sample size as per Kim, 2013). However, several distributions in the older adult sample were mildly problematic: performance on the Interpersonal Trust measure was borderline platykurtic, and Confidence demonstrated a truncated range. The latter also failed the Shapiro-Wilk normality test. To address non-normality we applied logarithmic and square root transformations to the variables Trust and Confidence, however these interventions did not significantly improve the data distributions. Of note, transformation techniques have limited efficacy in addressing truncation (Liu et al., 2021).

We opted to standardize each variable to z-scores and retained the original distribution properties. Visual inspection of the Q-Q plots, bivariate and residual scatterplots for the z-score variables, stratified by age group using fit lines, suggested pairwise linearity for each independent variable and that for each dependent variable, the spread of residuals was relatively uniform across values of the predicted scores.

Tabachnik and Fidell (2013) also note that between-group ANOVAs and regression analyses are generally robust to violations of normality assumptions with samples of $N > 20$ (i.e., central limit theorem). Thus, we retained z-score variables for all subsequent analyses.

Table 4.4. Distribution properties for primary study variables by age group

Variable	Young Adults (n = 76)				Older Adults (n = 46)			
	Mean (*SD*)	Range	Skew	Kurtosis	Mean (*SD*)	Range	Skew	Kurtosis
Crystallized Cog.	0.06 (*0.85*)	-1.62 – 1.70	-0.19	-0.72	0.11 (*0.68*)	-1.52 – 1.09	-0.70	-0.17
Fluid Cog.	0.00 (*0.68*)	-1.91 – 1.53	0.03	0.06	0.01 (*0.69*)	-1.35 – 1.49	0.19	-0.55
Global Cog.	0.41 (*2.27*)	-5.15 – 7.13	0.18	0.76	-0.63 (*3.15*)	-9.90 – 8.74	0.26	0.31
Confidence	50.60 (*8.78*)	31.0 – 63.00	-0.76	-0.40	61.80 (*4.10*)	54.00 – 70.0	0.13	-0.92
Cognitive ToM	0.22 (*0.75*)	-1.47 – 1.84	0.08	-0.58	-0.36 (*0.76*)	-2.03 – 1.05	-0.27	-0.41
Affective ToM	0.28 (*0.62*)	-1.90 – 1.72	-0.68	0.67	-0.44 (*0.74*)	-2.10 – 0.92	-0.48	-0.14
Trust	16.03 (*5.39*)	6.00 – 24.00	-0.36	-1.07	16.04 (*5.18*)	6.00 – 24.00	-0.29	-1.05
Purchase Intention	19.97 (*6.51*)	7.00 – 34.00	0.02	-0.76	16.97 (*8.73*)	5.00 – 35.00	0.68	-0.55
Deceit Detection	20.67 (*8.12*)	6.00 – 35.00	0.49	-0.97	25.33 (*7.80*)	8.00 – 35.0	-0.55	-0.61
Discrimination (d')	0.18 (*0.55*)	-1.00 – 1.00	-0.11	-0.79	0.42 (*0.49*)	-0.60 – 1.00	-0.42	-1.01
Response Bias (ß)	1.01 (*0.25*)	0.60 – 1.70	0.64	0.31	0.73 (*0.19*)	0.40 – 1.10	0.33	-0.98

Note. Crystallized Cog., Fluid Cog., Global Cog., Cognitive ToM and Affective ToM = z-score derived composite variables standardized to a *Mean* of 0; Trust = World Values Interpersonal Trust raw score (6 – 24); Purchase Intention raw score (5 – 35); Deceit Detection raw score (5 – 35).

Moderate ceiling effects were evident in the older adult group on Deceit Detection and Discrimination (both n = 5; 10.9%, respectively). More significant ceiling effects were also observed in the older adult group on the individual Confidence subscales (Fraudulent items: 19.6%; Legitimate items: 15.2%) though the sum Total score was more reasonably distributed (10.9%). As can be seen in histogram distributions (Appendix F), a considerable percentage of older adults were clustered at the high end of the distribution for Confidence and its subscales; conversely, other study variables' histograms more closely resembled a normal distribution.

Please see Appendix E for further details on treatment of Ceiling Effects. Because other revisions to test design (e.g., basal/ceiling method, addition of more items; Liu et al., 2021) were not possible, it is important to exercise caution when interpreting test performance on the Confidence measure and this potential threat to validity within our models is expanded upon in the Discussion.

4.1.5. Power Analysis

A priori power analysis is summarized in Table 4.5 (please see Appendix E for further details on Analytic Strategy and Power Analysis).

Table 4.5. Estimated sample size needed to detect small, medium, and large effect sizes

		Effect Size	
Objective 1		**Cohen's *d***	
(α = .05; 1 – ß = .80)	Small *d*= .20	Medium *d* = .5	Large *d* = .80
	121	56	42
Objective 2		**Cohen's f^2**	
(α = .05; 1 – ß = .80)	Small f^2 = .02	Medium f^2 = .15	Large f^2 = .35
# predictors = up to 9	210	93	49
Objective 3		**Cohen's f^2**	
(α = .05; 1 – ß = .80)	Small f^2 = .02	Medium f^2 = .15	Large f^2 = .35
# predictors = up to 9	210	93	49

Note. Power analyses were conducted using the G*Power calculator version 4.2.9 (Faul, Erdfelder, Buchner, & Lang, 2021).

Chapter 5. Results

5.1. Preliminary Analyses

5.1.1. Sample Characterization

Table 5.1 presents means and standard deviations for participant characteristics by age group. The samples were equivalent in gender and education distribution but differed in other demographic variables; younger adults had more ethnically diverse backgrounds (Φ =.49; medium effect size [*ES*]) but were not significantly more likely to report a primary language other than English (EAL; Φ = -.17; small *ES*).

The older adult sample was cognitively healthy (MMSE *M* = 28/30, *SD* = 1.62; Chapman et al., 2016) and reported significantly higher TV consumption *r*(120) = .59, 95% CI [.46, .69], and lower Internet exposure, *r*(120) = -.52, 95% CI [-.64, -.38]. As expected and consistent with theory (e.g., Salthouse, 2009) and past research (see Fischer et al., 2017; Walzak & Thornton, 2018; Baksh et al., 2018), younger adults outperformed older adults on most neurocognitive and social cognitive tasks with the exception of interpersonal trust, which was comparable (Appendix F Table F1).

Table 5.1. **Demographic and other characteristics by age group**

Variable	**Younger Adults (*n* = 76)**	**Older Adults (*n* = 46)**	**χ^2/t**	**Effect Size *g***	**Φ**
Age[a]	20.34 (*3.51*)	74.35 (*8.79*)	-47.71***	8.91	-
Range	*17 - 35*	*59 - 96*	-	-	-
Education[a]	13.37 (*1.71*)	13.88 (*2.34*)	-1.26	0.26	-
Range	*12 - 20*	*9 - 18*	-	-	-
Female[b] (%)	68.0	63.0	0.37	-	-0.06
Ethnicity[b] (%)			29.46***	-	0.49
Caucasian	32.9	78.3			
Asian	38.2	10.9			
Indigenous	2.6	6.5			
South Asian/Indian	17.1	2.2			
Hispanic	2.6	0			
Other	6.6	2.2			
EAL[b] (%)	27.6	15.2	3.50	-	-0.17
Employment Status[b] (% employed)			81.85***	-	0.83
Full-time/student	19.5	4.3			
Part-time/student	49.4	17.4			
Unemployed/retired	28.6	71.7			
Income[b]					
<$20,000	69	13	29.22*	-	0.27
$20,000-$60,000	5	30			
>$60,000	2	0			
Internet Usage[a]	33.76 (*16.98*)	13.65 (*14.54*)	6.52***	1.25	-
TV Exposure[a]	5.03 (*6.19*)	15.65 (*8.24*)	-7.35***	1.51	-
CES-D[a]	13.05 (*11.52*)	8.51 (*9.05*)	2.10*	0.51	
STICSA-State[a]	25.39 (*13.07*)	29.47 (*10.81*)	-1.76	0.32	
STICSA-Trait[a]	29.97 (*12.04*)	30.51 (*11.82*)	-0.24	0.05	
UCLA Loneliness Scale[a]	42.37 (*13.66*)	42.79 (*14.38*)	-0.16	0.01	
MMSE	-	28.15 (*1.62*)	-	-	-
Crystallized Cognition[a]	0.06 (0.23)	0.11 (0.34)	2.33*	.70	
Fluid Cognition[a]	0.21 (0.67)	0.00 (0.74)	1.92*	.65	
Global Cognition[a]	0.42 (*0.49*)	-0.64 (*0.58*)	2.05*	0.72	
Cognitive ToM[a]	0.22 (*0.82)*	-0.36 (*0.76*)	2.18**		
Affective ToM[a]	0.28 (*0.62)*	-0.44 (*0.73)*	2.56**		
Interpersonal Trust[a]	16.01 (*5.39*)	16.04 (*6.33*)	0.26	0.04	

Note. We present means and standard deviations as M (*SD*). EAL = reported English as an additional language; MMSE = Mini-Mental Status Examination (range = 0-30); Internet Usage and TV Exposure = # of hours per week; CES-D = Centre for Epidemiological Studies Depression Scale (range = 0-60); STICSA = State-Trait Inventory for Cognitive and Somatic Anxiety (range = 21-84); UCLA Loneliness Scale = University of California, Los Angeles Scale of Loneliness (range = 0-80)

[a]*p* value and Hedge's *g* derived from t-test (continuous data with unequal sample sizes; small ES $g \leq .20$; medium ES $g \geq .50$; large ES $g \geq .80$; very large ES $g \geq 1.30$; Hedges, 1981; Cohen, 1998).

[b]p value and phi coefficient (Φ) derived from χ^2 test (effect size for binary categorical data; small ES Φ ≤ .10; medium ES Φ ≥ .30; large ES Φ ≥ .50). *p < .05, **p < .01, ***p < .001.

5.1.2. Correlations

Table 5.2 presents Pearson correlation coefficients between FS outcomes and neurocognition (crystallized, fluid, global), context variables (confidence, reaction time), ToM (cognitive and affective), and interpersonal trust. Given extensive research documenting age differences in both the predictors and outcomes, we present correlations separately by age group. Because the crystallized and fluid cognition composites were not significantly or differentially associated with ESD outcomes (e.g., Purchase Intention/System 1 vs. Discrimination/System 2), we opted to retain the global cognition composite only for model parsimony.

See Appendix F, Tables 2-3 for correlation matrices between FS and additional variables of interest. Demographic, lifestyle, and socioemotional functioning variables (e.g., self-rated depression and anxiety symptoms) were considered as potential covariates given evidence linking gender, education, internet knowledge/experience, and psychological vulnerabilities to heightened FS (Beach et al., 2010; Lichtenberg et al., 2016; see Norris et al., 2019 for review). Apart from education, the majority of potential covariates did not show significant associations with ESD outcomes and were excluded from primary analysis models. Given that education was significantly associated with ESD outcomes in the older adult group only (Purchase Intention: $r[46] = -.58$, p = .000; Discrimination: $r[46] = .47$, p = .002), it was excluded from primary regression models because it is not a meaningful covariate in the younger adult group due to lack of opportunity for equivalent educational attainment (i.e., undergraduate university sample).

Table 5.2. **Intercorrelations between predictors and FS outcomes by age group**

	1	2	3	4	5	6	7	8	9	10	11
						Younger Adults, n = 76					
1. Crystallized Cog.	-	.24*	.45***	-.11	-.08	.37**	.23*	.17	.04	.07	.13
2. Fluid Cog.		-	.62***	-.04	-.13	.29*	.20	-.01	-.02	-.06	-.24*
3. Global Cog.			-	.08	-.02	.44***	.30**	.21	-.08	.09	-.10
4. Confidence				-	-.01	.09	-.03	.27*	.01	.16	.04
5. Deliberation Time					-	.08	-.03	.35**	-.41***	.59***	.01
6. Cognitive ToM						-	.39***	.31**	-.19	.28*	.09
7. Affective ToM							-	.14	-.25*	.14	.07
8. Interpersonal Trust								-	-.33**	.52***	.36**
9. Purchase Intention									-	-.80***	-.03
10. Discrimination										-	.12
11. Response Bias											-
						Older Adults, n = 46					
1. Crystallized Cog.	-	.11	.42**	.09	-.05	.44**	.25	.09	-.17	.25	.17
2. Fluid Cog.		-	.84***	-.36*	.05	.18	.30*	-.02	-.27	.26*	.11
3. Global Cog.			-	-.18	.01	.28	.34*	.06	-.31*	.41**	.08
4. Confidence				-	-.30*	.22	.01	-.15	.15	-.25	-.04
5. Deliberation Time					-	.04	.30*	.51***	-.04	-.01	.07*
6. Cognitive ToM						-	.39**	.18	-.19	.25	.24
7. Affective ToM							-	.41**	-.60***	.49**	.24
8. Interpersonal Trust								-	-.44**	.45**	.72**
9. Purchase Intention									-	-.76***	-.20
10. Discrimination										-	.42**
11. Response Bias											-

Note. Crystallized Cog. = z-score conversion of KBIT-II Verbal Knowledge subtest; Fluid Cog. = z-score sum of WAIS-III Arithmetic subtest (untimed), WAIS-III Letter/Number Sequencing subtest, DKEFS Color/Word Trial 3 score (seconds), WAIS=III Backwards Digit Span subtest, and WAIS-III Digit Symbol Coding subtest; Global Cog. = z-score sum of Crystallized Cog. and Fluid Cog; Cognitive ToM = z-score derived composite of STORIES + ESCoT-C; Affective ToM = z-score derived composite of RMET + ESCoT-A; Interpersonal Trust = World Values Interpersonal Trust score (range: 6-24).

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

5.2. Primary Analyses

5.2.1. Objective 1

Consistent with our hypotheses that deceit detection would show an inverse association with purchase intention given that preference for a specific offer/product elicits System 1 processing and strongly influences consumer decision-making (Asp et al., 2012; Denburg et al., 2017), poorer deceit detection was robustly associated with stronger purchase intention for fraudulent offers in the overall sample (*r*[120] = -.39, 95% CI [-.47, -.28]; medium ES; Cohen, 1998). Consistent with our hypotheses that slower deliberation time and higher confidence would facilitate more optimal decisions in the whole sample (i.e., lower purchase intentions and stronger deceit detection), stronger deceit detection was also associated with slower deliberation time (*r*[120] = .51, 95% CI [.37, .63]; medium/large ES) and higher confidence (*r*[120] = .34, 95% CI [.24, .62]; medium ES). Repeating analyses with legitimate/safe stimuli suggested that poorer detection (i.e., false alarm rate) was related to stronger purchase intention (*r*[120] = -.37, 95% CI [-.83, -.69]; medium ES), but not the other aforementioned decision-making factors. Spearman coefficients were consistent with Pearson's correlations in all analyses.

As highlighted in Table 5.3, direction of the associations were somewhat consistent in terms of direction when analyses were repeated within the age groups, although they were weaker in the older adult group. More broadly, distinct components of FS (i.e., purchase intentions and deceit detection) appear related and complementary across age groups.

Table 5.3. Intercorrelations between ESD task components – full sample and by age group

	1	2	3	4	5	6
Full Sample, N = 122						
1. Age Group[a]	-	*-.19**	*.28***	*.59****	*.59****	*.63****
2. Purchase Intention		-	*-.39****	*-.08*	*-.24***	*-.46****
3. Deceit Detection			-	*.34****	*.42***	*.51****
4. Confidence				-	*.33****	*.35****
5. Deliberation Time - PI					-	*.63****
6. Deliberation Time - DD						-
Younger Adults, n = 76						
1. Age	-	*-.14*	*.42****	*.19*	*.19*	*.18*
2. Purchase Intention		-	*-.59****	*.01*	*-.41****	*-.41****
3. Deceit Detection			-	*.35***	*.48****	*.46****
4. Confidence				-	*.08*	*-.01*
5. Deliberation Time - PI					-	*.59****
6. Deliberation Time - DD						-
Older Adults, n = 46						
1. Age	-	*.41***	*.03*	*.01*	*-.04*	*.06*
2. Purchase Intention		-	*.25**	*.15*	*-.46***	*-.14*
3. Deceit Detection			-	*.24**	*.26**	*.19*
4. Confidence				-	*-.27**	*-.09*
5. Deliberation Time - PI					-	*.34**
6. Deliberation Time - DD						-

Note. All reported associations are presented as Pearson correlation coefficients with the exception of age group associations which are Point biserial coefficients. PI – Fraud = Purchase Intention for fraudulent offers (5-35; higher scores indicate higher likelihood of purchasing/participating); DD – Fraud = Deceit Detection for fraudulent offers (5-35; higher scores indicate stronger deceit detection performance); Confidence = Confidence Rating in decision (10-70; higher scores indicate stronger confidence); Deliberation Time - PI = average response time in seconds during Purchase Intention trial; Deliberation Time – DD = average response time in seconds during Deceit Detection trial.
[a]All reported associations are presented as Pearson correlation coefficients, except for age group (0/1), which reflects Point-biserial correlation coefficients.
*p < .05, ** p < .01, ***p < .001.

5.2.2. Objective 2

Figures 5.1 and 5.2 depict mean scores by age group and the associated 95% confidence intervals (error bars) on the ESD subscales. Younger and older adults classified the stimuli with average rates of 59% and 72% accuracy, respectively. Contrary to our hypothesis that deceit detection would favour younger adults, one-way between subjects' ANOVAs revealed that for fraudulent items, older adults had stronger deceit detection (F[1,120] = 9.84, p = .002, η^2 = .19; large ES). Consistent with our predictions, they also showed lower purchase intention for fraudulent items (F[1,120] = 4.67, p = .033, η^2 = .04; small ES). Older adults also showed significantly higher confidence ratings irrespective of offer type (Fraudulent items: $F[1,120] = 57.61$, $p = .000$, $\eta^2 = .26$; very large ES; Legitimate items: $F[1,120] = 40.01$, $p = .000$, $\eta^2 = .21$; very large ES), and significantly slower deliberation time irrespective of FS condition (Purchase Intention: $F[1,120] = 63.76$, $p = .000$, $\eta^2 = .31$ (very large ES); Deceit Detection: $F[1,120] = 80.26$, $p = .000$, $\eta^2 = .42$ (very large ES). Interestingly, there were no significant age differences in performance on purchase intention for *legitimate offers* and on detecting false alarms (i.e., identifying a legitimate offer as fraudulent). Post-hoc ANOVA analyses to investigate features of the scale indicated that performance between age groups did not differ based on offer type (i.e., television advertisement, email, voice message). Further, for both age groups, deliberation times in the purchase intention condition were significantly faster ($M_{122} = 10.23$, $t[122] = 23.72$, $p = .000$, $D = 1.22$; large ES) relative to their deliberation times in the deceit detection condition ($M_{122} = 15.73$, $t[122] = 26.38$, $p = .000$, $D = 1.54$; large ES), providing initial evidence that across age groups, the purchase intention condition may elicit more automatic processing whereas the follow up deceit detection condition may evoke deliberative reasoning through its item prompts.

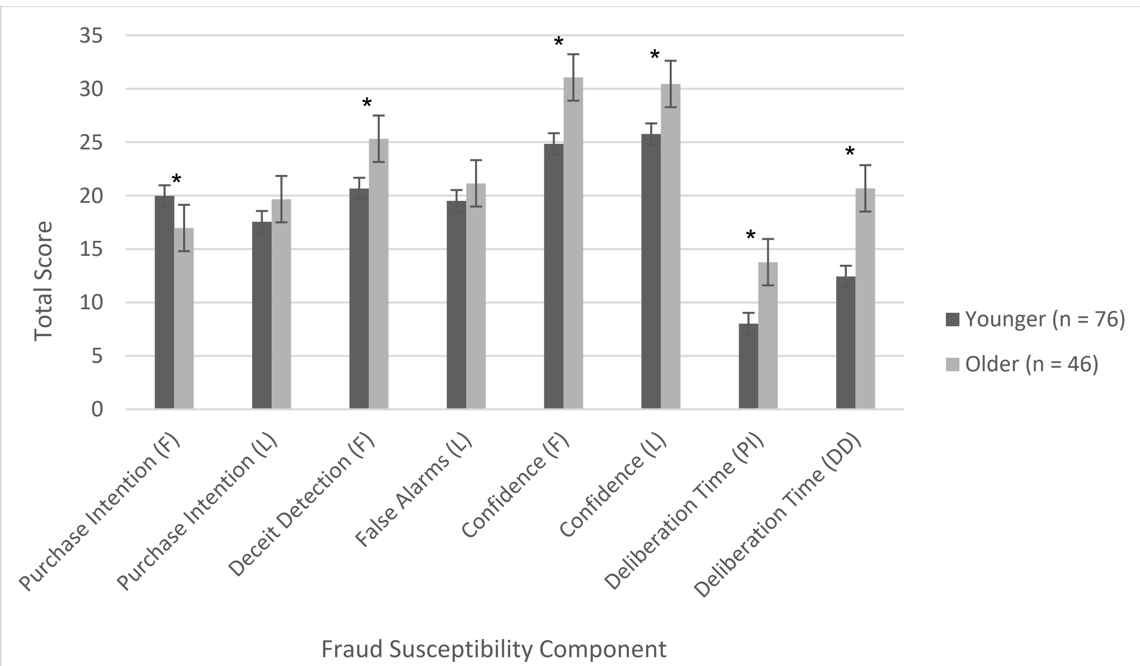

Figure 5.1. Mean scores on ESD Subscales (all items) and 95% confidence intervals for mean standard error
$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

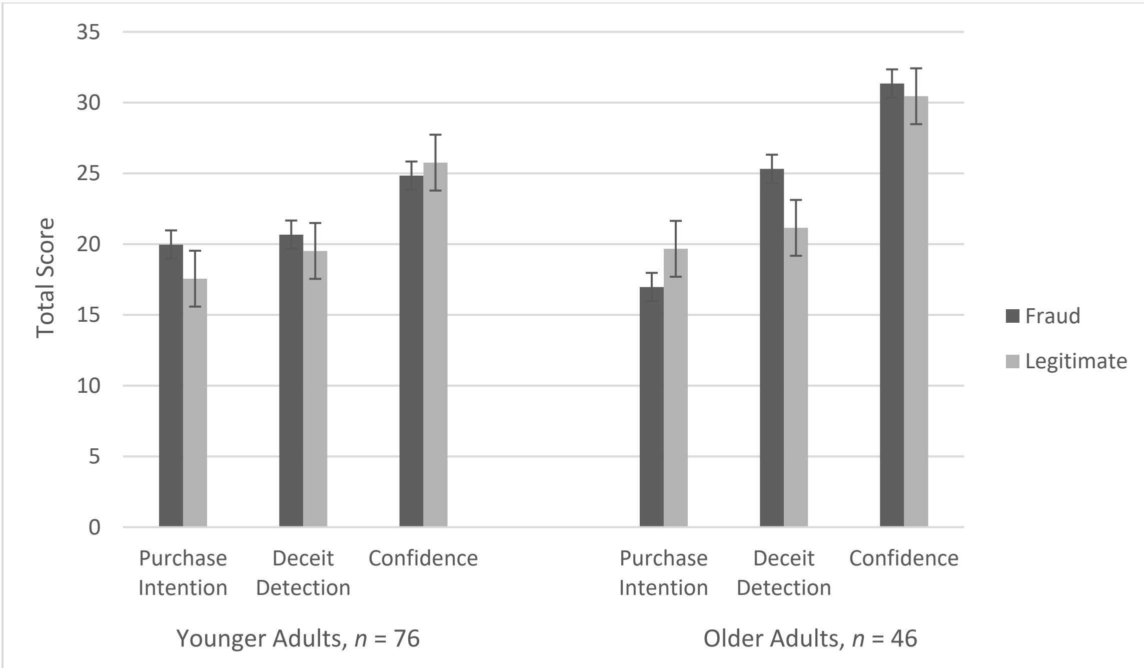

Figure 5.2. Mean scores on ESD subscales and 95% confidence intervals for mean standard error by age group
*p < .05, ** p < .01, ***p < .001

These results are consistent with results from SDT displayed in Table 5.4. Older adults had a higher hit rate than younger adults, $F(1,120) = 10.50$, $p = .002$, $\eta^2 = .08$ (medium ES) while false alarm rates were comparable, $F(1,120) = 1.015$, $p = .32$, $\eta^2 = .000$ (nonexistent ES). Contrary to the hypothesis, older adults were significantly better at discriminating between stimuli types (as measured by *d'*), $F(1,120) = 6.34$, $p = .01$, $\eta^2 = .05$ (medium ES) but consistent with our hypothesis, they were also significantly more cautious in their discernment approach (as measured by ß; i.e., a tendency towards classifying all stimuli as fraudulent/unsafe), $F(1,120) = 39.67$, $p = .000$, $\eta^2 = .17$ (large ES). Finally, scale-based AUC metrics derived from individual receiver operating characteristics (ROC) curves[6] indicated that neither age group ($M_{younger} = .80$, $M_{older} = .78$) demonstrated ineffective use of the ESD scale, $F(1,120) = 0.24$, $p = .63$, $\eta^2 = .000$ (nonexistent ES). The SDT-derived findings indicate that while older adults showed better discrimination, their stronger performance came at the cost of a more cautious

6 A maximum AUC statistic of 1 indicates perfect performance on the task, with no bias, while scores between 0 and 0.5 indicate ineffective use/misunderstanding of the task (Stanislaw & Todorov, 1999). Four participants in the older adult group showed ineffective use of the ESD, endorsing all items as “definitely fraudulent” regardless of stimuli type (Hit rate = 5, False Alarm rate = 5, AUC rating = 0.5, d' = 0). Results were comparable with and without this group (N = 4), so these participants were retained in subsequent analyses to preserve power.

response style (i.e., they were more liberal in classifying stimuli as fraudulent). On the other hand, younger adults on average showed a balanced, bias-free response style. Using regression methods in subsequent modelling, we examined purchase intention, discrimination (*d'),* and response bias (β) as primary outcomes given the compatibility of the results from SDT with the conventional analyses.

Table 5.4. Signal Detection Theory parameters of decision-making performance on the ESD task by age group

Age	Accuracy	AUC	Hit Rate	False Alarm Rate	Discrimination (*d'*)	Response Bias (β)
Younger adults (*n*=76)	5.93 (2.77)	.80 (0.18)	.57 (0.32)	.38 (0.29)	.18 (0.53)	1.01 (0.25)
Older adults (*n*=46)	7.20 (2.47)	.78 (0.21)	.76 (0.29)	.32 (0.35)	.42 (0.47)	.73 (0.19)

Note. Values displayed represent the group mean by age group. Values in parentheses represent the standard deviation of the mean. Shaded boxes represent significant contrasts (p < .05) between groups.

5.2.3. Objective 3

Model A: Purchase Intention. In the preliminary model, hierarchical regression revealed that global cognition was inversely associated with purchase intentions in the first block (β = -.20, p = .035, *95% CI* = [-1.07, -0.04]), consistent with our predictions regarding the affective demands of the purchase intention condition. However, it was non-contributory when entered with Block 2 variables. In terms of contextual factors, on-task confidence unexpectedly did not account for any significant variance in purchase intentions. All other Block 1 and 2 variables were retained for interaction effects. In Block 3, we tested age moderation of the independent variable effects (i.e., interactions). Consistent with hypotheses, age group did not interact with any model variables in contributing to purchase intention, suggesting relationships were not conditionalized.

In the final model (Table 5.5), poorer A-ToM was significantly associated with worse purchase intention choices (i.e., high intention for fraudulent items/products; β = -.33, p < .001, *95% CI* = [-2.19, -.19] as hypothesized, while C-ToM was not predictive of outcome. On the contrary to our hypotheses, *lower* trust predicted higher intention to purchase fraudulent products (β = -.24, p = .008, *95% CI* = [-.644, -.146]). Consistent with our predictions, slower deliberation time (β = -.36, p = .000, *95% CI* = [-.62, 0.20]) was associated with better purchase intention choices (i.e., low intention for fraudulent items/products). In the final model, as predicted age and neurocognition were less relevant overall; rather, deliberation time, A-ToM, and interpersonal trust emerged as the only significant predictors across age groups with all variables explaining approximately 36% of variance in purchase intention behaviour.

Table 5.5. Purchase intention (fraudulent items) regression model summarizing main effects – full sample

Predictor	*B*	*SE*	*β*	*t*	*p*	R^2	*F*	ΔR^2	ΔF
Block 1: Demographics & Neurocognition						.06	4.55*	--	--
Age Group	-3.57	1.4	-.23	-2.50	.014				
Global Cognition	-.56	.26	-.20	-2.13	.035				
Block 2: Contextual & Individual Differences.						.36	10.36***	.33	11.81***
Age Group	-2.89	1.85	-.19	-1.56	.122				
Global Cognition	-.27	.24	-.10	-1.15	.250				
Confidence	.06	.08	.01	0.80	.425				
Deliberation Time - PI	-.57	.17	-.36	-3.45	.000				
Cognitive ToM	.29	.88	.03	0.33	.740				
Affective ToM	-3.34	.95	-.33	-3.51	.000				
Interpersonal Trust	-.34	.13	-.24	-2.71	.008				

N = 122
Note. R^2 depicted here is the adjusted value to capture goodness of fit by adjusting for the number of variables in the model that are meaningfully contributing to variance. Significant p-values are indicated with * for the change in R^2 after the entry of each block of variables in the equation. Age in interaction terms = Age Group (0/1).
*p < .05, **p < .01, ***p < .001

Model B: Discrimination (d'). In the preliminary model, consistent with our hypotheses, global cognition was predictive of discrimination ability; specifically, persons with stronger global cognition (β = .22, *p* = .016, *95% CI* = [.006, .080]) showed more accurate discrimination across age groups. However, consistent with findings from above, it was no longer predictive when entered with Block 2 model variables.

Consistent with our prediction that C-ToM would emerge as a unique predictor beyond the effects of age and neurocognition, it was significantly associated with discrimination when entered with other variables (β = .21, *p* = .029, *95% CI* = [.006, .080]). In consideration with the previous model, we thus observed a hypothesized double dissociation of A-ToM and C-ToM in differentially predicting purchase intention (affective-based) and discrimination (deliberation-based). In terms of contextual variables, contrary to our prediction that confidence was an important context-specific factor relevant to discrimination skills, it did not contribute significant variance to the outcome across or within age groups (specifically hypothesized as relevant to older adults) relative to other variables in the model. However, consistent with our hypotheses, slower deliberation time was significantly associated with stronger discrimination when controlling for age, neurocognition, ToM, and confidence, particularly in the younger adult group (β = -0.71, *p* = .002, *95% CI* = [-0.92, -0.43]). While we hypothesized that lower interpersonal trust would be associated with better discrimination, results indicated that *higher* interpersonal trust predicted better discrimination, particularly in the younger adult group (β = -0.78, *p* = .005, *95% CI* = [-0.88, -0.36]). As noted, contrary to hypotheses we could not capture any moderation effects with respect to confidence in the older adult group. Similarly, contrary to hypotheses, no interactions were observed between age group and C-ToM or neurocognition (i.e., as being more relevant in younger adults).

The final model (Table 5.6) accounted for 36% of variance in discrimination, with age group moderation terms of deliberation time and interpersonal trust accounting for an additional 8% of model variance (see Figure 5.3).

Table 5.6. Discrimination (*d'*) regression model summarizing main and interaction effects – full sample

Predictor	*B*	*SE*	β	*t*	*p*	R^2	*F*	ΔR^2	ΔF
Block 1: Demographics & Neurocognition						.07	5.857*	--	--
Age Group	.26	.10	.25	2.69	.008				
Global Cognition	.04	.02	.22	2.43	.016				
Block 2: Contextual & Individual Differences						.36	10.32***	.31	11.22***
Age Group	.23	.13	.21	1.77	.079				
Global Cognition	.02	.02	.12	1.43	.156				
Confidence	.00	.01	.01	0.21	.834				
Deliberation Time	.01	.01	.14	1.32	.189				
Cognitive ToM	.13	.06	.19	2.34	.021				
Affective ToM	.05	.07	.06	0.69	.490				
Interpersonal Trust	.04	.011	.43	5.04	.000				
Block 3: Interactions						.42	10.28***	.06	6.47***
Age x Deliberation Time	-.03	.01	-.71	-3.17	.002				
Age x Interpersonal Trust	-.05	.02	-.78	-2.84	.005				

N = 122

Note. R^2 depicted here is the adjusted value to capture goodness of fit by adjusting for the number of variables in the model that are meaningfully contributing to variance. Significant p-values are indicated with * for the change in R^2 after the entry of each block of variables in the equation. Age in interaction terms = Age Group (0/1).

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

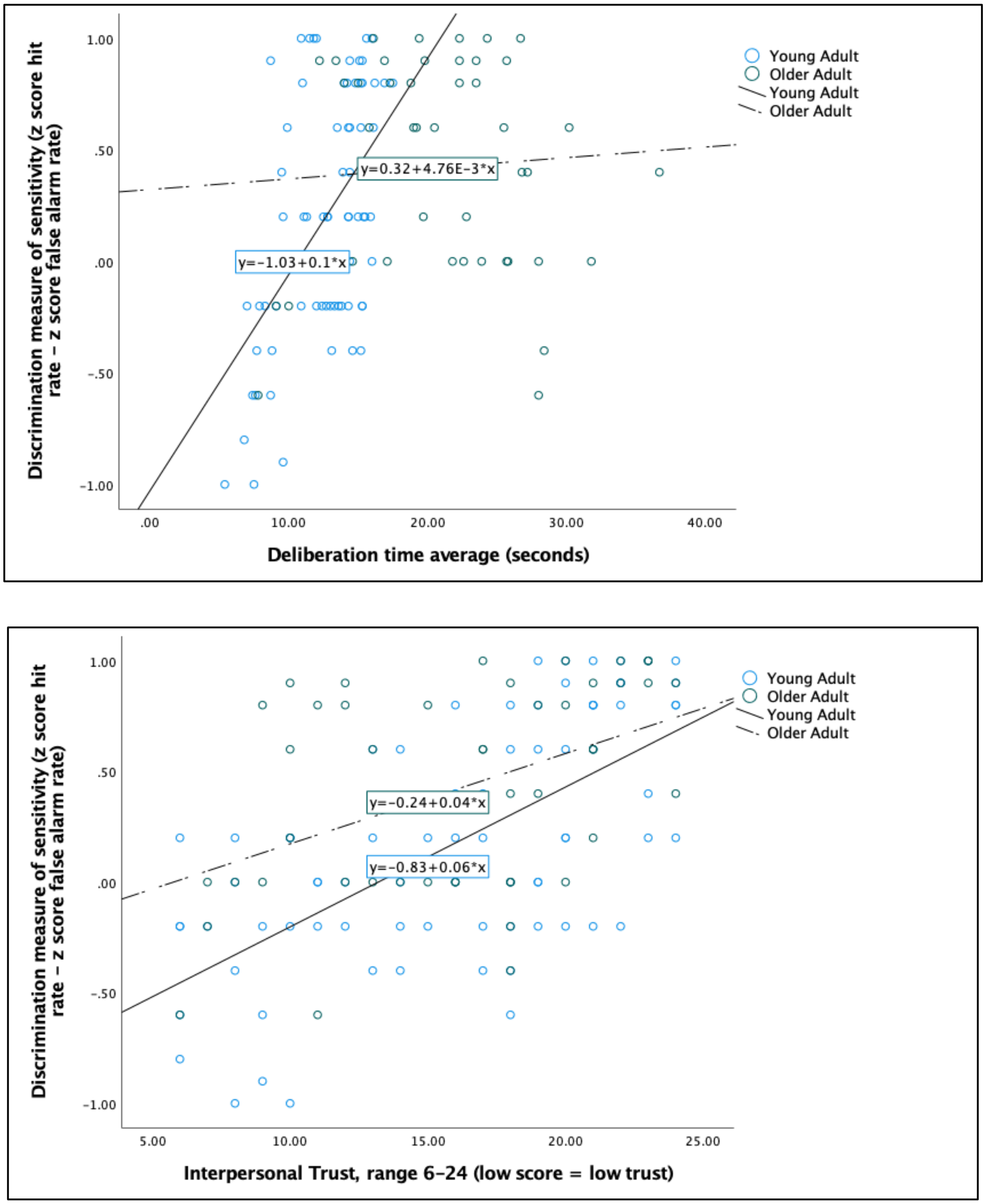

Figure 5.3. **Scatterplots of discrimination accuracy by deliberation time and by interpersonal trust, within age groups (N = 122)**

Note. Regression lines were generated by plotting the unstandardized predicted value against the respective predictor for each interaction term in the full model to test associations with discrimination accuracy.

Model C: Response Bias (ß). Older age (*β* = -.50, *p* = .000, *95% CI* = [-.772, -.392]) and lower interpersonal trust (*β* = .49, *p* = .000, *95% CI* = [0.13, .82]) were associated with greater response bias (i.e., greater propensity to classify stimuli as fraudulent/unsafe), after controlling for all variables in the model. Contrary to our hypotheses, confidence, deliberation time, and ToM were unrelated to response bias. This model accounted for 45% of the variance in bias in the full sample. There were no age-variant relationships, with lower trust consistently predicting a more cautious biased approach across age groups. As illustrated in Figure 5.4, older adults showed a bias with a consistently cautious response style, while some younger adults showed a bias towards liberal responding (i.e., classifying all offers as safe/legitimate; $\beta > 1$).

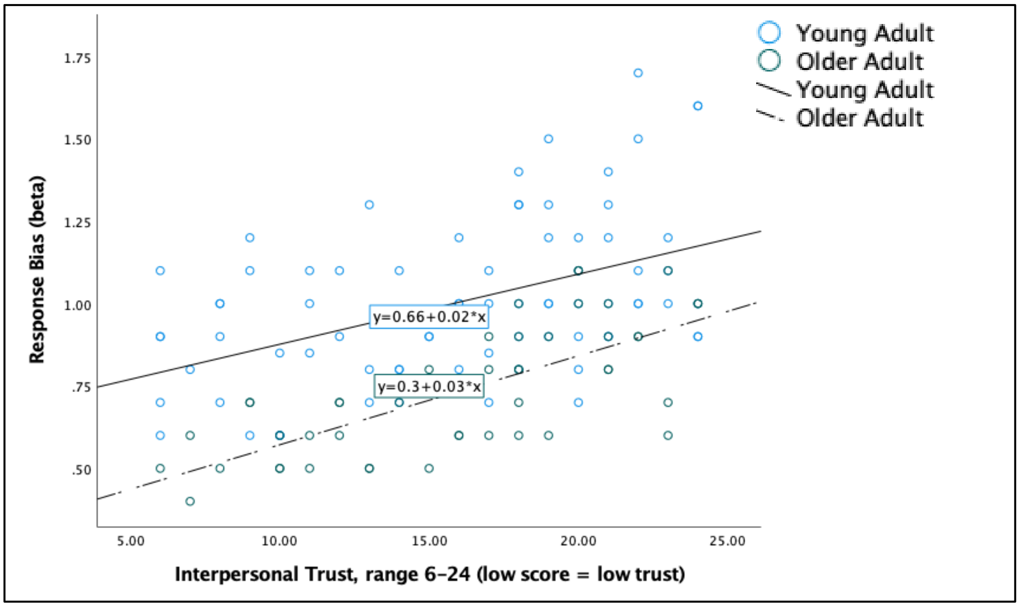

Figure 5.4. Scatterplot of response bias (β) by interpersonal trust, within age groups (N = 122)

Note. Regression lines were generated from a simple linear regression model testing associations between response bias and interpersonal trust.

Post-hoc Analysis. To address the potential confounding of age-related declines in processing speed (beginning around age 20; Salthouse, 2009), which could feasibly impact both younger and older adult samples, a post-hoc partial correlation was conducted to determine the relationship between discrimination (*d'*) and deliberation time whilst controlling for processing speed. Across age groups a moderate, positive partial correlation between discrimination and deliberation time remained only for the younger age group while controlling for processing speed (younger: $r(73) = .53$, $p < .001$; older: $r(43) = .048$, $p = .766$); as such, despite performing better on the task itself, older adults' slower deliberation time may very well be an artifact of neurocognitive age-associated slowing rather than reflective of more deliberative, effortful thinking.

We also investigated the effect of candidate predictors on the individual components of discrimination (i.e., deceit detection performance and false alarm performance individually) to determine if differential relationships may have been masked by the total scale score. See Appendix F, Table F.3 and F.4 for results. Interestingly, for the deceit detection model, consistent with predictions, both confidence (β = .21, *p* = .028, *95% CI* = [.63, .386]) and C-ToM (β = .26, *p* = .002, *95% CI* = [.142, 3.872]) accounted for significant variance in the outcome above and beyond the effects of age and neurocognition, along with interpersonal trust (β = .34, *p* = .000, *95% CI* = [.172, 2.922]). These variables explained 35% of the variance in deceit detection. Also consistent with predictions, slower deliberation time predicted better deceit detection scores only for younger adults (β = -.46, *p* = .041, *95% CI* = [.346, .872]), and the interaction term accounted for an additional 7% of variance in the final model (total R^2 = 0.42). No other interaction terms were significant. For the false alarm model (i.e., incorrectly detecting deceit when not present), significant predictors included lower confidence, lower interpersonal trust, and poorer C-ToM. In a similar trend to other models, less deliberation time was predictive of higher false alarm rate in the younger sample only (total R^2 = 0.33.

Chapter 6. Discussion

"I never thought this could happen to me" is a common expression of perplexity after being scammed. Despite a plethora of recent research on the topic, researchers remain divided with regards to the underlying mechanisms of fraud-related decision-making that cause countless individuals to be victimized, with rising crime rates and mounting public concern that have been particularly salient since the COVID-19 pandemic. Grounded in contemporary psychological theory incorporating contextual and person-centred attributes (Lichtenberg et al., 2016), we elucidated the aging effect of FS and select risks for fraudulent exploitation while mitigating prior research limitations. To our knowledge, this is the first study to examine the relative contributions of C-ToM and A-ToM to FS behaviours in both younger and older adults, while modelling a comprehensive set of theoretically and empirically relevant variables that have been the focus of emergent fraud research, especially in cognitive aging. We recruited an SDT-informed approach, the gold standard in recent FS study paradigms (e.g., Martin et al., 2018; Canfield et al., 2019; Jones et al., 2019; Sarno et al., 2020; O'Connor et al., 2021) in order to capture deeper facets of decision-making ability beyond accuracy (e.g., degree of bias). Further, our novel experimental task has shown evidence as differentiating System 1/System 2 processes while simulating real-world decision making with contextual demands and holds promise for future work with larger sample sizes.

6.1. Primary Findings

6.1.1. The Role of Age in FS

Contrary to our age-based predictions favouring younger adults, older adults performed significantly better on both the behavioural and discrimination-based components of the task; older adults were less interested in fraudulent offers, demonstrated stronger deceit detection ability, and discriminated between legitimate and fraudulent contexts with higher accuracy. Despite some evidence from population-based studies that older adults are overrepresented in fraud cases (Lichtenberg et al., 2016; Han et al., 2017) and findings from empirical work suggesting that older adults demonstrate poorer decision-making with age (Denburg et al., 2007; Rogalsky et al., 2012; Bauer et al., 2013, Yeh, 2013), especially in ambiguous or "risky" situations

(Rolison et al., 2017), our results did not support this age-related FS vulnerability. Rather, our results broadly showed that older adults exhibited equivalent or better decision-making on a lab-based judgement task and demonstrated highly developed scam-avoidant tactics relative to their younger counterparts; notably, they had an advantage not only on the component of the task that elicited intuitive, affective-based reasoning (in line with previous findings; e.g., Ebner et al., 2020; Gramble et al., 2014), but also on the discrimination-based component of the task which involves deliberative reasoning. As posited in previous work suggesting an age-related advantage, it is possible that age is a proxy for compensatory mechanisms that aid decision-making including life experience (Yu, Mottolla, et al., 2022), stronger emotional regulation (Ebner et al., 2020), and relatively spared emotional processing (Mueller et al., 2020).

Importantly, while older adults performed better in resisting fraud, consistent with our hypotheses they were also more biased and they were more likely to view offers as unsafe, regardless of intent; this defensive or “cautious” decision-making style of older adults has been previously reported (Canfield et al., 2019; Sarno et al., 2020; Grilli et al., 2021). Our results support work on similar lab-based judgment tasks asserting that relative to younger age groups, older age is associated with an inflated response bias (or “high suspicion strategy”; O’Connor et al., 2021). This finding coalesces with age-related heightened risk aversion (Rolison, Hanoch, & Wood, 2012; Lighthall, 2020 for review) and some evidence of reduced sensitivity to deception cues with age (Denburg et al., 2007; Asp et al., 2012; Castle et al., 2012; Ruffman, Murray, Halberstaft, & Vater, 2012; Ross, Grossman, & Schryer, 2014; Wood, Liu, Hanoch, & Estevez-Cores, 2016). This finding also supports age-related vulnerabilities identified in neuroimaging studies, including atrophy and decreased functional activation in areas relevant to detecting nuances of fraud such as the anterior insula and posterior superior temporal gyrus (Spreng et al., 2017), mid-temporal regions (Han et al., 2016c), right temporal and parietal regions (Lamar et al., 2020), and the vmPFC (Koestner, Hedgcock, Halfmann, & Denburg, 2016; Asp et al., 2012) and in frontal regions involved in deception/cooperation detection (Christ et al., 2009; Calso, Besnard, & Allain, 2020; El Haj, Antoine, & Nadrino, 2017).

Further, older adults tend to be more risk averse (White, Gummerum, Wood, & Hanoch, 2017) and focus on maximizing gains/minimizing losses (Ebner, Freund, & Baltes, 2006; Ross et al., 2014). More broadly, emerging evidence supports the notion that age is associated with an increased tendency to judge situations as unsafe (Butavicius, Taib, & Han, 2022; Grilli et al., 2020, Sarno et al., 2020). This finding is key because it illustrates that a unidimensional approach to FS decision-making (e.g., lacking incorporation of SDT-based metrics such as response bias) may mask important group differences and factors that strongly influence actual outcome (i.e., likelihood of falling for a scam). In addition, our results represent a novel contribution to the literature in that this response bias extends beyond the phishing context to include other types of stimuli as well (e.g., video-based advertisements, voice messages).

Incorporating SDT-based metrics is an important benchmark for future studies in FS-related decision-making, though their interpretive value in real-world settings remains unclear; for example, older adults' propensity towards considering most contexts as risky/unsafe may be protective in the context of fraud, but potentially maladaptive in the context of safe, non-misleading and potentially prosocial endeavors. We also posit whether this cautious approach reflects recent public messaging in recent years geared toward older adults, under the presumption that they must be more at risk for fraud victimization. For example, the majority of public health-style educational campaigns in the 21st century have focused exclusively on the older adult population (e.g., see Sur, DeLiema, & Brown, 2022), and in tandem have largely neglected younger adults as an at-risk group. It is possible that focusing educational targets on individuals in older adulthood is a misguided approach, particularly given that younger adults have demonstrated a habituation effect with technology (e.g., email monitoring; Vishwanath, 2016) and may be unaware of this potential blindspot in their judgment with regards to FS. Our results also highlight the relevance of including a variety of stimuli types beyond the phishing modality (e.g., video-based advertisements, voice messages) in order to capture real-world FS behaviours that extend beyond the computer.

6.1.2. Underlying Mechanisms in FS

Another central aim was to explore the psychological constructs that may explain variability in participant accuracy, and whether there are age-variant relationships; these questions are particularly salient given that we did not observe the anticipated decline in FS-related outcomes with age. We were particularly interested in contextual factors and individual differences that have been recently identified as central to fraud-related decision making (e.g., Modic & Lea, 2018; 2020) and may explain a lack of age differences or even superior performance amongst older adults. Importantly, though effects were large when analyzing age group differences on the ESD task itself, age appeared to be a less relevant factor when included in comprehensive modelling with other candidate predictors.

ToM was a moderately strong associate of FS depending on the performance outcome. Importantly, we found evidence of the hypothesized double dissociation of ToM skills in underlying FS performance across age groups; A-ToM was a significant predictor of better behavioural decision-making (i.e., making more optimal purchase decisions by resisting fraudulent offers), and C-ToM predicted discrimination-based decision-making (i.e., by accurately identifying deceit and false alarms, and discriminating between them). This aligns with our hypothesis suggesting that A-ToM may be particularly relevant in tasks with affective-based demands (e.g., purchase intentions; eliciting System 1 processing; Asp et al., 2012), while C-ToM may be important in tasks with deliberative-reasoning based elements (e.g., deceit detection and discrimination; eliciting System 2 processing; Spreng et al., 2017; Lieberman, 2007). Our results are novel as they represent the first investigation into the role of ToM in FS, including comparison across young and old age groups and with a diverse set of fraud outcomes (including affective-based and deliberative-based components). These findings contribute emerging evidence in support of overlapping ToM and decision-making networks (Shamay-Tsoory et al., 2006; Lieberman, 2007; Canfield et al. 2016) that are particularly relevant to FS-based judgements (see Kelley et al., 2023). Given that ToM is a marker of prosocial functioning across the lifespan (Preckel, Kanske, & Singer, 2018; Imuta et al., 2016), is impaired in various clinical populations (e.g., depression; Bora & Berk, 2016; epilepsy; Stewart et al., 2016; psychosis and schizophrenia; Bora, 2020; autism; Livingston et al., 2019), and holds clinical utility in predicting neurodegenerative decline (Henry, von Hippel, & Molenberghs, 2016). Our results provide initial evidence of the importance of ToM in FS, and ToM remains an important target for inclusion in future FS studies.

In addition to poorer ToM capacities, other robust risks for fraud were also identified, including decreased interpersonal trust. Contrary to our hypotheses and consistent with some recent work (e.g., Shao et al., 2019), both younger and older adults with *higher* interpersonal trust in our study showed more optimal purchase decisions. Consistent with hypotheses, those with lower trust exhibited inflated response bias (i.e., viewing all stimuli as fraudulent/unsafe; see Stanislaw & Todorov, 1998), though relationships were not conditionalized by age. Higher interpersonal trust also predicted higher accuracy in discriminating between fraudulent and legitimate stimuli, and this effect was stronger in younger adults. Trust has been associated with FS (i.e., lower levels of trust predictive of higher suspicion and rejection of genuine communications, and less accurate decisions; Hong et al., 2013) and decision-making more generally, and is relevant to many contexts including medical decisions (Lee & Lin, 2011) and financial literacy (Yu, Boyle, Mottolla, 2020). Empirical findings have been mixed, however, due to our limited knowledge of the relationships between trust and decision-making more generally (Shao et al., 2019; Bailey & Leon, 2019) as well as a lack of unifying definition and operationalization of this concept in the literature (e.g., "general trust"; Judges et al., 2017, Ebner et al., 2018 vs. "trust toward strangers"; Li & Fung, 2012; Poulin & Haase, 2015 vs. "naiveté"; Titus & Glover, 2001). Importantly, trust as a variable is often conflated with *credulity,* or a willingness to believe in the absence of reasonable proof (Shao et al., 2019), and a lack of distinction between these individual concepts in fraud research has likely suppressed important relationships.

Despite finding no significant mean differences in interpersonal trust in older versus younger participants in the current study, our findings align with research demonstrating that trust levels generally increase with age, and that this shift may be protective in terms of maintaining social abilities and connections (Kircanski et al., 2018) which preserves social cognitive skills that aid in fraud identification. Trust is essential for prosocial behaviour and those with lower trust tend to be less socially connected (O'Schilke, Reimann, & Cook, 2021), which has been identified as a potential risk factor for scam victimization in the elderly (Sur, DeLiema, & Brown, 2021) and indeed was associated with a nonoptimal "high suspicion strategy" across age groups in our study. Interestingly, C-ToM and A-ToM also showed moderately strong associations with trust in our study; individuals with stronger ToM capacities were also more trusting and better at discerning scenarios potentially involving fraud. This suggests that higher trust may be a marker of healthy interpersonal functioning in other domains (e.g., ToM), and supports evidence that stronger social cognitive skills portend a decrease in FS as reported here and by others (Sarno et al., 2020; Gavett et al., 2017; Mueller et al., 2020).

Consistent with our hypotheses, another important predictor of better FS outcomes was slower deliberation time, particularly for younger adults. These findings suggest that despite demonstrating stronger performance across outcomes, deliberation time is less relevant for older adults. Our findings align with some evidence to suggest that along with natural age-related slowing, older adults may sacrifice speed while making decisions on similar fraud detection tasks without significantly improving accuracy (Sarno et al., 2020). Further, deliberation time showed low to nonexistent correlations with FS outcomes at the zero-order level in the older adult group, suggesting that processing speed may have confounded any potential effects. Our results indicate that recent public health initiatives encouraging people to take time to think through decisions before acting on offers (e.g., the Take5 campaign) are particularly relevant to younger adults.

At the zero-order correlation level, there was also some evidence supporting the role of confidence in benefitting performance, but this contextual factor was not as relevant as ToM, deliberation time, and trust when included in comprehensive regression models. We also observed in follow up modelling that participants with higher confidence were less susceptible to fraud (i.e., higher deceit detection scores and lower false positive rate), which could reflect use of experience-based heuristics (e.g., “I know that the CRA and IRS do not ask for personal information via email”). In turn, a confident approach appeared unrelated to response bias and perhaps reflects excessive non-deliberative confidence (e.g., “Every email asking me to click a link must be fraudulent”). Although descriptive, our correlation analyses suggested that confidence held a relatively weaker association with FS in the older participants. However, restricted variance in the confidence ratings of older participants might explain why confidence did not moderate the age effect as we had hypothesized, and this limitation is discussed in more detail below. Finally, aligning with past applied decision-making work (Rolison, Hanoch, & Woord, 2012; Han, Barnes, Bennett, & Boyle, 2019), there was some evidence suggesting that older adults rated their confidence independent from performance. This observation might be explained by the fact that although confidence and decision-making accuracy are inherently confounded, older adults tend to use additional sources of information including expertise to make decisions (see Grimaldi et al., 2015; Zaval et al., 2015 for review). Further, higher confidence appears to facilitate more accurate discrimination when task demands exceed individual processing ability (O’Connor et al., 2022; Gamble, Boyle, & Yu, 2015); it is possible that our ESD task did not require heavy enough demands to elicit this association.

Other measures, notably age itself and neurocognitive constructs given prior attention in the literature, were not systematically or consistently linked to performance when contextual and social variables were included. Consistent with our hypothesis, age and traditional neurocognitive skills were less relevant to purchase intentions (Markovits, Doyon, & Simoneau, 2002; Stanovich & West, 1997; Stanovich, 2011), but contrary to our hypothesis, they were also less relevant to discrimination, in contrast from other findings supporting that individual differences in neurocognition are relevant to FS decisions (Grilli et al., 2021). We also did not observe the hypothesized moderation of neurocognitive skills being more relevant to younger adults than older, despite the fact that deliberative decisions tend to show more age effects than those that are experiential (Huang et al., 2015) and are particularly sensitive to aging. Again, it is possible that our ESD task did not elicit heavy task demands within the laboratory setting, or that other compensatory skills (e.g., ToM, trust) and contextual factors (e.g., deliberation time) were more relevant to FS decision-making. Aligning with recent work in cognitive aging (Ebner et al., 2020; Mueller et al., 2020), our results strongly support that neurocognitive skills appear to have a limited role in explaining variance in FS decision-making and are not as relevant when other factors (e.g, context, social cognition) are included in modelling.

Parallel work in decision-making and cyber-security literature suggests that higher education and experiential/lifestyle factors (e.g., familiarity with banking procedures, being targeted by scams, less internet use) are protective against fraud in older adults (Norris et al., 2019). The cohort differences observed here revealed that older adults engaged in more TV consumption and lower internet usage, and these factors showed moderately strong zero-order associations with FS outcomes. Their education level was also associated with ESD performance, perhaps reflecting a degree of cognitive reserve and attainment/life exposure. While these effects were not contributory in multifactor analyses that included age, they remain important targets for future investigation.

In sum, our data offer novel evidence that there are psychological markers (specifically, contextual as well as social influences) of vulnerability that increase likelihood of making erroneous fraud-related decisions across a number of real-world modalities beyond phishing. Using contemporary cognitive/affective ToM distinctions, we delineated the effects of various social cognitive contributors which appear more relevant to informing an FS risk profile than previously studied variables including traditional neurocognitive skills and age alone. We have also illustrated that these variables have nuanced relationships with different components of FS (i.e., behavioural and affective-based aspects vs. deliberation-based aspects), and that it is critical to study FS in a multi-factorial approach (i.e., by incorporating SDT-based metrics to capture response bias, for example). At the same time, our data extend previous work on individual differences in FS by modelling a diverse set of theorized predictors across young and older adult age groups, while controlling for a comprehensive set of relevant variables and demographic covariates previously linked with FS. While our findings provide only a partial explanation of performance, they offer valuable insight into the constructs that are less relevant to susceptibility, indicating where preventative resources should be focused (e.g., on younger adults with an emphasis on context-specific factors such as deliberation time; on individuals with social impairments) and where these may be less effective (e.g., with an exclusive focus on older adults, other specific demographic groups, or those with impairments in traditional neurocognitive skills).

6.1.3. FS Performance Patterns

We also explored the extent to which different components of decision-making on the ESD task were meaningfully associated, and whether accuracy in performance varied between participants. Decisions were overall highly error prone; no participant answered all questions correctly and mean performance ranged from 59% and 73% accuracy for younger and older adults, respectively.

In practical settings, misclassification of an offer or solicitation can result in fraud victimization and other consequences (e.g., neglecting to attend to pertinent tasks or correspondence). We note that the ecologically-valid nature of the ESD task, including inability to revisit stimuli, is specifically designed to mimic sophisticated scams that purport to come from well-known companies that are likely to be familiar to most participants (e.g., PayPal, Netflix). Based on average response rates across all participants and patterns between ESD components, it is clear scam susceptibility is not a “one size fits all” concept. In line with prior aging research (Denburg et al., 2007; Asp et al., 2012; Yao & Gozu, 2019), participants made more errors in detecting deceit when they had a strong preference toward buying the product or participating in the offer.

Further, there was a consistent trend across age groups of quicker deliberation time on the purchase intention condition compared to the deceit detection condition, suggesting that participants may have differentially engaged in depths of processing (see Stanovich, 1999) dependent on task demands and item prompts. Deliberation time also showed a strong positive correlation with deceit detection and an inverse relationship with purchase intention for fraudulent items. In addition, supporting recent evidence that confidence plays a role in decision making but may diverge from actual performance with age (Yu, Boyle, Mottola, 2020), findings indicated that stronger confidence was associated with more optimal decisions for younger adults only (r = .34), and not older adults (r = 1.12). Younger adults also showed high concordance between performance on different ESD components (purchase intention x deceit detection, r = -.39; i.e., if purchase intention was rated as high, deceit detection likely to be poor), while this relationship was non-existent in the older adults. With ceiling effect considerations in mind, this preliminary finding suggests that older adults may have used different information on which to base their decisions than the younger adults. Inclusion of likely assisted in better understanding the different approaches of younger and older adults.

One important consideration is whether old and young participants differed qualitatively in their approach to the ESD. As mentioned, prior work suggests that younger adults are less attentive to screen-based fraud deceit detection tasks due to stimuli habituation and employ more superficial reasoning when completing screen-based problem-solving tasks (Vishwanath, 2016; Amran, Zaaba, & Singh, 2018). Faster deliberation times apparently hindered accurate deceit detection across participants, supporting past suggestions that slow, more effortful and deliberative reasoning yields more accurate fraudulent judgments (see Yan & Gozu, 2012; Harrison, Vishwanath, & Rao, 2016; Li et al., 2016). In the current study, younger adults (M = 12.44 seconds) completed the ESD task faster than older adults (M = 21.18 seconds; t = -3.81, p = .004, g = .55; medium ES), perhaps reflecting less deliberation that contributes to FS. Although this pattern might be an artifact arising from laboratory conditions, internal time pressure (i.e., haste), or pressure generated by a perpetrator, may contribute to greater FS in the real world. Supplemental analyses suggest that “controlling” for processing speed did not erase the relationship between deceit detection and deliberation time in younger adults, and this is an important target for future experimental manipulation to examine the influences of affective framing (e.g., see Kircanski et al., 2018) and System 1/System 2 reasoning styles (e.g., see Jones et al., 2019) across age.

6.1.4. Ceiling Effects

Ceiling effects were observed for several study variables (i.e., individual confidence subscales in the older adult group) and it is important to consider how the truncated variance contributed by these participants may have influenced the model findings. Ceiling effects are particularly relevant in research establishing a baseline (e.g., for establishing change in serial assessment). For individuals at the ceiling, we assume that the maximum score does not represent their full capacity; it also hinders practitioner’s ability to detect decreases in cognitive functioning in the most capable individuals, and clouds comparison to other performances without such restriction in range. Ceiling effects are not uncommon in neuropsychological tests (Guilmette et al., 2020) and can be strongly associated with test misinterpretation and erroneous conclusions of brain damage (e.g., NAB Naming Test). Ceiling effects are particularly common in cognitive aging research (Harrington et al., 2017).

In this case, the relationship between decision confidence and FS outcomes is conditionalized due to the limitations of our data; because older adult confidence was at the ceiling, the obtained coefficients and associated effect sizes likely underestimate the true strength of the relationship in Models A, B, and C. If these variables showed an evenly distributed range of scores in the older adult group, we would logically expect the effect sizes with FS outcomes to be larger. The slope of the residualized regression line for older adult’s confidence was steeper than the younger adults’, but no significant interaction effect was found in the deceit detection model; without ceiling effects, it is possible we could have observed a significant interaction. In future work with the ESD task, it will be important to redesign and augment the confidence subscale by including more items and cross-battery analogues (e.g., confidence for other tasks).

6.2. Limitations and Future Directions

One explanation for the specificity of our results could be methodological; the novel ESD scale will require further investigation and cross-validation with a larger, diverse sample and differentiated age groups (e.g., dissociating young-old, middle-old, etc.). Due to sample size restraints in the present study, although the subgroup age ranges aligned with conventions in cognitive aging research within the fraud context, they lacked specificity in understanding the true nature of age-related changes across the lifespan due to the wide discrepancy between subgroups. Future research could consider extending our findings to middle age as well as earlier life phases such as late adolescence, given the central role of the internet in these age groups (Perrin & Duggan, 2015) and inclusion of these groups in recent studies (e.g., Ebner et al., 2020). Future study samples should also recruit patients with preclinical Alzheimer's disease/early mild cognitive impairment (Lichtenberg et al., 2016) to approximate true age-group differences, especially given emerging longitudinal evidence that decreased scam awareness may be a harbinger of pathologic cognitive aging (Boyle et al., 2019).

Another study limitation is that the ESD task may have not elicited enough emotional arousal to induce a "risk" context for participants, and thus the stimuli represented risk-avoidant scenarios with lower stakes. Research suggests that in this context, older adults would not experience a deterioration of their decision-making system and would be just as likely to exercise similar caution to younger adults (Samanez-Larkin et al., 2007; Rolison, Woof, & Hanoch, 2017). In this study, it is possible that they were not as susceptible to the persuasion tactics used in the ESD stimuli because they did not evoke a strong enough emotional response or emphasize realistic present-oriented events or payoffs (e.g., that may be approximated in a real-life scenario such as a classic "grandparent" phone scheme), or that task demands did not exceed their individual capacity (thus recruiting other skills such as confidence). Socioemotional variables and manipulation of mood/risk states are also important targets for future predictive modelling.

Restricted sampling and uneven subgroup sizes prevented us from understanding meaningful effects of chronological age on FS within groups. This is an important target for future studies given that middle age may represent a "golden era" of decision-making (e.g., the "sweet spot" of experience and skill; Agarwal et al., 2009), following an inverted "U" shape with advancing age. Our preliminary results supported that within the younger adult group, older age facilitated better deceit detection (r = .42), while in the older adult group this relationship was nonexistent (r = -0.12), suggesting a potential plateau of age effects across the lifespan. Given suggestion that prefrontal cortex dysfunction may be an important segmenting variable in identifying consumer groups that may be particularly susceptible to misleading advertising, future studies should also aim to link empirical findings to neuroanatomical correlates (see Lamar et al., 2020).

6.3. Conclusion

Guided by current perspectives on fraud risk within decision-making and aging research (Beach et al., 2013; James et al., 2014; Lichtenberg et al., 2015), we refined current operational definitions of FS by offering a methodological alternative to self-reported data and population-level statistics. It is our hope that the development of the ESD task will advance the field by emphasizing the importance of objective, behaviour-based, ecologically valid and psychometrically robust measures to assess dimensions of FS. In line with others (Kircanski et al., 2016; Wood et al., 2018; Shao et al., 2019), our approach has demonstrated that experimental manipulation of FS is a promising area for future research and has the potential to inform longer term interventions in the real world that can be tailored based on specific, individualized risk profiles amongst susceptible communities. As such, research with practically and theoretically informed goals should be prioritized in this rapidly growing field (Lea et al., 2009; Whitty, 2019) so that awareness campaigns are targeted to those who need them (e.g., young adults and those with interpersonal impairments, rather than elderly non-computer users).

Translation to real-world susceptibility is paramount to determine the true utility of predictors identified in the current study. Some initiatives in this regard are supportive of our results; for example, the Take 5 Campaign (developed by the Financial Fraud Action UK Group and The Metropolitan Police) encourages consumers to take time before immediately responding to messages. By emphasizing a time-buffer when interpreting potentially fraudulent communications, they endorse the peripheral/heuristic model of decision-making in the context of fraud. Younger adults, in particular, should take note of their relative heightened vulnerability to scams due to several metacognitive and interpersonal factors along with potential cohort effects (Vishwanath, 2016; Lichtenberg et al., 2016) that may be related to habituation and lack of experience.

In efforts to identify individuals at highest risk for fraud and provide targeted consumer education measures, it is clear that we have a ways to go. For example, it is unclear how the financial situation of fraud victims and other background variables may *mediate* their likelihood of engaging with fraudulent communications, and whether these relationships vary by fraud type; for example, some research suggests that individuals at financial disadvantage are more likely to fall victim to opportunity-based scams (DeLiema, Li, & Mottola, 2021), while other evidence indicates that persons with higher income and socioeconomic status are more likely to be victims of investment/financial fraud (e.g., see AARP, 2011; Policastro & Payne, 2015; Kieffer & Mottola, 2017). Further, people with physical and/or mental health conditions may be more likely to engage with fraudsters due to situational vulnerabilities such as loneliness, social isolation, and anxiety. Finally, personality factors have been known to interface with mood (Norris & Brookes, 2021), and it is possible that people with happier predispositions will be less likely to attend to the peripheral aspects of messages (i.e., cues to deception) and may be at greater fraud risk; on the contrary, it is also possible that people with lower baseline mood states may be at greater fraud risk due to impaired attention and concentration which thus reduces ability to detect deception cues. General models of risk and decision-making largely fail to explain what heuristics people use to differentiate legitimate and fraudulent messages; it is likely that extending this work to explore temporal effects (e.g, mood, emotion) and social cognitive factors (e.g., ToM) may provide a platform for broader contextual understanding of the mechanisms that underlie fraud susceptibility. Wider reviews to include offender characteristics (e.g., profiles of perpetrators) may also add value to this ongoing debate of who is most susceptible to fraud.

Real-world activities (such as resilience to fraud) require the individual to draw on an array of skills in tandem with context and accumulated experience. There is some evidence to suggest that everyday cognition is more robust to the aging process (Yeung et al., 2011) and some decision-making abilities may be more resilient to age (e.g., practical vs. social problems); in fact, older adults have been shown to perform better than younger adults on some everyday decision-making tasks involving the social context (Blanchard-Fields, Mienaltowski, & Seay, 2007), underscoring the notion that potential age-related differences may not be accurately captured by traditional cognitive measures alone. As summarized by Norris et al. (2019): “the majority of evidence and subsequent beliefs we have regarding the psychological factors associated with vulnerability to online fraud are at best anecdotal and at worst in danger of creating misleading paths (e.g., older people are “easy” targets)”; pp. 242. Given the limitations of current work in this field (i.e., insufficient grounding of psychological mechanisms, limited scope with regards to psychological theory), it is unlikely that attempts to limit fraud victimization will succeed. Policies designed to limit the impact of fraud should recognize the universal nature of compliance and that no single demographic is necessarily more or less vulnerable based on current evidence (Button et al., 2016). We are unable to stop the onslaught of fraudulent messaging, but we can limit its effectiveness via increased awareness and understanding. By gaining deeper insight into how and why fraud tactics work to exploit our already inherently flawed decision-making processes, we can create targeted, effective fraud prevention strategies.

As quoted by Berg (2015), “as a group, older people appear experienced, resourceful, and reflexive…they are consumers empowered with time, economic awareness and financial capability” (pg. 293). Indeed, the current study supports other work (e.g, Ross et al., 2014; Berg, 2015; Norris et al., 2019; Jones et al., 2019, O’Connor et al., 2022) underscoring that older people should not be considered as a particularly vulnerable consumer group, and that age does not tell the whole story. While older adults may be vulnerable in other aspects of their lives, the results of the present study are encouraging in that they continue to demonstrate resilience in many areas of everyday life. Nevertheless, analyzing deeper facets of decision-making (i.e., response bias) provide important considerations to better understand the potential consequences of different decision-making styles in everyday contexts such as susceptibility to fraud.

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Appendix A. Background on Fraud Susceptibility

6.4. Contemporary Perspectives on FS

Persuasive mechanisms are well researched across a variety of decision-making contexts, and a wide range of studies over the past 50 years have investigated individual differences among people in their ability to detect deception (e.g., see Ekman & O'Sullivan, 1991; Malone & DePaulo, 2001) with a goal to capture the essence of what underlies judgements in decision-making. The concepts of deception and truth have even been considered by great thinkers since ancient times, from Greek philosophers (e.g., Plato, Aristotle, Socrates) to Western philosophers (e.g., Kant). The ability to distinguish between cooperation and deception is a crucial advancement in the evolution of primate and human cognition and is considered a key component that defines complex, human-based social interactions (Brune & Brune-Cohrs, 2006). Detecting deception is also a key element of successful interpersonal relations in modern times (Rubin, 2017) that remains indispensable for effective communication in the 21st century (Walczyk et al., 2008). In particular, understanding changes to decision-making as we age has become increasingly salient (National Research Council; Carstensen & Hartel, 2006), with specific focus on the fraud context (Lighthall et al., 2020).

6.4.1. Definitions

Deception takes many forms, from personalized to generic, from financial to romantic. Investigations in psychology have typically defined deception as "an intentional and knowing attempt on the part of the message sender to create a false belief or false conclusion in the mind of the message receiver" (Buller & Burgoon, 1996; Zhou et al., 2004; Rubin, 2017). Deception may include falsification, omission, equivocation, and concealment. Fraud, in contrast, is a form of social engineering (Workman, 2008) which uses deception and other tactics to exploit victim vulnerabilities and manipulate individuals (e.g, into divulging confidential information).

A common fraud tactic involves spear-phishing attacks (Carr, 2011), which are targeted attempts to collect personal information from unsuspecting internet users. This approach is appealing due to its low cost, relative anonymity and widespread effectiveness (Carr, 2011). Further, its content is often undistinguishable from a legitimate email and usually evades modern spam-filtering strategies (Ebner et al., 2020). Spear-phishing is categorically different from spam (Hao, Syed, Feamster, Gray, & Krasser, 2009; Stone-Gross, Holz, Stringhini, & Vigna, 2011), which is typically conducted on a mass-market scale and sent in bulk, making detection by machine learning/text matching methods more likely. Other types of exploitation, such as sweepstakes scams and the notorious "grandparent scheme" rely on eliciting an intense emotional appeal that can often subvert the traditional decision-making process (Wood & Lichtenberg, 2017). Cognitively intact older adults often fall victim to these types of exploitation because they are relying on an evoked social need (e.g., wiring money to rescue grandchild from jail in a foreign country) and powerful persuasion tactics (e.g., urgency) rather than seeking other information to support or refute the evidence (Wood & Lichtenberg, 2017). Additional types of exploitation, including mass marketing fraud and false investment scams, also rely on persuasion tactics as well as sophisticated digital strategies (e.g., impersonating the victim's friend on Facebook for buy-in), which have become more prevalent in recent years. A final class of exploitation involves deception and coercion by trusted others (e.g., a friend, caregiver, or advisor) and the older adult may or may not be aware of the transaction. These cases may occur in many psychological contexts, from no awareness to implied consent, and may co-occur with other types of financial exploitation (Wood & Lichtenberg, 2017).

In this project, we focus specifically on fraud to describe cases with implied criminal deception intended to result in financial or exploitative gain. For ease of reading and to connect with current literature, unless otherwise specified we use the term 'fraud' broadly to include common instances of everyday coercion with the intent to mislead, including scams, phishing, spear-phishing, misleading advertisements, telemarketing, investment swindles, and romantic/dating fraud.

6.4.2. Deception Detection vs. Fraud Susceptibility

Classic deception detection is a meta-cognitive tool with central connections through the prefrontal cortex (notably, overlapping with the same neurocircuitry as theory of mind functions; Ruffman et al., 2012). It is most commonly studied in neuroanatomical research with a cognitive psychology focus (e.g., Prisoner Dilemma, cooperative-deceptive helping scenarios, misleading advertisements). FS, in contrast, represents a staged behavioural process (Modic, Anderson, & Palomaki, 2018) by which an individual is influenced by a variety of persuasive factors and exhibits biased decision-making, ultimately leading to inability to detect fraudulent communications. FS is also defined in terms of an individual's membership to a certain group of the population (e.g., older adults) based on demographic-level research on prevalence rates (e.g., Lichtenberg et al., 2016). FS is theorized to involve an array of influences including the social context and message factors themselves (e.g. elements of authority, scarcity, affect in deceptive advertisements; Fischer et al., 2013) as well as individual differences in motivation, emotion regulation, cognitive status, personality, self-control, trust, and experience/prior scam knowledge (Norris et al., 2019).

Empirical research in FS is diverse and multidisciplinary, integrating conceptual perspectives from a wide variety of fields including psychology (mainly with cognitive psychology or social psychology focus), criminology, consumer behaviour and economics, and gerontology. However, fraud researchers have not yet achieved a robust, testable theoretical model of FS to unify a somewhat disparate literature and guide empirical work; this dissertation will address this topic and attempt to incorporate findings from a diverse set of theoretical orientations.

6.4.3. Individual and Societal Costs of Fraud

Fraudulent crimes have critical impact on both the independent functioning of individuals in society (Wood et al., 2016) as well as broader societal and economic processes. Research has identified a number of serious physiological and psychological consequences associated with fraud victimization including: depression and anxiety, suicide, inflated rates of other mental and physical health declines (Alves & Wilson, 2008; Lichtenberg et al., 2015; Vishwanath et al., 2016; Wood & Lichtenberg, 2017; DeLiema, Mottolla, & Deevy. 2017), loss of trust (Shao et al., 2019), feelings of anger, shame, and remorse (Burnes et al., 2017; Button, Lewis, & Tapley, 2014), higher levels of withdrawal and social isolation (Han et al., 2016), and reduced life satisfaction (Lichtenberg et al., 2015; Norris et al., 2019). Amongst older adults, fraud victimization is also associated with higher rates of hospitalization and long-term care admissions (Dong & Simon, 2013) and mortality (Ebner et al., 2020). From an economic perspective, older adults typically cannot return to the workforce to recoup financial losses following exploitation, resulting in particularly devastating personal implications and broader societal impact (Shao et al., 2019). While less self-report data is available on younger adult samples in this regard (Norris et al., 2019), protection from fraud represents an important goal of both public health and crime prevention communities alike.

6.5. Measurement of FS

Almost as diverse as modern scams themselves, the current tools to measure FS are hindered by significant variability and inconsistent operationalization. The majority of published measures used to assess FS lack ecological validity, a major criticism that has influenced a push towards increasingly performance-based measures of exploitation risk in empirical work (Spreng, Karlawish & Marson, 2016).

6.5.1. Indirect Methods

The majority of studies focused on FS characteristics are based on retrospective reports and consumer complaints from actual fraud victims. Although such studies offer valuable insights into what might make people good candidates for fraud, research suggests that relative to victims of violent crime, fraud victims are unwilling to report their experience to the authorities (Van Wyk & Mason, 2001; Wood et al., 2016). Further, adults who have been victimized by fraud are also challenging to recruit for research studies (Spreng et al., 2017), hampering efforts to characterize risk profiles. Findings from previous studies may simply reflect the features of the sampled population (Jones et al., 2019), or could represent reporting errors or biases (James, Boyle, & Bennett, 2014). Data derived from epidemiological and population-based approaches also obscure meaningful differences in determining individual fraud risk (Norris et al., 2019) and are notoriously inaccurate due to widespread stigma surrounding fraud victimization (Spreng et al., 2017). As such, relying on prevalence rates extrapolated from consumer databases, documented reports, and criminal complaints on public record likely do not reflect FS (Spreng et al., 2017; Norris et al., 2019).

6.5.2. Direct Methods

In experimental work, researchers have adopted a vast array of approaches in their operationalization of FS as an empirical construct.

Self-Report Approaches. Some laboratory-based groups have developed a number of self-report scales to complement demographic-based surveys (e.g., the Susceptibility to Scams Survey; James et al., 2014; the Age Associated Financial Vulnerability Survey; Lachs & Han, 2015; the Financial Industry Regulatory Authority Risk Meter; FINRA, 2013; Susceptibility to Persuasion scale; Modic, Anderson, & Palomaki 2018). Other approaches rely heavily on the assessment of cognitive skills (Boyle et al., 2012; James et al., 2012; Marson, 2001) in tandem with self-report scales on fraud experiences. Some instruments using self-report inventories to assess a parallel skill, financial competence, have been clinically validated for use with adults, but neglect to include items specific to fraud/exploitation (e.g., the Financial Capacity Instrument - FCI; Marson et al., 2000; the Assessment of Competence for Everyday Decision-Making - ACED; Lai & Karlawish, 2007).

In general, scales and inventories have been criticized for their reliance on self-report information and unidimensional approaches (Norris et al., 2019), neglecting to address an important collection of factors that may be operating beyond the individual's consciousness during the decision-making process (e.g., context; interplay of cognitive, social, and emotional variables; individual differences).

Performance-Based Approaches. FS is also assessed via employment of hypothetical scenarios/judgment tasks that contain elements of deceit or ambiguity (e.g., product advertisements, sweepstakes lotto, phishing emails, investment propositions) delivered through various mediums (e.g., mail, smartphone, computer; see Vishwanath et al., 2011) to track differences in response patterns as a proxy for FS. In this context, FS has been characterized as a multidimensional behaviour involving (1) the likelihood of an individual responding to a fraudulent offer in the real world and (2) context-specific factors such as reaction time (Parrish, Bailey, & Courtney, 2009). Other more conservative approaches have quantified this outcome as a dichotomous measure of whether or not participants clicked on fraudulent hyperlinks (Vishwanath, 2015; Iuga et al., 2016), or gave their information to a phishing email request (Sheng et al., 2010).

Recent studies leading the narrative on the underlying psychological processes of FS (Yan et al., 2012; Oliveira et al., 2017; Jones et al., 2018; Ebner et al., 2020; Sarno et al., 2020; Hakim et al., 2020; Grilli et al., 2021; O'Connor, Judges, Lee, & Evans, 2021) have measured performance-based scale responses regarding (1) awareness of deceit and (2) ability to detect deceit, in the specific context of phishing emails. There has been limited extension to other modalities (e.g., telemarketing voice messages, video-based advertisements) in which fraud tactics are commonly employed, despite the fact that imposter scams and online shopping/consumer scams were the most commonly reported instances of fraud in 2020 (FTC, 2021).

6.5.3. Methodological Considerations

There are several relevant methodological considerations for study designs as the field pushes for higher ecological validity in FS research. For example, in FS role-play paradigms, participants are asked to use a character's account and determine which messages are fraudulent. As argued by Parsons et al. (2014) and Jones et al. (2015), these task designs limit ecological validity and prompt socially desirable responses, making them somewhat problematic measures of susceptibility. Parsons et al. (2014) also provided evidence of subject expectancy effects in these designs, showing that participants who were primed beforehand with the nature of the study (e.g., fraud detection) exhibited higher accuracy in identifying phishing emails. Evidently, methodological designs in this area that lack face validity hamper the integrity of the studies themselves and subsequent extensions. Research designs in which participants are sent phishing emails and their response rates are tracked likely hold the highest ecological validity in this area, followed by approximated lab-based tasks (e.g., see Luo et al., 2013; Vishwanath et al., 2016); hopefully, these studies represent a trend toward a growing literature that emphasizes the importance of generalizability to the real-world context without confounding priming/expectancy/observer effects (Norris et al., 2019).

As mentioned, the field also lacks a unifying classification system regarding types or categories of fraud, if differentiated at all (e.g., phishing vs. financial vs. romantic fraud). Further, a plethora of definitions exist concerning the nature of "fraud" depending on discipline and theoretical approach; this variability is directly reflected in the wide array of assessment tools used to measure FS. Inconsistency of findings may also be due to the use of tasks that are unsuitable for examining *robust* tendencies in FS and its relationships to individual difference variables; studies in this field often limit their distribution of accuracy scores in fraud detection by employing few items, or by using a small sample of study participants (Harrison et al., 2016; Wang et al., 2012). Further, FS studies often neglect to include a comprehensive set of measures to control for relevant variables when examining possible relationships (Jackson, Kleitman, & Stankov, 2016). Such methodological designs limit the validation of the relationships between FS and other variables and reduces our ability to pinpoint individual differences.

6.6. Summary

While the proliferation of psychological fraud research is exciting and relevant, progress is limited by inconsistent definitions, imprecise measurement, and poor study design. The field has generally emphasized a shift towards larger samples, more stimuli within FS tasks, sufficiently comprehensive sets of control variables, and more ecologically-valid experimental measures to address these issues. The specific interest of this dissertation lies in addressing these priorities by developing and employing an experimental tool to measure various aspects of decision-making in the fraud context.

6.7. Individual Differences in FS

As illustrated in the main body of the dissertation, protection from fraud evidently comprises a broad range of conceptual, pragmatic, and judgment abilities employed across a range of everyday settings. Both the content and context of fraud messages are designed to exploit certain behavioural and demographic "vulnerabilities" inherent to being human: for example, states and traits such as loneliness, impulsivity, greed, and naivete (Duffield & Grabosky, 2001; Norris et al., 2019). Even when primed with the possibility of being deceived, humans are notoriously poor lie detectors (Vrij et al., 2012); the robustly studied *truth-bias,* for example, suggests that people are more inclined to naturally assume truth rather than deception in interpersonal interactions (Rubin, 2017) and are able to correctly detect lies at an accuracy rate of only 54% (i.e., just above chance; Rubin & Conroy 2012). To date, the majority of psychological fraud research has largely addressed the role of age-related cognitive changes on decision-making with limited investigation into other individual differences or age effects in cohorts other than older adults.

Summarized in Figure A.1, findings in empirical fraud research indicate that scams indeed enlist a wide array of deceiver influences (e.g., persuasive messaging factors) that are designed to target and exploit weaknesses in decision-making (i.e., receiver influences) and thus increase FS (Ferreira & Lenzini; Fischer et al., 2013; Modic

& Lea, 2013; Whitty, 2013). Early experimental fraud research commonly focused on the nature and manipulation of the scam message itself (see Chang & Chong, 2010; Fischer et al., 2016; Harrison et a., 2016a), while more contemporary studies investigate the role of individual differences (i.e., both experiential and dispositional factors) which are relevant in the real-world context.

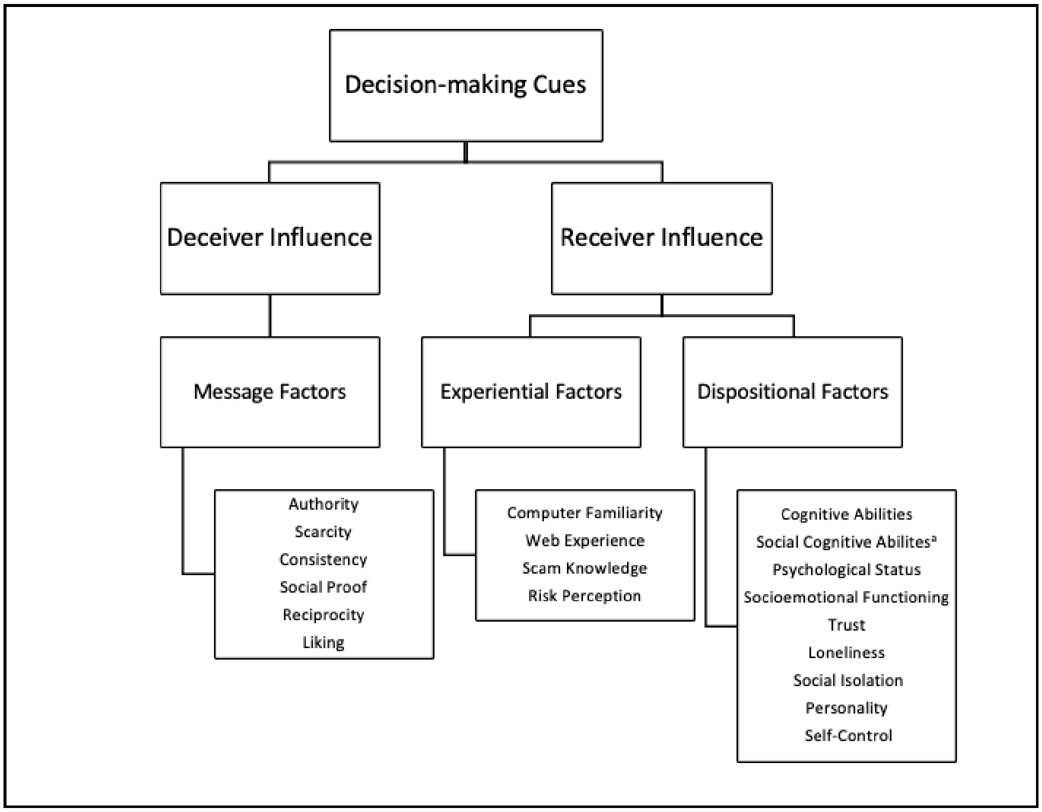

Figure A.1. Summary of proposed conceptual variables and processes relevant to FS. *Adapted from Norris et al. (2019)*

6.7.1. Deceiver Influences

Messages with features such as (a) strong source credibility (Luo et al., 2013) and (b) quality arguments have been identified as particularly effective in phishing scam simulations (Luo et al., 2013), as well as (c) time-limited elements (e.g., opportunities emphasizing the necessity of a quick response; Wang et al., 2012). Vishwanath and colleagues (2016) found that FS was more probable on a smartphone rather than other digital mediums (computer or laptop screen) due to increased cognitive demands of the smaller screen size and habituation (e.g., routine engagement) which were hypothesized to lower accuracy of email filtering. Findings from these types of studies, focused on message factors themselves, make the assumption that fraudulent victimization occurs when elements of the messages (both content and modality) produce “visceral triggers” (Norris et al., 2019) which reduce cognitive effort and lower the likelihood of accurately assessing the authenticity of the message.

Qualitative and quantitative research portray a consistent picture regarding relevance of message factors in the FS context (see Fisher et al., 2013 for review). Four critical features (i.e., message factors) make people more likely to respond to deceptive communications: 1) high motivation triggers based on the size of the reward; 2) trust generated by using “official” logos or authoritative language that distract from message content itself (i.e., source credibility); 3) social influence designed to gain compliance (e.g., liking, reciprocation); and 4) the urgency or scarcity of the opportunity (e.g., time-limited responses). Of note, mixed support for these four features are found in predictive modelling, concluding that other elements such as personality and decision confidence may have stronger explanatory power in determining who is likely to be victimized by fraud. Because the likelihood of FS is also linked to decision-making errors (e.g., via heuristics or judgement inaccuracies), findings suggest that message factors alone are insufficient in predicting FS. Other work on substantiated fraud victims found that vulnerability was not specific to the type of persuasive technique (Office of Fair Trading, Exeter University 2009). In sum, empirical findings support the notion that message factors in isolation cannot account for differences in FS – these findings lend further support for the relevance of individual differences in determining how fraudulent messages are designed, and who they are likely to exploit.

6.8. Receiver Influences

As discussed in the main body of the dissertation, literature on fraud shares a common conclusion in that the *individual* must be central to the fraud victimization process, a crucial determinant in explaining why “so many people all over the world, so often, react to completely worthless scam offers (Fischer et al., 2013, pg 2060).” When it comes to fraud, despite investment in sophisticated anti-virus software and firewalls, attacks continue because they exploit another inherent weakness in the system: the individual (Harrison et al., 2016b, pg. 265). Current receiver influences assessed in the literature can be broadly considered under two main categories (Norris et al., 2019; see Figure 1): *experiential* factors (e.g., computer familiarity, scam knowledge, risk perception; Modic & Lea, 2013) and *dispositional* factors (e.g., demographics, personality, social functioning, psychological well-being; Purkait et al., 2014).

6.8.1. Experiential Factors

Research on the expertise of the end-user suggests that resilience to fraud victimization is linked to knowledge of scams and security, higher levels of computer self-efficacy, and more Internet experience (Wright & Marett, 2010; Modic & Lea, 2013), though no consistent relationship has been found (Kleitman et al., 2018). Interestingly, internet usage patterns alone are not necessarily protective; individuals with significantly high, consistent email volume may actually be *more likely* to respond to fraudulent messages than those who use email less (e.g., habituation effect; see also Vishwanath, 2015). Other investigations (Zielinska et al., 2015) have compared computer novices and experts on their performance in logically connecting elements of phishing emails, suggesting that novices employ different, simpler strategies than experts when making decisions about deceptive messages which may help or hinder fraud detection. Supporting these findings, Harrison et al. (2016) found that email confidence, experience and knowledge significantly moderated the association between individual processing style and FS (with phishing attack scams). In sum, interactions between competence (e.g., usage/experience/knowledge about computers and scams) and other individual factors such as habituation, self control, processing style and engagement may explain how certain people become victims of fraud.

6.8.2. Dispositional Factors

A recent review examining fraud typologies and victim profiles (Button et al., 2016) concluded that “what is most striking about the scams is that the profiles cover almost everybody; hence almost anyone could become the victim of a scam” (pg. 24). Thus, although we can derive a list of demographic variations and cognitive characteristics of “the typical fraud victim,” (e.g., age, gender, personality, cognition), evidence suggests that individual psychological and social differences as well as context are critical in explanations of why some individuals are more likely to fall victim to fraud than others. As illustrated below, compromised decision-making may be influenced by other non-cognitive, non-age-related, context-specific factors.

Personality. Personality factors have been investigated as potential correlates with FS, though most studies failed to integrate any established psychological theory in linking results. A number of exploratory studies on the Big 5 personality characteristics have offered mixed findings; Pattinson (2011) found that only agreeableness was related to increased likelihood of FS, while other studies have identified risk factors including low conscientiousness (Chuchuen & Chanvarasuth, 2015; Judges et al., 2017), neuroticism (Cho et al., 2016), extraversion (Alseadoon et al., 2015; Lawson et al., 2020), introversion (Hong et al., 2013), impulsivity (particularly for financial rewards; Chen et al., 2017), and low self-control (especially for time-limited messages; van Wilsem, 2011; Reisig & Holtfreter, 2013). Pattinson et al. (2011)7 found that in general, personality factors were less predictive of FS than computer familiarity. Despite robust relationships between some trait variables and FS –such as trustworthiness and attention to stimuli (Purkait, 2012; Moody, Galletta & Dunn, 2017; Alseadoon et al., 2015; Halevi et al., 2015) – the vast majority of findings are inconsistent within the literature. For example, one of the Big 5 personality factors, Openness, correlated positively with detection accuracy in one study (Alseadoon et al., 2015) but negatively in another (Halevi et al., 2015). Other empirical work has reported low correlations between personality factors and phishing detection (r = -.11 to .18; Pattinson et al., 2011).

Heuristics & Biases. Some studies have examined FS through the lens of individual differences in heuristics and judgment errors. Chang and Chong (2010) identified affect, availability, and representative heuristics as relevant to the decision-making errors that result in increased likelihood of being defrauded. In addition, anchoring (the tendency to use previously learned information as a baseline for later decision-making) was found to compromise individuals’ ability to identify fraudulent websites (Iuga et al., 2016). In a report on substantiated fraud victims (Office of Fair Trading, 2009), people who showed above average vulnerability to scams were not poor decision-makers in general; rather, they appeared to demonstrate above average “openness to persuasion” in social interactions which the authors suspected was related to bias induced by message factors in the scams themselves.

[7] Of note, Pattison et al. (2011) used a role-play scenario to attain these results, an approach that has noted methodological limitations as highlighted in Appendix A section 1.2.3.

Social Norms. One particular source of bias in the decision-making process lies in social norms, which are rules of thumb based on social knowledge (Office of Fair Trading, 2009)[8]. Norm arousal is a classic means of persuasion (Doob & Ecker, 1970), and shared social norms are powerful determinants of decision-making that allow us to reach agreeable outcomes that may diverge from what would be predicted in rational choice theory, for example. The social norm of 'fairness,' for example, is influential in the widely tested experimental game called "the ultimatum bargaining game," because it operates to produce outcomes very different from those predicted by rationality (Thaler, 1988; Guth & Tietz, 1990). While the role of norms has not been examined in empirical work on FS to date, they are a well-documented bias present in decision-making research. Further, it is possible that scams are designed by negotiators who understand but do not share social norms that often govern behaviour. Scam content often activates specific norms that bias our decision-making process (e.g., fraudulent charities that show images of impoverished orphans to activate the basic helping norm; Batson, 1998; Doob & Ecker, 1970). Social networks have also been shown to induce social norms (Liu et al. (2017), supporting parallel evidence in population-based research that socially isolated people are disproportionately likely to be fraud victims (Lichtenberg et al., 2016).

Psychological and Socioemotional Functioning. Psychological vulnerabilities including depressive symptoms (Lichtenberg et al., 2016), loneliness (James, Boyle, & Bennett, 2014) and low social engagement/withdrawal (Lichtenberg, Ficker, & Rahman-Filipiak, 2015) have been associated with increased FS in some epidemiological work. In contrast, negative mood has also been linked to *lower* risk of FS, due to heavier reliance on context-specific, verbally-based cues (Forgas & East, 2008) and greater attentiveness to detail of messages (Matovic, Koch, & Forgas, 2014). It is well-established that detecting deception relies on the ability to monitor untrustworthiness and negative information, which may shift with advancing age (i.e., the positivity bias; Carstensen, 1992; Reed, Chan, & Mikels, 2014), potentially increasing the likelihood of making more risky decisions when potential loss is involved (Best & Charness, 2015; Tymula et al., 2013). Further, because of its reliance on nonverbal cues and more shallow information processing heuristics, higher mood (e.g., positive affective

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[8] Using a social norm is not inherently an error in judgment that leads to biased decision-making, but fraud victims have been shown to misclassify situations by believing certain norms to be relevant to their decision when in reality they are not (OFT Report, Study 3; 2009).

state) could impair one's ability to detect deception (Ebner et al., 2020). While the role of socioemotional functioning with regards to fraud offers promise, findings are mixed: Ebner et al. (2020) found that greater positive affect was actually associated with both *greater* fraud awareness as well as *lower* susceptibility in both middle-old and young age groups, with no significant effects observed in other age groups. Research on substantiated fraud victims suggests that targeted individuals were less capable in regulating and controlling their emotions (Office of Fair Trading, 2009).

Interpersonal Functioning. Some studies have incorporated other social variables into models of FS; amongst older adults, Lichtenberg et al. (2013) found that low social needs fulfillment was significantly associated with high fraud prevalence. This finding is consistent with the work of Liu et al. (2017), who found that daily negative interactions within one's social network was a unique and significant predictor of being financially exploited. These studies support the importance of considering the social world in FS models, with broader links to population-based findings that highlight the roles of loneliness and low social engagement in heightening vulnerability to fraud (e.g., see Lichtenberg et al., 2016). Indeed, more recent work devoted to the development of validated FS scales (see Modic & Lea, 2013; Modic et al., 2018) has highlighted the importance of social influence and interpersonal functioning in persuasion/decision-making models.

Appendix B. Theory of Mind Literature Review

Decision-making is a complex process that relies on integration of social appraisals with affective and cognitive information. As such, the capacity for monitoring and understanding mental state information (i.e., theory of mind; ToM; Premack & Woodruff, 1978; Brothers & Ring, 1992) is an important prerequisite in making appropriate decisions in the context of fraud. As mentioned, ToM functions are differentiated into cognitive and affective components that share overlapping neurocircuitry with deception detection; Ruffman et al., 2012).

6.9. ToM and Social Cognition

ToM is a powerful social cognitive tool that allows us to reason about others' mental states in order to better navigate the social world by decoding intent and predicting behaviour. It is defined as the ability to both understand and predict the behaviours of other people by making inferences about their mental states, intentions, feelings, and knowledge (Perner & Wimmer, 1985; Brothers & Ring, 1992); in essence, ToM describes the meta-cognitive ability of "putting oneself in another's shoes." ToM is widely recognized as a skillset unique to humans in response to increasing complexity of communication and social behaviours (Lissek et al., 2007). It is a cognitive mechanism that is always "online," (van der Wel, Sebanz, & Knoblich, 2014)[9] explaining the human tendency to sometimes ascribe mental states to inanimate objects such as cars (Brune, 2001). Given that ToM requires significant computational resources for monitoring (Lissek et al., 2007) and has been robustly linked to more traditional cognitive skills (e.g., executive functioning, semantic memory; see de Belvis et al., 2008; Fischer et al., 2014) as well as health (Fischer et al., 2016; Walzak & Thornton, 2018) and quality of life (Ahmed & Miller, 2013), it is unsurprising that defects in ToM result in severely compromised social competence (Happe et al., 1996). ToM impairments have also been described in an array of neuropsychiatric and neurodegenerative conditions (e.g., autism, schizophrenia, fronto-temporal dementia; Brune et al., 2008; Poletti, Enrici &

[9] As a result of replication crisis, recent work has called for theoretical and empirical distinctions of *factive* vs. *non-factive* ToM (e.g., what others know, see, or hear vs. beliefs in a false-belief paradigm). See Holland & Phillips (2020) for extended discussion on this topic. The majority of studies to date in the ToM literature have focused on non-factive mental states (Barone et al., 2019), including the present dissertation.

Adenzato, 2012) as well as in aging (Sandoz et al., 2014; Moran, 2013; Henry, Phillips, Ruffman, & Bailey, 2013).

6.9.1. The Multidimensional Structure of ToM

Contemporary perspectives on ToM support its categorization into distinct cognitive or “cold” (C-ToM) and affective or “hot” (A-ToM) domains (Shamay-Tsoory & Peretz, 2007; Kablbe et al., 2010; Wang & Su, 2013) with differentiated neuroanatomical structures (Kalbe et al., 2010) that overlap with (but are distinct from; Torralva et al. 2007) decision-making. It is important to note that although they conceptually overlap, A-ToM is not the same as empathy, which refers specifically to the experience of feeling and experiencing another person’s emotions (Shamay-Tsoory, 2011). Evidence suggests that while C-ToM skills, closely linked with executive functioning (Wade et al., 2015) robustly decline with age (Fisher et al., 2017; Walzak & Thornton, 2018), A-ToM skills are more resilient to the aging process (Baksh et al., 2018; Cavallini et al., 2016; Otsuka et al., 2021).

6.9.2. Predictors of C-ToM and A-ToM

A number of neuropsychological predictors have also been implicated in C-ToM expression among older adults specifically, including executive skills (Wang & Su, 2013), abstract reasoning (Ahmed & Miller, 2011), attention and working memory (McKinnon & Moscovitch, 2007), processing speed (Fischer et al., 2014), and semantic and episodic memory (Fischer et al., 2014; Fischer et al., 2017). Further, preliminary findings suggest that the relationship between C-ToM and non-cognitive risk factors such as vascular illness burden may be mediated by executive functioning (Walzak & Thornton, 2018).

While links between neuropsychological functioning and C-ToM are well established (Rosi et al., 2016; Sandoz et al., 2014; Moran, 2013), there is less empirical support for links between neuropsychological functioning and A-ToM (Duval et al., 2011, Li et al., 2013), partly due to lack of reliable control of cognitive variables within a single model (e.g., Cavallini et al., 2013, Yildirm et al., 2019). However, a handful of studies have suggested that poor A-ToM abilities appear to be associated with reduced executive functioning (Fischer et al., 2017; Wang & Su, 2013; Li et al., 2013) and semantic memory (Fischer et al., 2017). Research demonstrates more generally that intact ToM skills are an essential component of social communication skills (Cutting & Dunn, 2006; Moran, 2013) and may also predict greater engagement in social activities among older adults (Bailey et al., 2008; Rosi et al., 2016). Further, age-related declines in social functioning (Bailey et al., 2008; Lecce, et al., 2015) and social intelligence, defined as the ability to successfully cope with social context (Yeh, 2013), is, at least partly, attributable to a reduction in ToM skills. These findings suggest that ToM is an essential prerequisite for good interpersonal functioning in aging and that the age-related decline in ToM is potentially critical for older people's social adjustment which, in turn, impacts on cognitive and physical status (Leopold et al., 2009; Boyd, 2011) and thus everyday functioning. Nonetheless, the role of ToM in important everyday functions such as FS remains unexplored to date.

6.10. The Relationship Between ToM and Decision-Making

Neuroanatomical support for the potential link between ToM and decision-making in the context of fraud is emerging. The ventromedial prefrontal cortex (vmPFC) is one of the primary neural regions that has been implicated in decision-making under uncertainty (Xie et al., 2011), with additional recruitment of the amygdala, insula, ventral striatum, and dorsolateral prefrontal cortex as decisions become more transparent (Lawrence, Jollant, O'Daly, Zelaya, & Phillips, 2009). Interestingly, individuals with damage to the vmPFC have also demonstrated high intention to purchase products from misleading advertisements and were particularly credulous to misleading ads, relative to patients with other areas of brain damage and healthy controls (Asp et al., 2012). In another study on deceptive advertisements, cognitively-intact older adults and younger adults responded similarly to the misleading ads, but older adults with vmPFC impairment showed significant declines in their ability to detect fraudulent stimuli relative to the healthy age groups (Denburg et al., 2007).

Notably, these findings suggest a region of functional overlap between areas supporting risky decision-making and those supporting ToM (Xi et al., 2011). ToM relies upon the prefrontal cortex, with suggested dissociations between ventromedial regions supporting affective ToM and dorsolateral regions supporting C-ToM (Sebastian et al., 2012; Shamay-Tsoory et al., 2006). Brain regions supporting risky decision-making show greatest overlap with those supporting A-ToM (ventromedial prefrontal cortex), and potential overlap with C-ToM regions (dorsolateral prefrontal cortex) as decisions are more explicit, or when greater cognitive support is required to make a decision (i.e., as in older age; Rogalsky et al., 2012).

With the exception of some emerging empirical evidence reviewed in the main body of the dissertation, existing research has been limited in untangling whether reduced performance on laboratory tasks of ToM may translate into other areas of performance. But theoretical interpretations of empirical work are compelling; for example, one study found that individuals' engagement in a financial decision-making paradigm activated neural circuitry associated with ToM more closely than classical reward circuitry (Evans, Fleming, Dolan, & Averbeck, 2011). It is unclear how poor ToM performance in the laboratory may extend into real world vulnerability in areas such as risky decision-making (James, Boyle, & Bennett, 2014) and FS (Pinkser & McFarland, 2010).

6.11. Relevant Theoretical Models to ToM and FS

6.11.1. Individual Differences

In the context of a potentially fraudulent scenario, the individual is engaging in active decision-making about the credibility of the source and forming judgments about how to respond (Jones et al., 2019). In considering the array of proposed deceiver and receiver influences in the fraud literature that span psychological research and extend to other disciplines (see Appendix A, Figure 1.1), it is evident that a unifying theory is needed to disentangle and link these various constructs that help to explain individual differences in susceptibility (Williams, Beardmore, & Joinson, 2017). Although the exploration of individual differences in FS is relatively novel, particularly with respect to ToM, and there is no systematic literature to specify how these empirically established constructs may be connected, the individual differences approach has prevailed as a common lens through which to view FS decision-making (see Norris et al., 2019 for review). In this dissertation, we attempt to align a range of social cognitive and decision-making constructs that have not been analyzed in a single model before in order to better define the neuropsychological profile of a vulnerable individual. From related fields, there is reason to consider the predictive utility of several theoretical models related to individual differences which we explore and integrate below.

6.11.2. Neuropsychological Theories

Given that much of the work in fraud research concerns age-related cognitive declines, and older adults more generally, the frontal lobe theory of aging (Craik, 1986; West, 1996; O'Sullivan et al., 2001; West et al., 2002) is commonly cited in FS models and has relevance to ToM. Dominant in neuropsychological cognitive aging research, the frontal lobe theory posits that age-related cognitive changes in healthy older adults reflect anatomical changes in the frontal lobe, with specific deterioration of the prefrontal cortex (e.g., reduced cortical volume, increased white matter abnormalities, functional under- or over-activation; Cabeza et al., 2002; Raz et al., 2005; Fjell et al., 2009). These age-related structural abnormalities have been robustly correlated with poorer executive performance and weaker working memory (e.g., Raz et al., 2007; Cardenas et al., 2011; Salthouse, 2011). Some neuroanatomical researchers have extended the frontal lobe theory to include links to more classic deception detection skills, which are thought to lie in the prefrontal cortex and which mediate doubt (e.g., see Asp et al., 2012; false tagging theory). By linking frontal lobe dysfunction with deceit detection, some have argued that older adults are more vulnerable to inaccurate information and lack an appropriate level of doubt when filtering out misleading messages (Denburg et al., 2007; Asp et al., 2012).

Frontal Lobe Models of Cognitive Aging. Frontal lobe models generally take a global cognitive approach, neglecting to consider the important subdivision into the dorsolateral and ventromedial regions, which have demonstrated (a) differential rates of morphological change (e.g., see West, 2000) and (b) differential susceptibility to age effects (e.g., see MacPherson, Phillips, & Della Sala, 2003). For instance, while executive function and working memory are dependent on the dorsolateral prefrontal cortex, emotional regulation and social decision-making abilities rely on the ventromedial prefrontal cortex. Only the former set of skills have been established as robustly declining with age; age-related differences are not found in the majority of tasks dependent on ventromedial prefrontal dysfunction, supporting a specific *dorsolateral prefrontal* theory of cognitive changes with age (MacPherson, Phillips, & Della Sala, 2003; Otsuka et al., 2021) rather than a global decline in frontal-lobe function. More recent cognitive aging work has supported that frontal lobe decline is not uniform, demonstrating robust age effects on tasks involving executive function and working memory (i.e., tasks sensitive to dorsolateral PFC dysfunction; Wisconsin Card Sorting Task, Stroop Task), with relatively spared emotional processing and social decision-making (i.e., tasks sensitive to ventromedial PFC dysfunction; Gambling Task, Faux Pas Task). Importantly, ToM domains have also shown neuroanatomical differentiation (cognitive ToM – dorsolateral PFC, affective ToM – ventromedial PFC; Shamay-Tsoory et al., 2006).

Compensatory Models. Extensions of this theoretical work have addressed the apparent critical role of the frontal lobes in *counteracting* the effects of aging. The influential STAC model (The Scaffolding Theory of Aging and Cognition; Park & Reuter-Lorenz, 2009; for review see Reuter-Lorenz & Park, 2014) integrated structural and functional neuroimaging evidence with neuropsychological findings to propose that "behaviour is maintained at a relatively high level with age, despite neural challenges and functional deterioration, due to continuous engagement of compensatory scaffolding – the recruitment of additional circuitry that shores up declining structure whose functioning has become noisy, ineffective, or both.." (Park & Reuter-Lorenz, 2009, p. 10). The STAC model, in essence, provides an explanation for why healthy older adults do not show uniform declines in all cognitive and decision-making areas; by relying on scaffolding processes in the prefrontal cortex, they are able to compensate for declines in cognitive functioning as a result of changes in neurochemistry, neuroanatomy, and functional activation.

Predictions from the STAC model are supported by robust functional neuroimaging findings comparing older and younger adults that demonstrate (a) increased frontal activity paired with reduced posterior activity with age (posterior-anterior shift in aging; PASA model; Grady et al., 1994; Davis et al., 2008) and (b) reduced lateralization of prefrontal activity with age (HAROLD model; Cabeza, 2002). Both the posterior-anterior shift and reduction in hemispheric asymmetry have been attributed to functional compensation mechanisms (e.g., see Berlingeri et al. 2013; Cipolotti et al., 2015). In opposition to the frontal lobe theory, the STAC model offers a competing view that may explain a relative age advantage on fraud detection tasks; when the PFC is engaged while making judgments about fraud, it is possible that older adults could be bolstered by compensatory strategies (e.g., A-ToM skills) which may be protective against traditional age-related declines. More broadly, other relevant compensatory models (e.g., AIM; Samanez-Larkin & Knutson, 2015) capitalize on the gains predicted by socioemotional selectivity theory to illustrate how preserved crystallized abilities and age-related shifts in affective goals may collectively influence decision behaviours in a context-relevant way.

6.11.3. Critiques

While these key theoretical models of aging offer a compelling lens through which to consider the cognitive components of FS, they lack the specificity to understand precise aspects in the decision-making process that are targeted and exploited by a persuasive message (i.e., other variables in Figure 1.1). Further, they do not address lifespan or individual differences, which are frequently cited in fraud literature (e.g., Jones et al., 2018; Norris et al., 2019; Ebner et al., 2020). The creators of the STAC model later offered a revised version (STAC-r; Reuter-Lorenz & Park, 2014) to incorporate life-course factors (intellectual engagement, education, SES, stress, head trauma, cognitive training), but the model still lacks sufficient integration of the key variables cited as relevant to fraudulent exploitation (e.g., social factors), as well as explanatory power for other age groups of interest (e.g., younger adults).

Considering the process of fraud more specifically, converging evidence supports it as being a staged sequence: (1) plausibility of the offer, (2) interaction with the fraudster, and (3) losing utility to fraud (Modic & Lea, 2013; Modic, Anderson, & Palomaki, 2018). Supporting this idea, Lichtenberg et al.'s (2015) neuropsychological theoretical model of FS emphasizes a staged consideration of *contextual* factors including excessive persuasion, undue influence, and socioemotional functioning which directly impact neurocognitive abilities (*intellectual* factors) that underlie decision-making. However, application of this theoretical model to real-world fraud cases is insufficient, with minimal mapping to other important concepts or firm rooting in psychological theory (see Norris et al., 2019).

6.11.4. Dual System Theories of Reasoning

More broadly within individual differences and cognitive science, there is evidence to consider dual-system theories of reasoning (Stanovich, 1999; Kahneman, 2000; Evans, 2003; Lieberman, 2007a; 2007b) as being fundamental to the decision-making process in the fraud context[10]. Such theories posit that there are two psychological systems underpinning behavioural responses, and their differential deployment depends on both (a) the individual's characteristics as well as (b) the cognitive strain induced by the scenario. Dual-system models are defined by System 1 (intuitive; reliance on immediate and emotional responses) and System 2 (rational; reliance on measured, cognitively-involved responses) processing strategies to make decisions. While System 1 is usually dominant in decision-making contexts (Jones et al., 2018) and produces a response bias to endorse believable conclusions (Evans & Stanovich, 2013), System 2 reasoning allows for suppression of the intuitive response, increasing likelihood of hypothetical reasoning and consideration of future consequences (thus, seemingly better decision outcomes). Some studies have shown that individual differences (e.g., weaknesses in cognition; Markovits, Doyon, & Simoneau, 2002) may affect the probability of deploying System 2 processing, which in turn could impair deceit detection and other decision-making outcomes; these differences can occur between and also within subjects because dual-system reasoning also relies on context.

Common manipulations to demonstrate the evidence of dual processing are designed to either (a) increase System 2 processing effort through instruction or motivation, or (b) decrease System 2 responses by employing concurrent tasks that heavily load working memory (e.g., speeded tasks; Evans & Stanovich, 2013). There is also psychometric evidence which demonstrates that cognitive ability is strongly correlated with System 2 processing, whereas System 1 processing is not (Evans & Stanovich, 2013). Individuals with higher cognitive ability tend to demonstrate fewer belief biases (in theory, because they are more able to engage with System 2 thinking; Stanovich & West, 1997), but have been shown to employ better reasoning only if actually motivated to do so (e.g., by being specifically instructed to reason logically and draw firm conclusions; Stanovich, 2011). Similarly, neuroimaging evidence shows that when people are engaging in System 2 processing, the dorsolateral prefrontal cortex and parietal lobes – areas of the brain responsible for overriding the emotional brain (i.e., ventromedial/limbic circuits; Greene et al., 2004) – were more highly active. A

[10] This dissertation draws from dual-processing theories that are default-interventionist in structure (see Evans, 2007b; Kahneman, 2011; Evans & Stanovich, 2013), assuming that System 1 processing is the default, generating fast intuitive responses upon which System 2 processing may or may not interfere. This theoretical stance is in opposition to parallel-competitive theories in which both systems operate in tandem.

popular experimental approach to manipulate processing style (System 1 vs. System 2) is time pressure; for example, participants told to take their time and read the stimuli carefully in a susceptibility to email fraud study (Yan & Gozu, 2012), thus using a rational reasoning style, correctly identified more emails fraudulent compared to another group who was told to provide rapid responses upon first look (i.e., intuitive).

6.12. Application to ToM

Returning to the investigation of social cognitive variables in the context of fraud, it is evident that the differential ToM domains (C-ToM and A-ToM; Shamay-Tsoory, 2007) closely align with the theoretical perspective of dual-system models in social cognitive neuroscience (see Liberman, 2007a; 2007b), creating an explanatory link to illustrate how seemingly capable, cognitively intact individuals may be persuaded into exploitative or highly disadvantageous situations. Compelling work in social cognitive neuroscience, summarized in Figure 2.1, posits that different neural systems support *automatic* processing (the intuitive, reflexive *X-System;* the ventromedial prefrontal cortex, subcortical projections to amygdala) vs. *controlled* processes (the rational, reflective *C-System;* lateral prefrontal cortex, medial temporal lobe; Lieberman; 2007), constituting a core-processing distinction between neural regions during social decision-making. As shown in Figure 2.2, higher order ToM functions have been implicated in both the automatic X-system and the controlled C-system, and although not differentiated into components by Lieberman (2007), there are clear neurocircuitry overlaps with cognitive/affective ToM domains based on parallel neuroimaging lines of work (see Shamay-Tsoory, 2007). Further, Stanovich (1999, 2011) showed that individual differences are important in decision-making contexts when people are motivated by context and instruction to generate accurate responses.

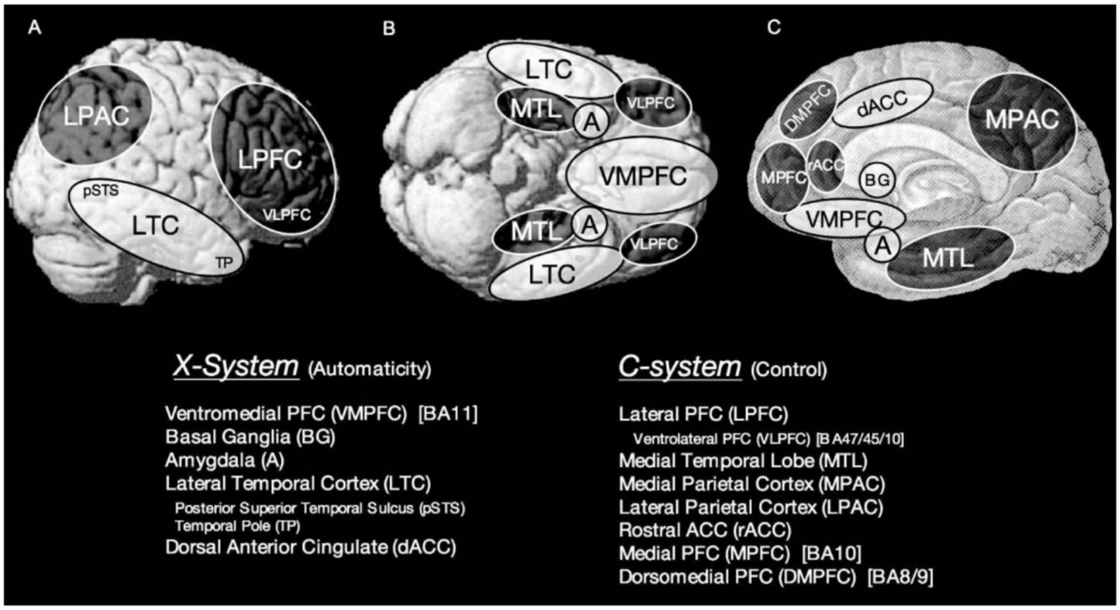

Figure B.1. Hypothesized neural correlates of the X-System (supporting reflexive social cognition/System 1 processing) and the C-System (supporting reflective social cognition/System 2 processing) on a canonical brain rendering from (A) lateral, (B) ventral, and (C) medial views. *Source: Lieberman (2007), pp. 262*

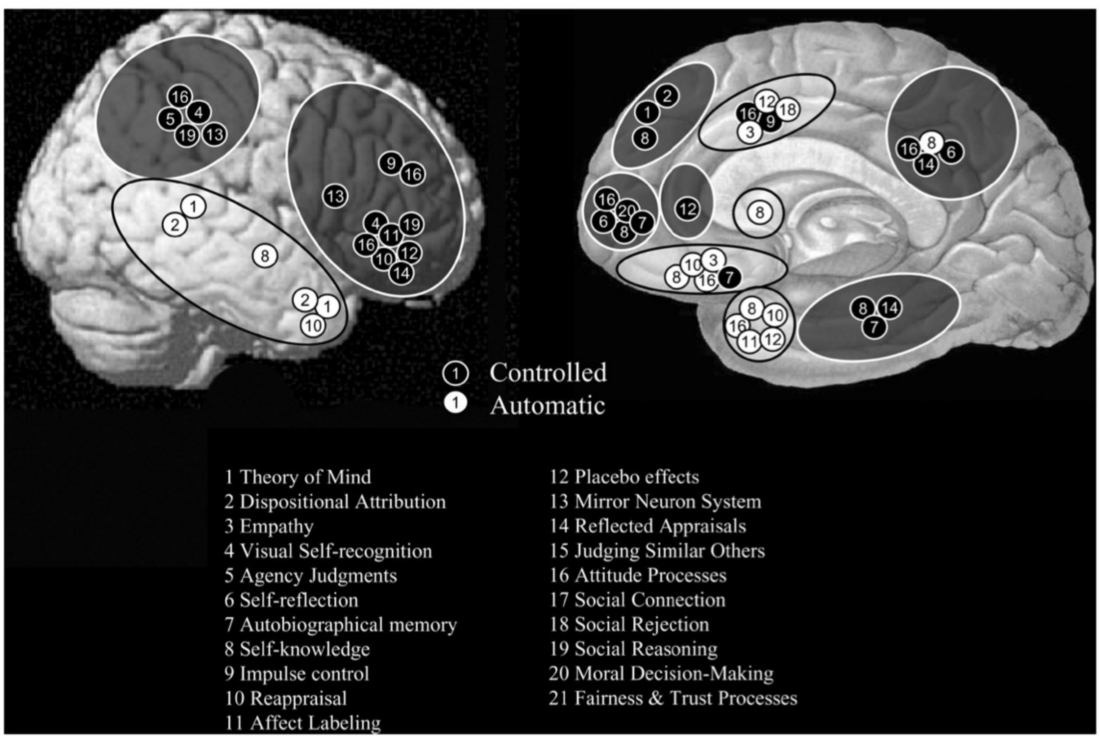

Figure B.2. Neural correlates of automatic and controlled higher order functions from multiple domains of social cognition. *Source: Lieberman (2007), pp. 277*

Note. Controlled (C-System/System 1) processes are represented by black circles and automatic (X-System/System 2) processes are represented by white circles. ToM functions are illustrated with (1).

Thus, from both a theoretical and neuroanatomical standpoint, there is strong rationale to consider the differential roles of cognitive and affective ToM in social decision-making, particularly within the fraud context.

Appendix C. Participant Recruitment and Data Preparation

Prior to main analyses, we checked the dependent and independent variables of interest for accuracy of data entry, missing values, outliers, and fit between variable distributions and the assumptions of our initial analyses and regression analyses. Prior to data screening, two participants (1 young, 1 older) were excluded following examiners' notes documenting low/inconsistent effort and/or inability to appropriately engage in the neurocognitive tests. All other cases were deemed appropriate and retained in screening analyses.

6.13. Missing Data

Decisions regarding missing data were based on the proportion of missing data and guidelines provided for the measures (i.e., total and subscale scores were not calculated if ≥ 10% of items were missing). Although there was a low proportion of missing data across all participants for the dependent measures on the ESD task (0.00%), sample sizes for other measures (e.g., Theory of Mind and Neurocognitive measures) varied across the sample due to time constraints and fatigue which occasionally limited collection of the full battery. Nevertheless rates of missing data were still negligible (21 out of approximately 1800 cells or ~1%), and as such, pairwise deletion was deemed most suitable to retain power by excluding cases that were missing data only for that particular analysis (Tabachnik & Fidell, 2013). Multiple imputation was used to impute missing ESCoT scores, using existing relationships between legacy C-ToM and A-ToM measures for the full sample, as described in the main body of the dissertation.

6.14. Outliers & Assumption Screening

At the univariate level, we examined normality using Q-Q plots and histograms for the demographic, neurocognitive, social cognitive, and ESD variables. Outliers were assessed on main study variables through inspection of z-scores for each variable to identify cases for transformation or removal. We used a pre-defined alpha of .001 to identify outlying cells on each variable (defined as those with z-scores greater than |3.29|

from the mean value of all other cells; Tabachnik & Fiddell, 2013). One case in the younger adult sample was flagged for falling |3.76| outside of the mean for Part B of the ESD Task; this participant was also noted to have fluctuating attention throughout the assessment and borderline English fluency on the language screening measure (responding with both English *and* another language for 3/4 criteria). When included in initial data screening for multivariate outliers (Mahalanobis' D^2, scatterplots of externally studentized residuals against centred leverage values), this participant was also an extreme outlier across the set of dependent variables and was excluded from the final sample. We examined variables separately for the remaining n = 76 younger and n = 46 older adults (final sample N = 122).

Descriptive statistics for each continuous variable were examined to determine the central tendency of the data (mean, median, mode), variability (range, standard deviation), and distribution shape (kurtosis and skew). The Shapiro-Wilk (S-W) test of normality was employed to test the assumption that the study variable distributions followed a normal curve ($p \geq .05$). Given that non-normality is less likely to be detected in smaller samples ($N < 2000$), the S-W statistic was chosen over the Kolmogorov-Smirnov (KMS) statistic as it is generally more sensitive to smaller sample sizes. Visual inspection of the scatterplots for the z-score dependent variables against each independent variable using general and lowess fit lines suggested pairwise linearity for each dependent variable. Further, no issues with normality were identified once the variables were translated into composite indicators. Thus, we retained z-score dependent variables for all subsequent analyses.

At the multivariate level, visual inspection of Q-Q plots and scatterplots for residuals using general fit lines and lowess fit lines suggested that, for each dependent variable, the spread of residuals was relatively uniform across values of the predicted scores. We then examined Cook's D, standardized DFBETAS, and scatterplots of externally studentized residuals against centred leverage values to assess for any cases with extreme influence for each dependent variable. After removal of the problematic younger participant described above, no cases emerged as influential multivariate outliers. Further, the regression models were not adversely affected by homoscedascity (i.e., using Fmax estimates) or multicollinearity between predictor variables (i.e., Low Condition Indices < 30). In sum, all parametric assumptions of multiple linear regression were met for all models.

Appendix D. Measures: Scoring & Sample Items

6.15. ESD Task

6.15.1. Development

Sampled from real-world settings, items were selected to address a number of deceiver influences (e.g., message factors – see Appendix A) based on important work by Fischer et al. (2013) identifying the key elements of persuasive messaging. Stimuli generally included high motivation triggers (e.g, by emphasizing high rewards, either monetary or wellness related), use of “official” logos and authoritative tone/language to boost source credibility (e.g., email headers from real companies, presentation of scientific data), aspects of social influence (e.g., charity requests for donations to people in need), and urgency or scarcity cues (e.g., emphasis on the time-limited nature of the opportunity). Given evidence from substantiated fraud victims demonstrating that vulnerability is independent of specific persuasive technique (Exeter, 2009), these message elements were not manipulated or analyzed separately. Rather, each stimuli contained a combination of these techniques to closely approximate real-world persuasion (e.g., a voice message from an “RCMP officer” requesting that the individual respond immediately with their personal information lest they avoid legal consequences for a CRA tax crime).

Half of the scenarios (5 items) in the ESD reflected genuine advertising that were reproduced in full with Fair Use copyright permissions for research purposes (based on an intellectual property rights analysis conducted by an SFU library specialist, June 2017). The legitimate items comprised the following stimuli: Costco membership (email), HerbaLife product advertisement (television commercial), Big Brother Vancouver newsletter (email), Red Cross Canada donation request (email), and TD Bank Loss Prevention Services (voice message). In turn, the other half of the scenarios (5 items) reflected false advertising where the authors’ intent was to mislead readers. The fraudulent stimuli included: Canada Revenue Agency tax crime scam (voice message), PayPal phishing attempt (email), Canada Revenue Agency income rebate scam (email), SeroVital bogus product advertisement (television commercial), and a Netflix phishing attempt (email; see Figure 1.4 for sample). The fraudulent and legitimate stimuli were matched where possible by including examples from the same types of companies (e.g., health and wellness) and similar requests (e.g., resetting passwords, confirming membership). Emails were standardized with font size kept constant.

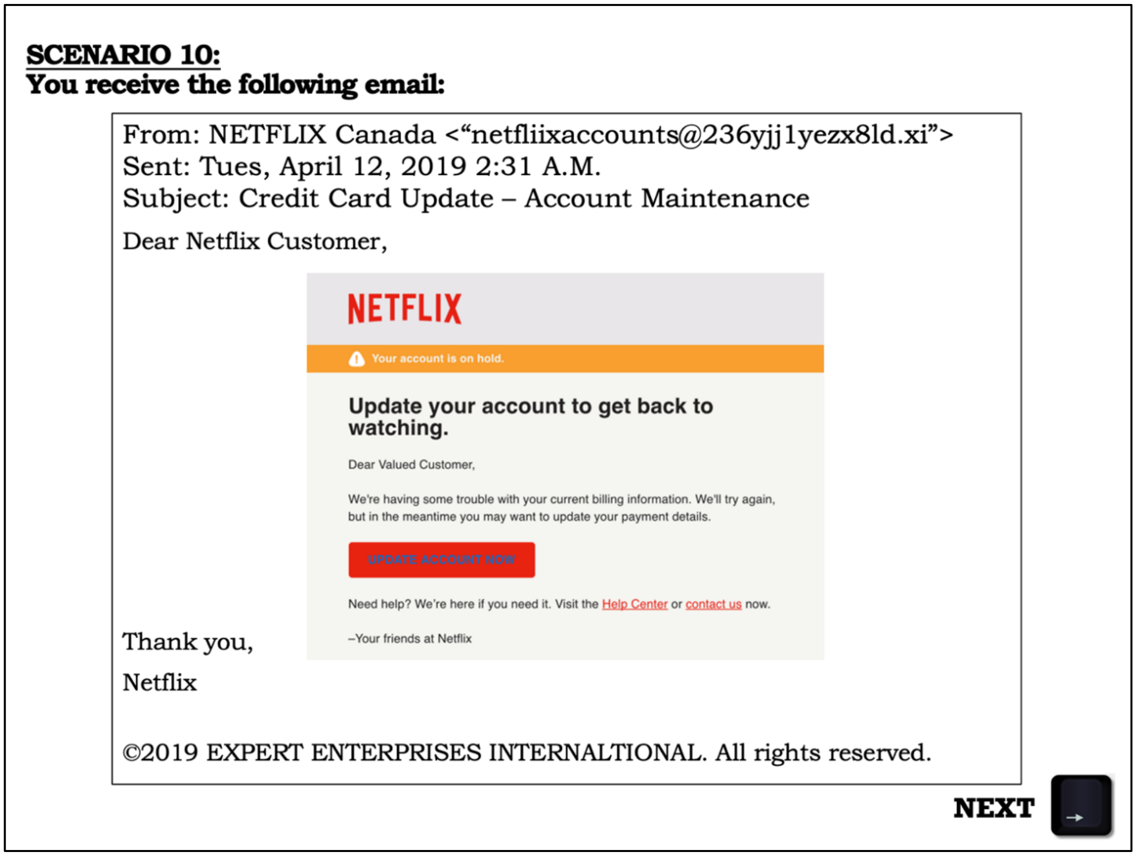

Figure D.1. Stimuli sample (fraudulent phishing email).

The measure was programmed using PsychoPy software (Peirce, 2009) and presented on a 22" Dell Professional P190S Monitor at a resolution of 1280 x 1040 pixels with participants seated approximately 20 inches away, making the visual angle of the display roughly 36° x 30°. Stimuli were presented one at a time on the screen to maximize face validity to real-world situations (e.g., emails on a computer, TV screen). This task was not time limited for the present study, but participants were not allowed to revisit scenarios after completing them in an attempt to simulate typical, realistic media exposure. The ESD was programmed with time manipulation features (i.e., item time pressure: a countdown clock in the corner of each stimuli; task time pressure: whole task constrained to 10 minutes) for future work.

6.15.2. Pilot Studies

In initial pilot trials (*n* = 8, *n* = 12), we included the first and last items as “control” advertisements at the beginning and the end of the task to minimize primacy and recency effects (as per the paradigm design presented in Asp et al., 2012). Primacy and recency effects have also been identified as important principles in impression formation research within social psychology (Bhargave & Montgomery, 2013; Petronko & Perrin, 1970). However, we found no measurable differences in response patterns to these items in our pilot samples, suggesting that participants did not place greater weight on the first or last item when forming judgments and confidence ratings. We thus retained Items 1 and 10 to contribute to the total score, which in turn increased range of sampling and strengthened psychometric scale properties.

In their post-experiment feedback, several participants mentioned that they disregarded the items because the scenario was not applicable to them (e.g., “I don’t have a Netflix account, so I didn’t even bother to read it”). Thus, we also revised the task after Pilot Study I to include tailored prompts in each item query, specifically instructing participants to place themselves within each scenario in order to better approximate real-world propositions (e.g., “*Assuming you are a Netflix subscriber*, how likely are you to click the link as requested to update your account information?”). This revision was designed in response to floor effects detected in the pilot sample (i.e., some participants tended to show weak saliency and discrimination across all items).

6.15.3. Signal Detection Theory

In research on judgment and decision-making, it is a well known platitude that nearly all reasoning takes place in the presence of some uncertainty (Heeger, 2007), and contemporary fraud research has emphasized the use of appropriate metrics to capture this ambiguity (i.e., SDT-derived scores). SDT offers both a precise language and graphic notation for analyzing decision-making variables in risky or uncertain contexts, providing direct application to the types of decision problems presented in fraud scenarios. Applied to the ESD task, SDT analyzes four possible decision-making outcomes when participants are asked to a) decide how interested they are in the advertisement and (b) make a decision about whether or not the advertisements they viewed were meant to mislead. The possible decision outcomes are as follows (Table

1.1): (1) hits (correctly classifying fraudulent offers as unsafe); (2) correct rejections (correctly classifying legitimate offers as safe); (3) misses (incorrectly classifying fraudulent offers as safe, i.e., missing the signal when it was present), and (4) false alarms (incorrectly classifying the legitimate offer as unsafe, i.e., detecting the signal when it was not present).

Table D.1. Conversion of ordinal scale data to dichotomized responses

		Stimuli	
		Legitimate	Fraudulent
Response	Likely (4-7)	False Alarm Score: 0	Hit Score: 1
	Unlikely (1-3)	Correct Rejection Score: 1	Miss Score: 0

Note. Participant is asked *"How likely is it that this advertisement is trying to mislead you?"* (1- not likely, 4- somewhat likely, 7- very likely)"

Both signals (fraudulent stimuli) and noise (legitimate stimuli) can be represented as distributions that vary in terms of the decision variable (here, deceit detection/credulity). Discrimination ability (*d'*) measures the distance between the signal and noise distributions. As *d'* increases, the distance between the distributions increases, and signal and noise are perceived as more distinct. The decision threshold, also known as *response bias*, is measured in terms of the distance from where the distributions intersect. The point of intersection is a decision threshold of 0, indicating no bias toward identifying stimuli as signals or noise. In this context of this project (and fraud studies more generally; see Canfield et al., 2019), a more negative decision threshold (i.e., lower response bias value) captures the tendency to perceive uncertain stimuli as fraudulent, or unsafe. Negative decision thresholds will be referenced as "cautious" (recognizing that trying to avoid rejecting legitimate emails is also a form of caution).

Response bias can be measured with a variety of metrics, the most common of which are Beta (*ß*) or Criterion c (C; MacMillan, 1999). *ß* has dominated SDT-informed FS investigations (e.g., see Canfield et la., 2016; Grilli et al., 2017; Jones et al., 2019; Sarno et al., 2020) and is effective in capturing whether performance differences are due to changes in sensitivity to misleading offers (*d'*) or response bias shifts (ß). However, response criterion C has been favoured in some recent work (e.g., O'Connor et al., 2021, Sarno et al., 2021) because its conservative and liberal bounds are more balanced. While *ß* scores are limited to 0-1 for lenient responders and can be any number above 1 for conservative responders (Green & Swets, 1988), in response criterion C, lenient responders have scores that are <0, conservative responders have scores that are >0, and unbiased responders have scores of 0 (Stanislaw & Todorov, 1999). To extend foundational work while acknowledging recent trends in SDT-informed research, we used *ß* scores in our main analyses and calculated supplementary response criterion C scores (Table X, below) for robustness.

6.15.4. Scoring Scheme

Raw scores on the deceit detection trial of ESD task were calculated using the following primary performance outcomes: (a) the offer was fraudulent, and the participant identified it as such (1 – hit; score of 4-7), (b) the offer was fraudulent, and the participant identified it as legitimate (0 – miss; score of 1-3), (c) the offer was legitimate, and the participant identified it fraudulent (0 - false alarm; score of 4-7), and (d) the offer was legitimate, and the participant identified it as such (1 - correct rejection; score 1-3).

Using this criteria, we derived ordinal sums for legitimate and fraudulent stimuli respectively (based on scale responses of 1-7 on each item) as well as a dichotomized accuracy sums (based on derived scores of 0 or 1 on each item). The scoring scheme for hits and false alarms by item is presented in Table D.2. Standardized false alarm rate was calculated by dividing the number of false alarms by the total number of legitimate stimuli, and standardized hit rate was calculated by dividing the number of hits by the total number of fraudulent stimuli.

Table D.2. ESD scoring scheme for detecting item-level hits and false alarms

	Response	
Scale Item	Hits	False Alarms
Legitimate/Email “Costco”		**YES** (4-7) no (1-3)
Legitimate/TV Ad “HerbaLife”		**YES** (4-7) no (1-3)
Fraudulent/Voice Message “CRA Crime”	**YES** (4-7) no (1-3)	
Legitimate/Email “Big Brother Vancouver”		**YES** (4-7) no (1-3)
Fraudulent/Email “PayPal”	**YES** (4-7) no (1-3)	
Fraudulent/Email “CRA Tax Rebate”	**YES** (4-7) no (1-3)	
Legitimate/Email “Red Cross Canada”		**YES** (4-7) no (1-3)
Fraudulent/TV Ad “SeroVital”	**YES** (4-7) no (1-3)	
Legitimate/Voice Message “TD Bank Loss Prevention”		**YES** (4-7) no (1-3)
Fraudulent/Email “Netflix”	**YES** (4-7) no (1-3)	

Note. Hit = YES response on signal (fraudulent) trial (/5); False alarm = YES response on noise (legitimate) trial (/5)

Discrimination (*d’*) scores were calculated by subtracting standardized false alarm rate from the standardized hit rate, where higher scores represent greater accuracy. To supplement the primary response bias (ß) metric in main analyses, we also calculated the Criterion C metric for robustness due to the measuring limitations of ß described above in regards to score boundaries. Criterion C was calculated by summing standardized hit and false alarm rates and multiplying by -.5 (see Stanislaw & Todorov, 1999 for more details), with scores farther from zero indicating greater bias in one’s responding. Negative values indicate a bias toward classifying offers as fraudulent and positive values indicate a bias toward classifying offers as legitimate. Trends were consistent irrespective of response bias metric; older adults uniformly demonstrated a cautious approach, in that they were more lenient/liberal in classifying offers as fraudulent relative to younger adults.

6.16. Cognitive ToM Measures

6.16.1. Strange Stories Test (Stories)

Stories is an advanced test of ToM that specifically assesses c-ToM (Happé, 1994; Happé et al., 1998). Originally developed for use in research on autism spectrum disorder, this test is now one of the most commonly used measures to assess ToM in aging (Happe, 1998). Stories has strong face validity, approximating everyday situations where participants are required to infer motivations that can lie behind everyday comments (i.e., double bluffs, mistakes, persuasion, and white lies). The test also includes control vignettes that require participants to make inferences about the physical causality of events. Performance on the control vignettes is used to tease apart circumscribed errors in ToM from difficulties with general story comprehension (Charlton et al., 2009).

Participants were encouraged to take as much time as needed to read the 12 vignettes and were not permitted to refer back to them once they felt they understood (see Happé et al., 1998; Happé et al., 1999). Participants were then asked one critical question to assess their understanding of each vignette, of the form "*Why did [the character] say/do that?*" As per Happé (1994), administrators could provide one standardized query to any unclear response.

Scoring criteria assessed completeness and accuracy of responses (*2* = complete & accurate, *1* = partial or implied, *0* = incorrect or irrelevant; Happé et al., 1998). Thus, to receive full credit, participants needed to make both a complete and accurate inference about the vignette content (whether ToM/control). When participants provided both correct and incorrect responses, the better answer will receive full credit. Similarly, if a response contained both mental state and non-mental state inferences, it was scored for the mental state. Scores were summed to represent total cognitive ToM performance (*range* = 0-16); where high scores on the ToM stories reflected more accurate understanding of mental states. Higher scores on control stories reflected good comprehension of story material.

Moderate to strong inter-rater reliability is reported for Stories across studies (94%, Fischer et al., 2013; see also 87%, Ahmed & Miller, 2011; 71%, Charlton et al., 2009; 87%, Happé et al., 1998).

6.16.2. The Reading the Mind in the Eyes Test – Revised (Eyes test)

The Eyes test is an advanced test of ToM that assesses affective mentalizing (Baron-Cohen et al., 2001); participants are required to attribute *emotional states* to each picture, and not infer about the content of each mental state. Originally developed for use in autism research, the Eyes test is now routinely employed in developmental and adult research to assess variability in affective ToM (Kirkland et al., 2013). Participants were presented with 36 black-and-white photographs of human eyes and asked to indicate which of four descriptors best represented what the person in the picture was feeling.

Administration of the Eyes test adhered to standard protocol published in Baron-Cohen et al. (2001), publicly available from the University of Cambridge Autism Research Center. Each pair of eyes was standardized for size (15 cm x 6 cm) and portion of the face that was shown (top of eyebrows to midway down the ridge of the nose). To control for variability in vocabulary between participants, we provided a glossary of all terms used in the test and encouraged participants to consult it any time during the test. Participants also completed a practice item to ensure grasp of the task prior to beginning the test, and made their responses by circling their descriptor of choice on a response sheet. They were given as long as needed to respond to each item and complete the task. Given that attribution of more basic emotions (e.g., happy, sad) show ceiling effects across populations (Baron-Cohen et al., 2001; Duval et al., 2011), only complex mental states that arise in social interactions were used in this test (e.g., jealous, panicked), and target mental states were matched to foil options. Items are scored as correct (1-point) and incorrect (0-points), and we summed the total number of correctly identified mental states to index affective ToM. Higher scores indicated stronger affective ToM (*range* = 0-36).

Research supports the Eyes test as having discriminant validity to distinguish clinical populations with ToM deficits from healthy controls (autism: Baron-Cohen et al., 2001; dementia: Fernandez-Duque et al., 2009), and it is commonly used in studies of ToM and cognitive aging (Bailey & Henry, 2008; Duval et al., 2011). However, despite its widespread use in the research context, internal consistency for the Eyes test is generally poor (e.g., Thornton, O'Rourke, & Thornton, 2017: ICC = .48; Vallente et al., 2013: ICC = .39).

6.16.3. Edinburgh Social Cognition Test (ESCoT)

Existing ToM measures carry a number of well-documented limitations in their use and application including: unitary assessment of ToM (neglecting differential cognitive/affective components; Duval et al., 2011, Baksh et al., 2018), performance predicted by measures of intelligence (suggesting measurement error; Henry et al., 2013), and low ecological validity (Shamay-Tsoory & Aharon-Peretz, 2007). To address some of these limitations, we used the ESCoT (Baksh et al., 2018) as an advanced measure of cognitive/affective ToM concepts to complement the Eyes test and Stories. The ESCoT is an animated test of social vignettes that assess four domains of social cognition: cognitive ToM (What is X thinking?); affective ToM (How does X feel at the end of the animation?); interpersonal understanding of social norms (Did X behave as other people should behave?); and intrapersonal understanding of social norms (Would you have acted the same as X in the animation?). Participants worked through one practice vignette with the examiner to ensure comprehension of instructions followed by administration of the 10 test vignettes. The four subscales were each scored for accuracy and completeness of verbatim responses (*range* = 0-30) and can also be reliably summed for a total combined social cognition score (*ESCoT total score range* = 0-120). Higher scores indicated stronger ToM performance and better understanding of inter/intrapersonal norms.

The ESCoT demonstrated strong sensitivity to age when administered to a healthy population of older, middle-aged and younger adults; across the lifespan, older age predicted poorer performance on cognitive and affective ToM subscales as well as interpersonal, but not intrapersonal, understanding of social norms (Baksh et al., 2018). The ESCoT has also been validated in a sample of adults with ASD, showing convergent validity with established social cognition tests (e.g. Eyes; r = .33; Baksh et al., 2020) and sensitivity to social cognitive deficits found in both healthy and clinical populations (Baksh et al., 2020). Furthermore, unlike traditional laboratory-based ToM tests, performance was not predicted by measures of intelligence in the test sample (Baksh et al., 2018). The ESCoT demonstrated strong inter-rater reliability (91%) between independent raters in preliminary analyses of pilot data.

6.17. Neurocognitive Measures

6.17.1. Executive Functions & Attention

The Color-Word Interference subtest (Condition 3) from the Delis-Kaplan Executive Function System will be used to assess *cognitive inhibition* (D-KEFS; Delis, Kaplan, & Kramer, 2001). Participants viewed a page of colour words printed in discordant-coloured ink and were required to inhibit their dominant response (reading the word) in order to perform a less-dominant task (naming the ink colour). The Color-Word test has demonstrated adequate reliability in younger and older adults aged up to age 89 (r = .75; Delis et al., 2001).

We used the Wechsler Adult Intelligence Scale-III (WAIS-III; Wechsler, 1997) Letter-number Sequencing (LNS) subtest to assess *working memory*. In this test, the administrator read aloud sequences containing numbers and letters and participants were asked to recall each sequence stating first the numbers in ascending order, followed by the letters in alphabetical order. The number of sequences correctly recalled was used to reflect working memory. The LNS subtest has been normed on Canadian populations, and demonstrates high split-half reliability in adults up to age 84 (test-retest; r_{xx} = .83; Wechsler, 1997).

To assess basic auditory attention, we used the WAIS-III *Backwards Digit Span* subtest (WAIS-III DS; Wechsler, 1997). This measure required participants to listen to sequences of numbers and recall them in reverse order. We used the number of correctly recalled sequences as our outcome measure of attention. Items of the WAIS-III DS subtest have demonstrated high internal consistency reliability across clinical populations (e.g., α = .92; Wechsler, 1997).

6.17.2. Numeracy

The WAIS-III *Arithmetic* subtest was used to assess numeracy (Wechsler, 1997). In this test, the administrator read aloud mathematical word problems and participants were asked to respond, with no time limit. The number of correctly answered word problems was used to reflect numeracy as well as concentration and reasoning. The Arithmetic subtest has been normed on Canadian populations and demonstrates good reliability in healthy adult samples up to age 90 (test-retest; r_{xx} = .63; Wechsler, 1997).

6.17.3. Processing Speed

The WAIS-III *Digit Symbol Coding* subtest (Coding; Wechsler, 1997) was used to index speed of processing. Participants are provided with a coding key of nine numbers, each matched to a specific symbol. Within a 120-second period, participants used this key to fill in rows of empty boxes with the symbol that correctly corresponded to the number indicated above each box. The total number of symbols correctly transcribed within the time limit served as an estimate of processing speed. The Coding subtest has been widely used in younger and older adults and demonstrates high reliability (test-retest; r = .84; Wechsler, 1997).

6.17.4. Semantic Memory

The Kaufman Brief Intelligence Test, 2nd Edition (KBIT-2; Kaufman & Kaufman, 2004) Verbal Knowledge subtest was used to assess participants' verbal intellectual functioning (i.e., semantic memory; Salthouse, 2009). The KBIT-2 is a brief, individually administered assessment of verbal intelligence that assesses knowledge of word meanings and general information. Reliability statistics presented in the manual for this measure indicate good internal consistency reliability in younger and older adults (*r*'s = .86 - .96; test–retest reliability = .88 - .92).

Appendix E. Statistical Analyses

6.18. Preliminary Analyses: Analytic Strategy

Prior to conducting primary analyses, we characterized the study sample by examining group differences in demographics, lifestyle, and psychological functioning/well-being. We analysed age differences and corresponding effect sizes using chi-squared tests/coefficient phi for categorical variables (small ES $\Phi \leq .10$; medium ES $\Phi \geq .30$; large ES $\Phi \geq .50$) and independent samples t-tests/Hedge's g (due to unequal group sizes) for continuous variables (small ES $g \leq .20$; medium ES $g \geq .50$; large ES $g \geq .80$; very large ES $g \geq 1.30$; Hedges, 1981; Cohen, 1998). We also explored neurocognitive and social cognitive performance between groups to ensure alignment with theoretical and empirical convention (e.g., age-related trends for crystallized and fluid skills; see Salthouse, 2009).

6.19. Primary Analyses: Analytic Strategy

Objective 1: Descriptive analysis of FS response patterns. We used zero-order Pearson and point-biserial bivariate correlations to investigate inter-relationships between ESD scale responses within and across age groups.

Objective 2: Age differences in FS. We conducted one-way between-subjects ANOVAs for each of (1) purchase intention, deceit detection, confidence, and response time as functions of age (younger adults vs. older adults). Primary FS findings were verified for robustness by analyzing age effects on SDT-derived parameters including (2) scale-based AUC-value, dichotomized accuracy score, hit rate, false alarm rate, discrimination [d'], and response bias [β] (Green & Swets, 1966; Stanislaw & Todorov, 1999) in line with recent approaches in fraud research (e.g., see Jones et al., 2018; Grilli et al., 2021; O'Connor et al., 2021).

Objective 3: Predictors and modifiers of FS. Prior to conducting regression analyses, we followed several steps in order to reduce the number of control variables included in analyses and to optimize model specification. We first examined bivariate zero-order and partial Pearson correlations between FS and the demographic, lifestyle, and neurocognitive variables of interest to identify control variables important for inclusion in final models. Only variables correlated with the respective FS outcome at an a priori cutoff of $r > .30$ (Cohen, 1988) were included in main regression models with candidate predictors.

We then verified that no multivariate outliers (i.e., determined by extreme values of Mahalanobis distance) or influential points (i.e., using Cook's distance <1.00) were identified (see Tabachnik & Fidell, 2013), and that our regression models were not adversely affected by homoscedasticity (i.e., using F_{max} estimates) or multicollinearity between predictors (i.e., low condition indices <30). Indicators of normality suggested that the FS data fell within the normal range and satisfied requirements for parametric testing (Tabachnik & Fidell, 2013); all other parametric assumptions of multiple linear regression (MLR) were verified for all models prior to running analyses, and model fit was verified using residual plots.

Hierarchical linear regression was used to determine the contribution of the primary continuous variables of interest (neurocognition, deliberation time, confidence, C-ToM, A-ToM, and interpersonal trust) to FS outcomes (Model A: Purchase Intention; Model B: Discrimination; Model C: Response Bias). As well, Age Group and Age Group moderating effects on continuous variables were evaluated. Age group (dummy-coded), demographic covariates, and neurocognitive performance were entered on Block 1. On the second Block centered scores for contextual factors (deliberation time, on-task confidence) and individual differences (C-ToM, A-ToM, and interpersonal trust) were entered. On the final Block the interaction terms were entered. The final model involved refinement by deletion of all non-contributory terms ($p > .10$) and any non-significant Age Group interactions ($p > 0.05$).

Interaction Effects. We tested for potential age group moderation effects on the final block in respective models (e.g., Age Group x confidence). As mentioned, continuous variables involved in interaction analyses were centered to reduce non-essential collinearity (Cohen, Cohen, Aiken, & West, 2003; Schielzeth, 2010). .Following the same steps as the main regression models, interaction terms between Age Group and the continuous variable of interest (e.g., age x cognitiveToM) were entered onto the fourth step, following entry of other predictors. If a significant $\Delta R2$ was found (i.e., demonstrating an interaction between age and cognitive ToM which accounted for a significant proportion of variance in Purchase Intention), results would suggest that the relationship between the variable of interest and FS varies depending on age.

6.20. Power Analysis

Objectives 1 & 2. To evaluate performance characteristics and the presence and magnitude of age differences in FS behaviours amongst younger and older adults, a priori power analysis suggested that a sample of 66 was required at an alpha level of .05 to detect a medium effect as per Cohen's guidelines. This calculation was based on an analytic approach employing one-way between-subjects ANOVAs for each FS outcome. Of note, recent studies (Sawyer et al., 2014, O'Connor et al., 2021) found effect sizes ranging from $\eta p^2 = .25$ to $\eta p^2 = .47$ to detect age differences in email classification tasks.

Objective 3: Given the novel nature of these research questions and lack of empirical guidance regarding effect sizes for similar research questions, we set our assumptions upon detecting a moderate effect size (Cohen's $f^2 = 0.15$ for regression analyses). Based on detecting an effect size of $f^2 = 0.15$ ($\alpha = 0.05$, $1 - \beta = 0.80$) using regression analyses with a set of nine independent variables in Objectives 2 and 3 (age group, fluid cognition, crystallized cognition, confidence, response time, cognitive ToM, affective ToM, interpersonal trust, respective age group interaction term) and one outcome (Model 1: Purchase Intention, Model 2: Deceit Detection, Model 3: Discrimination), Cohen (1992) recommended a sample size of $N = 93$ to yield reliable results. Our sample size of N = 122 per group exceeds these recommendations for all models and allows for more sophisticated modelling approaches in the future.

6.21. Ceiling Effects

To appraise ceiling effects, we calculated the number of individuals obtaining maximum, or perfect, scores (ceiling) in the respective age distributions (Table E.1). Analyses included main study variables and associated subscales.

Table E.1. Frequency of ceiling scores by age group

Variable	Younger Adults (*n* = 76)		Older Adults (*n* = 46)	
	Ceiling score	*n* / % at ceiling	Ceiling score	% at ceiling
Crystallized Cog.	1.70*	2 / 2.6	1.08*	3 / 6.5
Fluid Cog.	1.53*	1 / 1.3	1.49*	1 / 2.2
Global Cog.	7.13*	1 / 1.3	8.74*	1 / 2.2
Confidence	63.00	2 / 2.6	70.00	5 / 10.9
Fraud	35.00	1 / 1.3	35.00	9 / 19.6
Legitimate	32.00	6 / 7.9	35.00	7 / 15.2
Cognitive ToM	1.84*	1 / 1.3	1.05*	1 / 2.2
Affective ToM	1.72*	1 / 1.3	0.92*	1 / 2.2
Trust	24.00	5 / 6.6	24.00	2 / 4.3
Purchase Intention	34.00	2 / 2.6	35.00	3 / 6.5
Deceit Detection	35.00	4 / 5.3	35.00	5 / 10.9
Discrimination (d')	1.00*	6 / 7.9	1.00*	5 / 10.9
Response Bias (ß)	1.70*	1 / 1.3	1.10*	3 / 6.5

Note. *Because these scores were derived from pooled estimates rather than pre-existing scales, ceiling score represents highest score from distribution selected for ceiling, not absolute ceiling.

Of particular concern for primary analyses was the Confidence subscales in the older adult group, specifically given their relevance to age-group moderation hypotheses. As illustrated in Appendix F, we attempted to truncate the range of the confidence variables with ceiling effects in order to more closely approximate a normal range of performance scores, as well as apply logarithmic and reflected transformations. However, this adjustment did not alter model findings. There is also a systematic relationship between subscales demonstrating ceiling effects and affiliated reliability estimate (i.e., the presence of ceiling effects lowers the reliability estimate; Liu et al., 2021). In this project however, reliability estimates for the study variables in question fell within adequate range (>0.70; Strauss, Sherman, & Spreen, 2006).

Appendix F. Supplementary Tables & Figures

Table F.1. Sample characterization of health conditions by age group (% diagnosed)

Variable	Younger Adults (*n* = 76)	Older Adults (*n* = 46)
Hypertension	2.60	38.10
Type II diabetes	0.00	14.30
High cholesterol	0.00	31.00
Cardiovascular disease	1.30	19.00
Osteoporosis	0.00	35.70
Osteoarthritis	0.00	25.00
Rheumatoid arthritis	0.00	9.50
Thyroid dysfunction	1.30	14.30

Note. Vascular and nonvascular risk percentages include all individuals who self-reported a physician's diagnosis of condition at time of testing and were currently being treated for condition at time of testing

Table F.2. Mean neurocognitive and social cognitive performance by age group

Variable	Young Adults (n = 76)	Older Adults (n = 46)	t-test statistic	Effect size *g*	Correlation with Deceit Detection	Correlation with Discrimination
Semantic Memory	46.75 (6.02)	53.89 (4.71)	-6.87***	-1.29	.17	.19*
Numeracy	13.74 (3.21)	11.26 (3.63)	3.92***	-.03	.04	.02
Working Memory	11.18 (2.73)	8.67 (2.58)	5.02***	+.91	-.12	-.05
Inhibition[a]	44.57 (8.01)	77.39 (6.29)	-8.51***	+1.32	.22*	.20*
Auditory Attention	9.13 (1.53)	6.46 (1.66)	8.90***	+.10	-.22*	-.09
Processing Speed	85.79 (13.84)	55.10(15.38)	10.75***	+1.40	-.23*	-.13
Cognitive ToM	21.13 (3.94)	18.17 (5.17)	3.56**	+.74	.10	.31**
Affective ToM	22.43 (4.00)	19.02 (3.96)	4.59***	+.93	.10	.24**
Interpersonal Trust	16.88 (5.39)	16.39 (6.33)	.44	-0.08	.37***	.45***

Note. We present means and standard deviations as M (SD). Semantic memory = KBIT-II Verbal Knowledge subtest (range: 0-60); Numeracy = WAIS-III Arithmetic subtest (untimed; range: 0-22); Working memory = WAIS-III Letter/Number Sequencing subtest (range: 0-21); Inhibition = DKEFS Color/Word Trial 3 score (seconds); Auditory attention = WAIS=III Backwards Digit Span subtest (range: 0-15); Processing Speed = WAIS-III Digit Symbol Coding subtest; Cognitive ToM = ESCoT Cognitive score (range: 0 -30); Affective ToM = ESCoT Affective score (range: 0-30); Interpersonal Trust = World Values Interpersonal Trust score (range: 6-24). Effect sizes are reported with (+) indicating a younger age advantage and (-) indicating an older age advantage.

[a]Response Inhibition scores represent a timed measure, with higher scores indicating slower/worse performance.

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

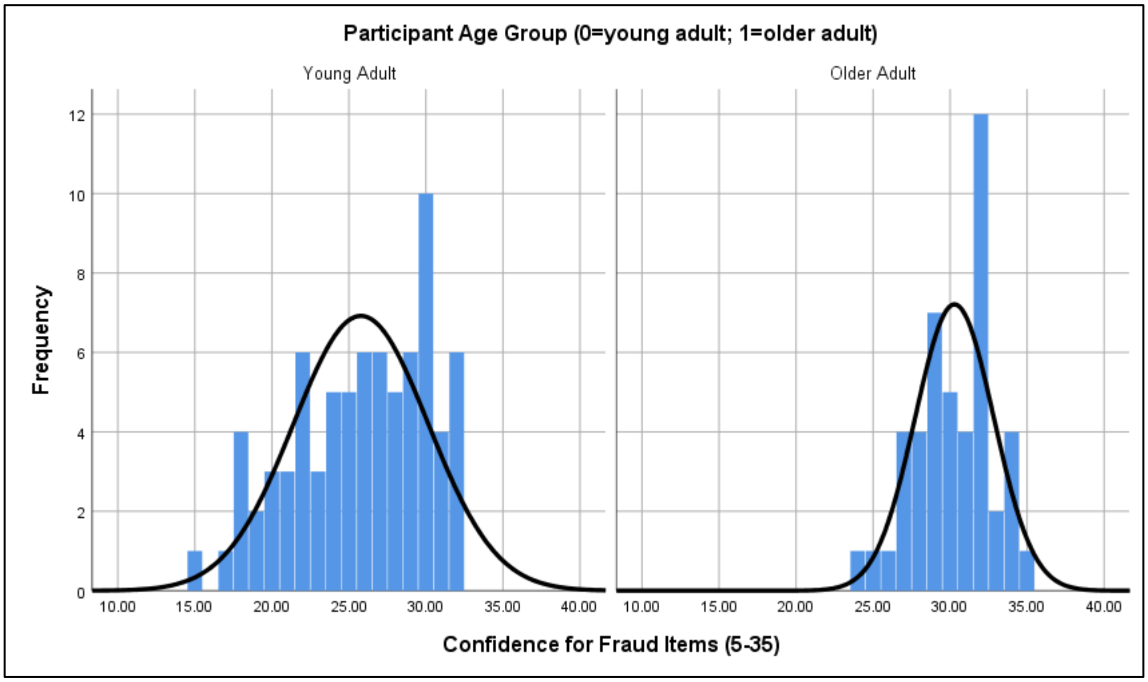

Figure F.1. Confidence Distributions – Fraud Items

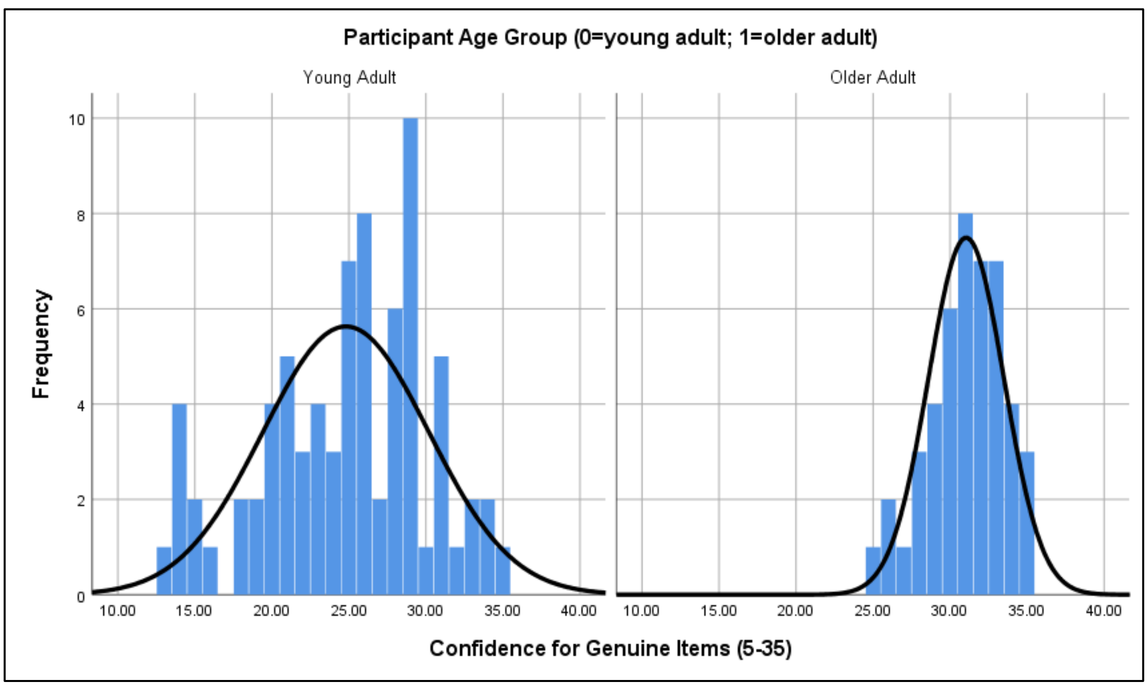

Figure F.2. Confidence Distributions – Genuine Items

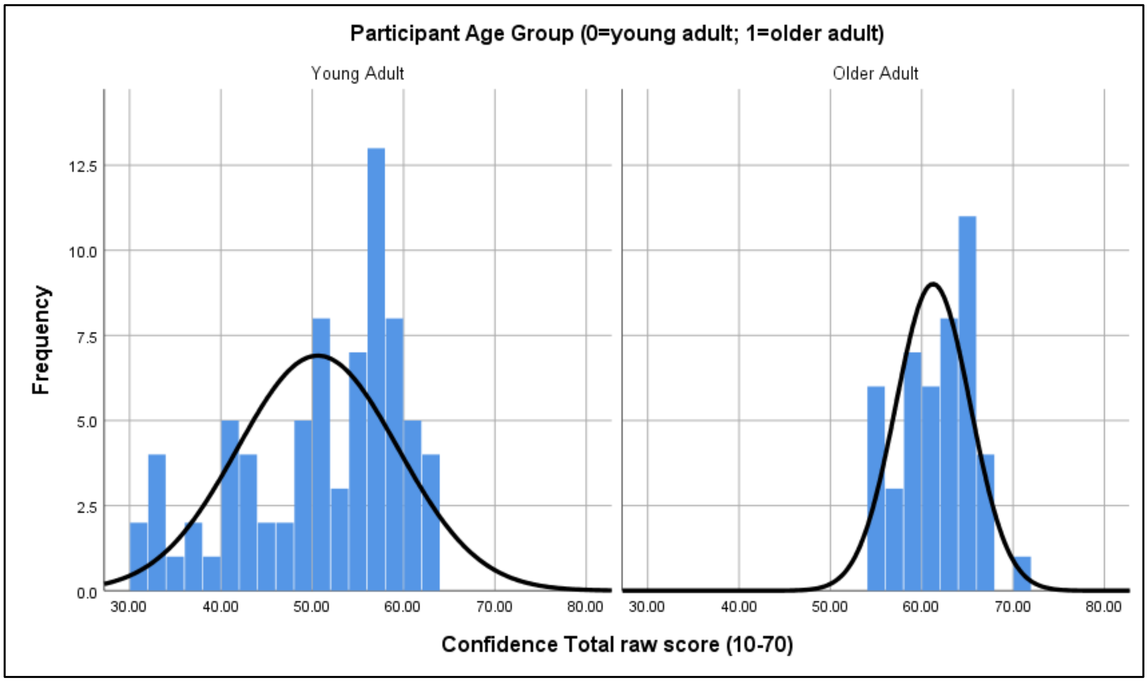

Figure F.3. Confidence Distributions – Total Score

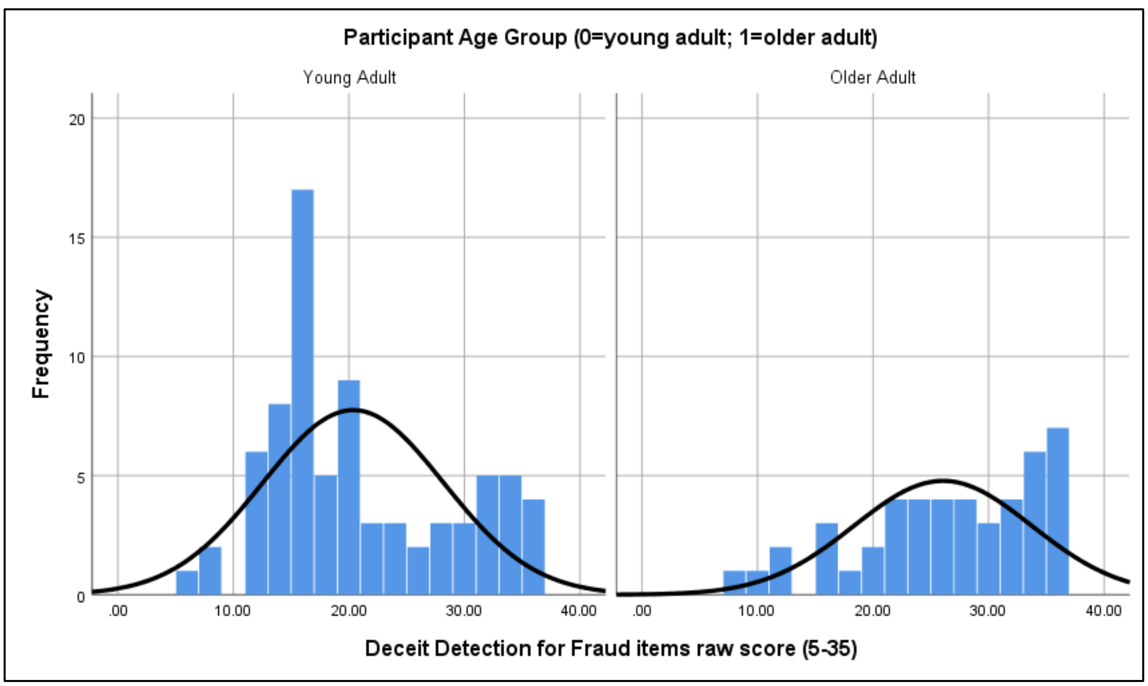

Figure F.4. Deceit Detection Distributions

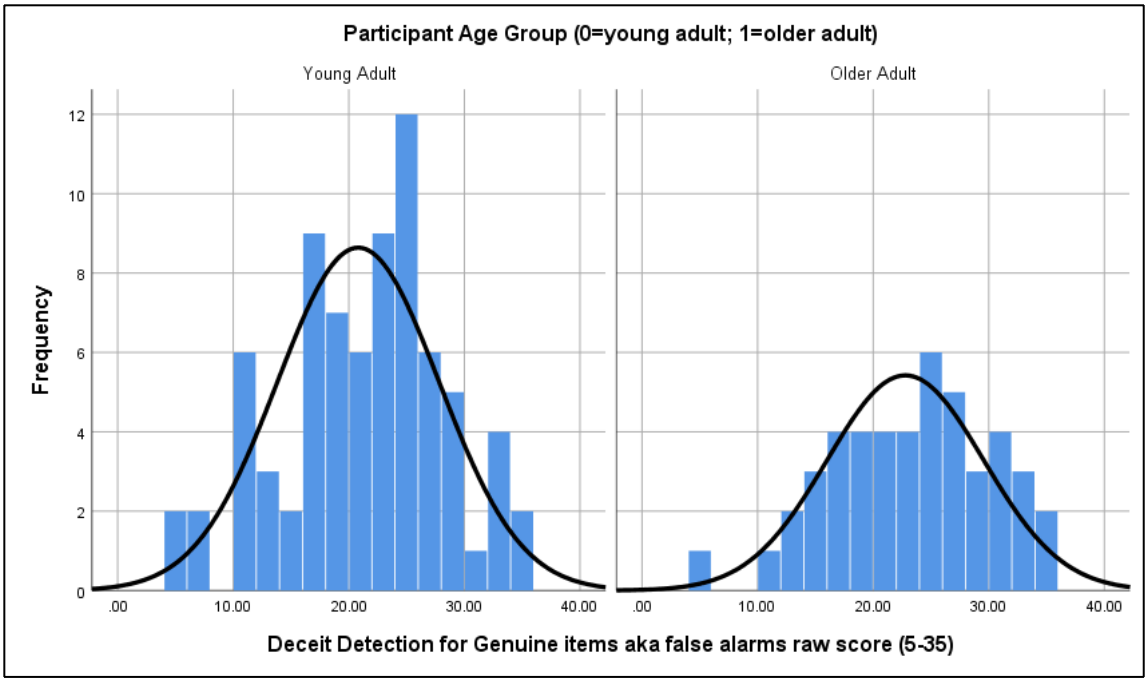

Figure F.5. False Alarm Distributions

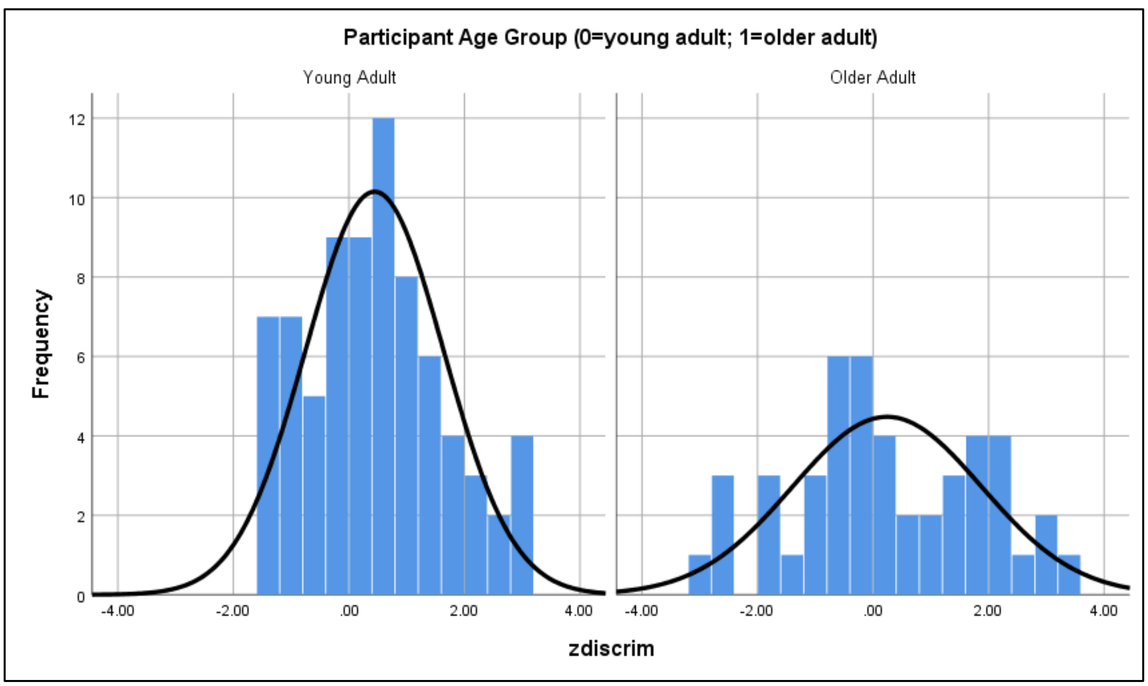

Figure F.6. Discrimination Distributions

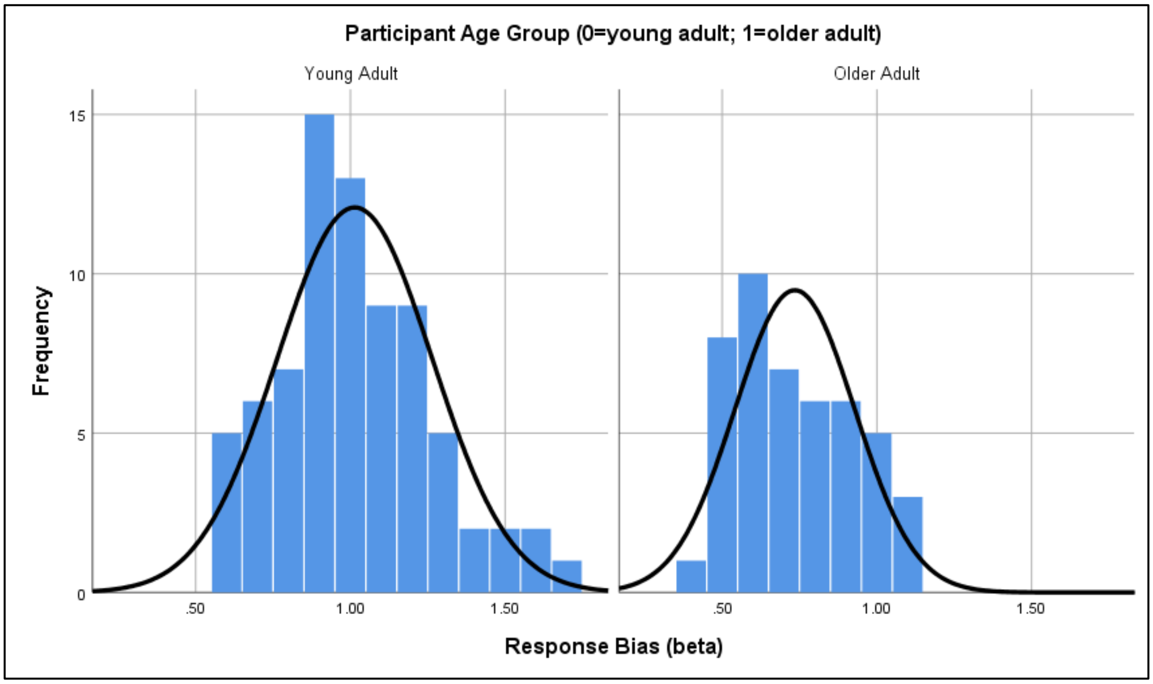

Figure F.7. Response Bias Distributions

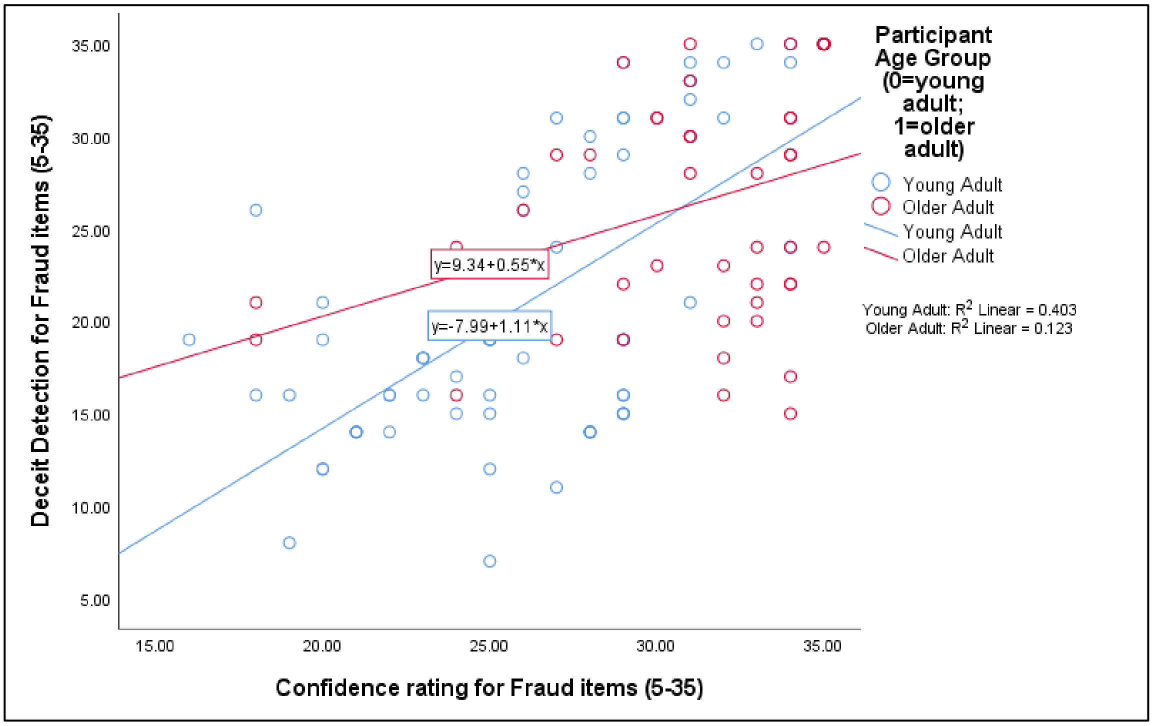

Figure F.8. Confidence rating x Deceit Detection score: cut confidence score >15

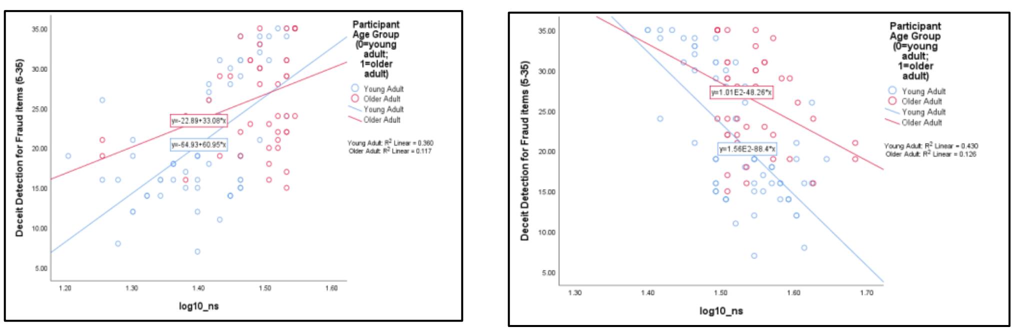

Figure F.9. Confidence rating x Deceit Detection score: log10 transformation and reflection

Reflecting and log transforming the confidence variable did not optimize the model (e.g., by revealing a significant age group x confidence interaction term), nor did truncating the range of confidence scores from 15, 25, and 28 in order to see if there would be an effect. Further, as shown in the 95% prediction interval lines (similar to confidence intervals, but for the predicted value of y), the standard error of the point estimate in modelling is large, reflecting the lack of data for the older adult group. Thus, interaction terms including confidence contain large standard error and suggest a sampling issue. There was some indication that an interaction may exist, but thoroughly investigating that effect would require a larger sample of older adults. Due to the theoretical (eg., psychological) reasons to suspect an age-confidence interaction may exist, we intend to study it further in future work.

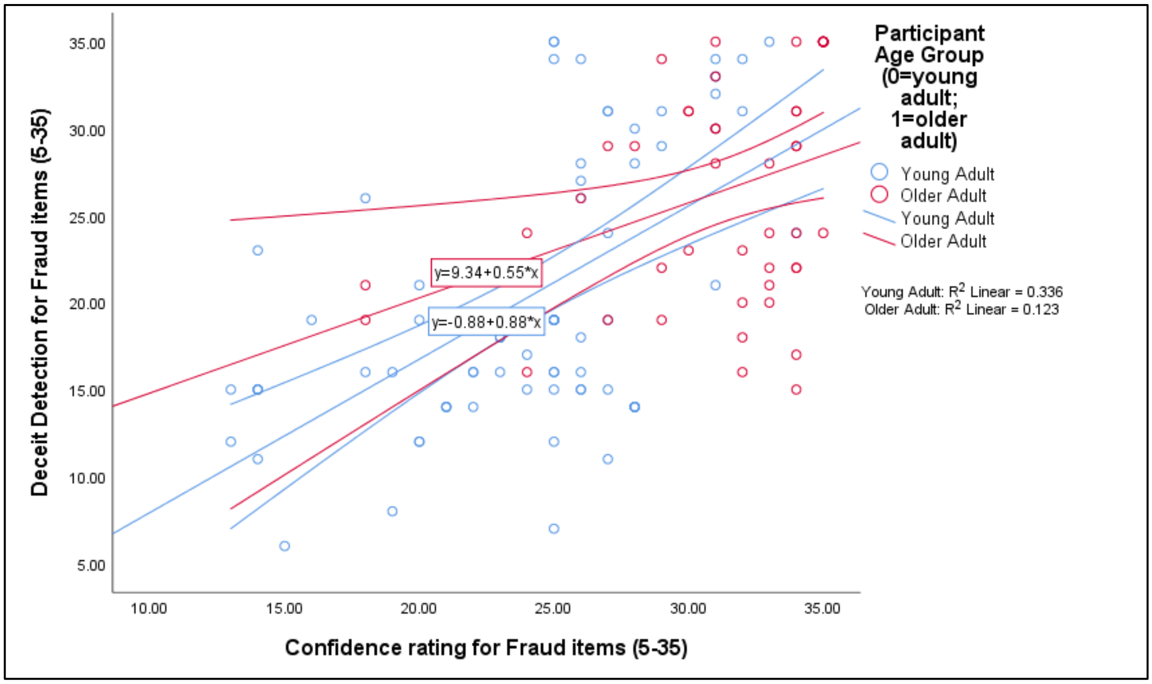

Figure F.10 & F.11. Confidence rating x Deceit Detection score: full range & prediction intervals (above) and truncated range at >25 with prediction intervals (below)

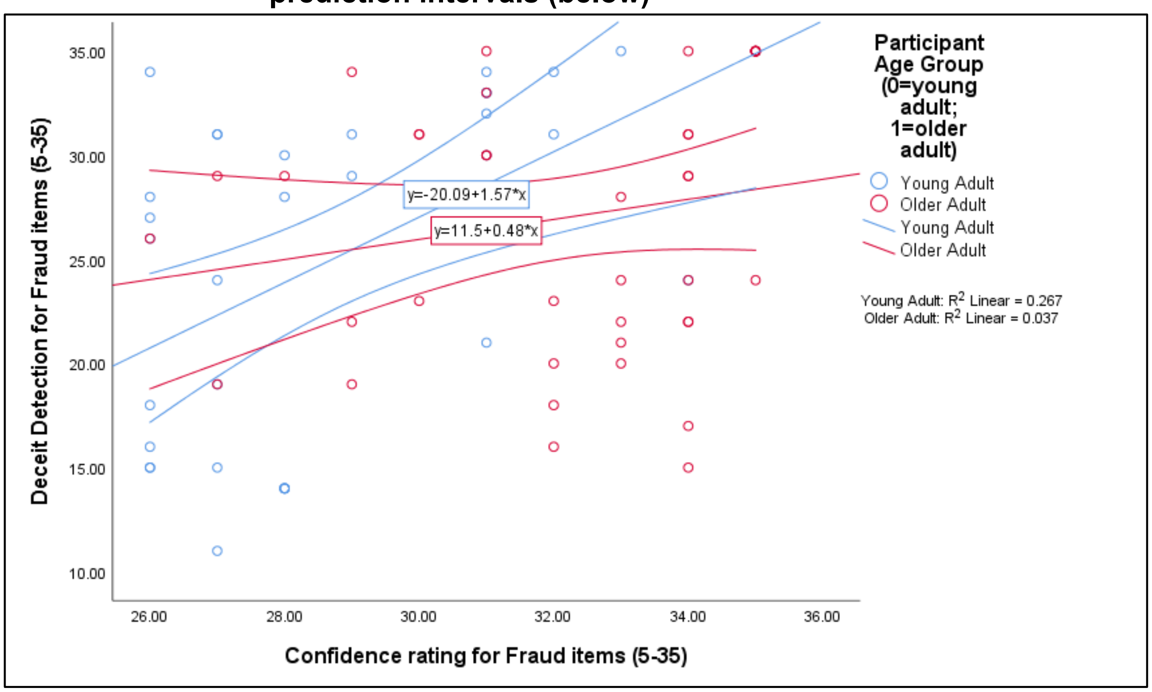

Table F.3. Intercorrelations between demographic/lifestyle covariates and FS outcomes by age group

	1	2	3	4	5	6	7	8	9
Younger Adults, n = 76									
1. Age	-	*-.02*	*.67***	*.06*	*-.08*	*.28**	*-.14*	*.31***	*.04*
2. Gender[a]		-	*.03*	*.12*	*-.04*	*-.06*	*.08*	*.07*	*.03*
3. Education			-	*-.13*	*-.07*	*.06*	*-.06*	*.16*	*.15*
4. Tech. Familiarity				-	*.46****	*.15*	*- .21*	*.13*	*.03*
5. Internet Exposure					-	*.14*	*.00*	*.00*	*.08*
6. TV Exposure						-	*-.20*	*.28**	*.09*
7. Purchase Intention							-	*-.80****	*-.11*
8. Discrimination								-	*.26**
9. Response Bias									-
Older Adults, n = 46									
1. Age	-	*.05*	*-.32**	*-.26**	*-.12*	*.07*	*.42****	*-.35**	*.02*
2. Gender[a]		-	*-.25*	*.11*	*-.11*	*.40***	*-.10*	*.06*	*-.01*
3. Education			-	*-.04*	*-.10*	*-.29*	*-.58****	*.48***	*.27*
4. Tech. Familiarity				-	*.36**	*.13*	*-.12*	*-.09*	*-.10*
5. Internet Exposure					-	*.01*	*.19*	*-.21*	*-.19*
6. TV Exposure						-	*.05*	*-.24*	*-.23*
7. Purchase Intention							-	*-.26***	*-.28*
8. Discrimination								-	*.42***
9. Response Bias									-

Note. We report age in chronological years and gender as 0 = male, 1 = female. Tech. Familiarity = Total raw score on Technology Use & Familiarity Questionnaire; Internet and TV Exposure = estimated # of hours weekly. Income was also included in correlational analyses but did not show any significant associations to ESD outcomes (income x purchase intention: $r = -.15$; income x discrimination: $r = .22$; income x response bias: $r = -.11$) and is not depicted in the table due to space.

[a]All reported associations are presented as Pearson correlation coefficients, except for gender (M/F) associations which reflect Point-biserial correlation coefficients.

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

Table F.4. **Deceit detection regression model summarizing main and interaction effects – full sample**

Predictor	*B*	*SE*	*β*	*t*	*p*	R^2	*F*	ΔR^2	ΔF
Block 1: Demographics & Neurocognition						.08	6.04**	--	--
Age Group	5.22	1.52	.31	3.42	.001				
Global Cognition	.33	.28	.11	1.19	.235				
Block 2: Contextual & Individual Difference Factors						.35	9.84***	.29	10.37***
Age Group	2.23	1.98	.13	1.11	.267				
Global Cognition	.11	.25	.04	.45	.655				
Confidence	.18	.08	.21	2.22	.028				
Deliberation Time	.13	.14	.09	.90	.369				
Cognitive ToM	2.63	.85	.26	3.11	.002				
Affective ToM	-.53	1.02	-.05	-.52	.607				
Interpersonal Trust	.52	.13	.34	3.94	.000				
Block 3: Interactions						.42	10.28***	.06	6.47***
Age x Deliberation Time	- .33	.16	-.46	-2.07	.041				

N = 122
Note. R^2 depicted here is the adjusted value to capture goodness of fit by adjusting for the number of variables in the model that are meaningfully contributing to variance. Significant p-values are indicated with * for the change in R^2 after the entry of each block of variables in the equation. Age in interaction terms = Age Group (0/1).
*p < .05, **p < .01, ***p < .001

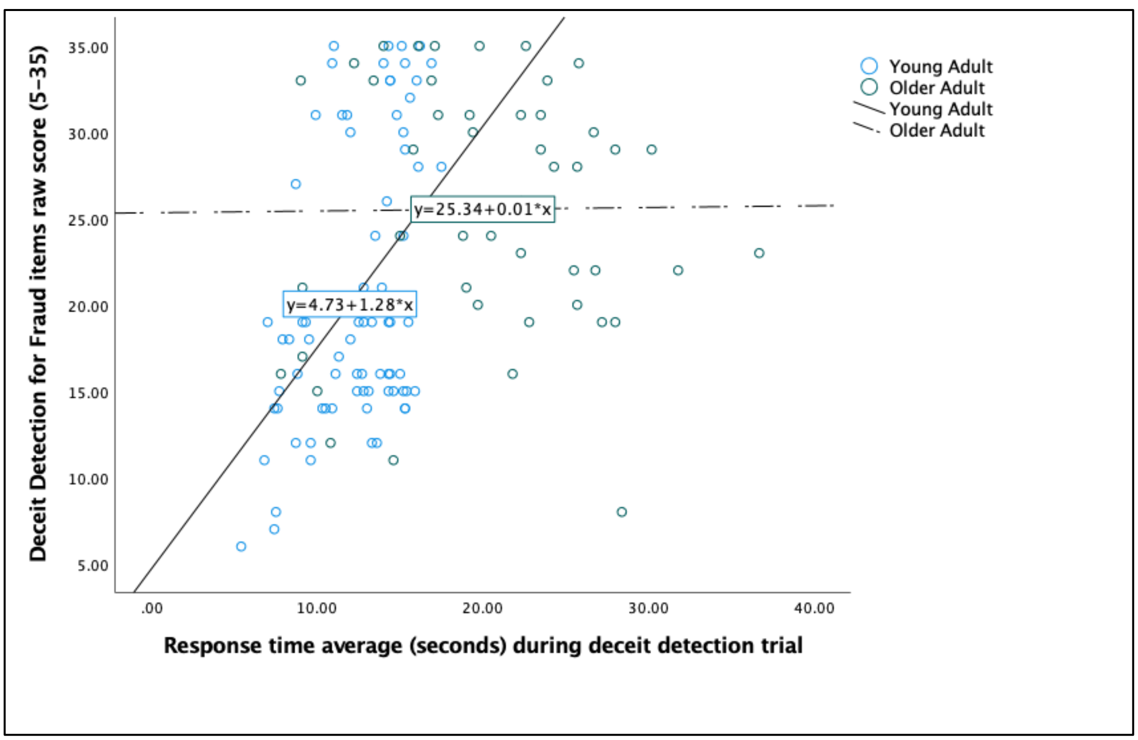

Figure F.12. Scatterplot of deceit detection accuracy by deliberation time, within age groups (N = 122)

Table F.5. **False alarm rate regression model summarizing main and interaction effects – full sample**

Predictor	*B*	*SE*	*β*	*t*	*p*	R^2	*F*	ΔR^2	ΔF
Block 1: Demographics & Neurocognition						.01	1.20	--	--
Age Group	1.25	1.66	.07	.752	.454				
Global Cognition	-.36	.30	-.11	-1.19	.237				
Block 2: Contextual & Individual Difference Factors						.30	6.45***	.27	8.39***
Age Group	4.26	2.25	.24	1.90	.061				
Global Cognition	-.11	.28	-.04	-.40	.687				
Confidence	-.19	.09	-.22	-2.13	.035				
Deliberation Time	-.14	.16	-.09	-.87	.388				
Cognitive ToM	-2.45	.95	-.23	-2.57	.012				
Affective ToM	.10	1.15	.01	.087	.931				
Interpersonal Trust	-.53	.15	-.33	-3.58	.000				
Block 3: Interactions						.33	6.43***	.03	4.72*
Age x Deliberation Time	- .39	.18	-.52	-2.17	.032				

N = 122
Note. R^2 depicted here is the adjusted value to capture goodness of fit by adjusting for the number of variables in the model that are meaningfully contributing to variance. Significant p-values are indicated with * for the change in R^2 after the entry of each block of variables in the equation. Age in interaction terms = Age Group (0/1).
*p < .05, **p < .01, ***p < .001