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Department of Psychological and Behavioural Science

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THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Investment Decisions in the Age of AI: The effect of decision stakes and perspective on the uptake of algorithmic advice.

PB410 MSc Dissertation

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Abstract

Financial institutions have begun to invest in AI-supported algorithms that provide an automated financial advisory service. These solutions are low-cost, allowing individuals who cannot afford a human financial advisor to manage their finances in a comparable way. For such technology to reach its true potential, consumer trust and adoption are essential. Existing research largely demonstrates that humans are averse to algorithms showing *algorithm aversion*. However, further research has found the opposite: *algorithm appreciation*. The coexistence of algorithm appreciation and aversion has spurred research into how different decision environments may shape the adoption of algorithms. The present study investigated whether two factors influence the uptake of algorithmic advice: the stakes of the decision and who the decision will impact (decision perspective). The *Judge Advisor System* (JAS) paradigm was employed to test the influence of decision stakes (high versus low), decision perspective (self versus other), and source of advice (AI versus human) on the weight placed on advice in investment decisions (N =384). In line with predictions, participants favoured advice framed as coming from a human versus AI. However, contrary to what was hypothesised, there was no effect of decision stakes or perspective on the weight placed on algorithmic advice. An unanticipated effect emerged where a greater weight was placed on advice which recommended investing a lower versus higher investment amount compared to participants' original judgement. Crucially, subgroup analyses revealed the preference for a human advisor was observed only for advice recommending a lower investment amount.

Keywords: artificial intelligence (AI), financial decision-making, algorithm aversion, algorithm appreciation

Introduction

The rapid advancement of digital technology has given rise to the ‘second machine age’ marked by widespread technological progress (Brynjolfsson & McAfee, 2014). Central to this ongoing innovation lies artificial intelligence (AI), defined as the use of computer systems to execute tasks typically requiring human understanding (Bawack et al., 2021). AI’s transformative potential is already evident across various industries, including healthcare, education, and entertainment (Cheishvili, 2021), with predictions that AI will contribute $15.7 trillion to worldwide economic growth by 2030 (*PWC,* n.d.). This ‘AI revolution’ (Cheishvili, 2021) has posed an interesting challenge: to what degree will we embrace AI?

The financial sector stands out as having significant potential for AI integration (McKendrick, 2023), particularly within financial advisory services. Seeking expert financial advice is an effective way to support better financial decisions, whereby such advice can enhance financial decision-making (Cruciani, 2017) and substitute for financial literacy deficits (Hung & Yoong, 2013). However, traditional forms of human-to-human financial advice are high-cost, rendering them more accessible to high-income individuals (Collins, 2012; Frost, 2023). When considering that low-income groups tend to have poorer financial literacy (Zhan et al., 2006), it is argued that individuals who could benefit most from financial advice may struggle to afford it.

AI can rapidly process large datasets to support the analysis of complex financial information at an unprecedented rate (Venkataramakrishnan, 2023). These capabilities position algorithms as an effective decision tool, being shown to help limit behavioural biases which typically hinder financial decisions (Back et al., 2023; D’Acunto et al., 2019). Recognising AI’s potential, financial institutions have begun investing heavily in AI-supported algorithms that provide an automated financial advisory service (Jung et al., 2019). These solutions can not only support better financial decisions but they additionally have the benefit of being low-cost (Matthews, 2023). Therefore, AI-powered advisory could support the democratisation of the financial industry by allowing individuals who cannot afford a human financial advisor to manage their finances in a more accessible yet comparable way (Jung et al., 2019).

Due to the link between financial decision-making and financial well-being (Greenberg & Hershfield, 2019), increasing access to such services could have a significant knock-on effect on users. However, consumer trust and adoption are essential for AI to reach its full potential. This stands particularly true within the financial context, where entrusting money to another entity entails inherent risks and vulnerabilities (Szeli, 2020). Existing research demonstrates that humans are largely averse to algorithms displaying *algorithm aversion* (Dietvorst et al., 2015). Although this has been challenged by other research, which has found the opposite: *algorithm appreciation* (Logg et al., 2019). The divergent findings of algorithm aversion versus appreciation have encouraged research into the specific decision environments where individuals may favour versus reject algorithms.

The present study proposes two additional factors that may contribute to individuals' use of algorithms in decision-making: the stakes of the decision and who the decision will impact. We employ a vignette experiment to examine the influence of these factors on the uptake of algorithmic advice within a financial decision-making context. Overall, the present aims to enhance and broaden our understanding of the potential of automated financial advisory services.

Literature Review

The potential of algorithmic advice

It is a robust finding that incorporating advice from others can help people make better decisions (Yaniv, 2004). Combining a minimum of two opinions and thus averaging these opinions cancels out decision errors (Soll & Larrick, 2009), helping to improve both decision quality (See et al., 2011) and confidence (Van Swol & Ludutsky, 2007). Moreover, AI-generated advice can offer additional benefits compared to human-generated advice. Seminal work led by Meehl (1954) demonstrated the superior performance of statistical over human prediction, with even the simplest algorithms outperforming human expert judgement (Grove et al., 2000). At present, advancements in AI support increasingly sophisticated algorithms that excel in tasks spanning from medical diagnostics (Tang, 2019) to advanced image classification (Russakovsky et al., 2015).

Nevertheless, it is important to recognise that AI is human-made, meaning even the most up-to-date algorithms are susceptible to bias (Ferrer et al., 2021; Nelson, 2019). AI systems additionally lack the high flexibility of thinking and unique level of sensemaking observed in humans (Autor, 2015; Verganti et al., 2020). Consequently, by combining the strengths of both algorithmic and human capabilities, humans and machines can align to enhance each other's abilities (Miller, 2018). Hence, algorithms should augment, rather than replace, human decision-makers (Zytek et al., 2021) following a 'human in the loop' approach (Brooks, 2021). In this sense, algorithms are best suited to advise on financial decisions rather than autonomously make them.

Within the financial domain, algorithms can swiftly summarise and analyse a vast amount of information to perform complex financial operations (Venkataramakrishnan, 2023). Accordingly, it has been demonstrated that algorithmic support can improve financial decision-making by reducing common behavioural biases (Back et al., 2023; D'Acunto et al., 2019). Furthermore, when considering that information costs underly limited stock market participation (Vissing-Jorgensen, 2003), algorithms can reduce this cost by rapidly acquiring and processing relevant information. Therefore, automated financial advisory can not only improve financial decision-making but additionally promote financial participation and inclusion (Bianchi & Brière, 2021).

Algorithm aversion versus appreciation

Despite the potential of AI, empirical evidence suggests that individuals lack trust in their capabilities. Humans exhibit *algorithm aversion*, rejecting algorithms in favour of identical human support (Dietvorst et al., 2015). This phenomenon is particularly pronounced when choosing between a human expert and an algorithm (Jussupow et al., 2020; Promberger & Baron, 2006). However, individuals have also been shown to favour advice from a friend (Yeomans et al., 2019) or their own judgement over algorithms (Dietvorst et al., 2018). Even when individuals are explicitly informed that the algorithm surpasses human performance, algorithm aversion persists (Castelo et al., 2019). Bigman and Gray (2018) only found a preference for algorithmic advice when the algorithm's success rate was framed as being 15% greater than the human. Various domains, including medical decisions (Lennartz et al., 2021; Longoni et al., 2019), recruitment decisions (Highhouse, 2008) and legal decisions (Yalcin et al., 2023), have all provided evidence of algorithm aversion.

Numerous explanations have been proposed for algorithm aversion. The opaque nature of algorithms, often referred to as the "black box" problem (Von Eschenbach, 2021), means users lack a meaningful interpretation of how algorithmic judgement is generated (Schoeffer et al., 2021). This limited understanding contributes to decreased trust in algorithms (Ashoori & Weisz, 2019; Yeomans et al., 2019). Instead, people prefer human advisors who can justify their decisions (Önkal et al., 2009). Furthermore, people incorrectly believe that algorithms cannot learn and improve in the same way humans can (Highhouse, 2008; Reich et al., 2023). Accordingly, individuals lose confidence in algorithms faster than humans, despite making equivalent mistakes (Dietvorst et al., 2015).

Moreover, algorithm aversion may be driven by "uniqueness neglect", where individuals perceive algorithms as incapable of considering their unique characteristics (Longoni et al., 2019). Uniqueness neglect builds upon the "broken leg" hypothesis depicted by Meehl (1954). According to this hypothesis, humans reject statistical models as they may overlook critical information. This classic example outlines how a regression model that predicts movie attendance based on past behaviour and demographic information expects a specific person to attend the movie. However, the model fails to recognise that the person has broken their leg, preventing them from leaving home. Hence, individuals may believe that algorithms cannot incorporate the breadth of insight that a human can offer.

Crucially, an aversion to algorithms has been demonstrated to extend to the financial domain. In financial investment decisions (Larkin et al., 2022; Niszczota & Kaszás, 2020; Zhang et al., 2021) or financial forecasting tasks (Filiz et al., 2021; Önkal et al., 2009), individuals reject algorithms. Furthermore, Zhang et al. (2021) found that compared to automated advisors, individuals placed greater trust in human advisors, had greater performance expectations, and were more willing to hire a human advisor. When considering a positive perception of the advisor predicts the uptake of advice (Johnson & Johnson, 2017), algorithm aversion poses a significant risk to AI-supported financial advisory services.

Despite extensive evidence of algorithm aversion, Logg et al.'s (2019) landmark study found the opposite; *algorithm appreciation*. Across a series of non-financial tasks, participants placed significantly greater weight on human over algorithmic advice (Logg et al., 2019). A recent meta-analysis revealed that the overwhelming finding is algorithm aversion (Mahmud et al., 2022). However, the coexistence of algorithm appreciation and aversion has spurred research into how different decision environments may shape the adoption of algorithms. The perceived objectivity versus subjectivity of the task (Castelo et al., 2019), the description of the human advisor (Jussupow et al., 2020), whether the decision goal is framed as utilitarian versus hedonic (Longoni & Cian, 2022), and the difficulty of the task (Bogert et al., 2021), have all been demonstrated to explain differences in algorithm acceptance. The present study proposes that two additional factors may contribute to differences in algorithm acceptance: decision stakes and perspective.

Decision Stakes

Financial decisions are shaped by a trade-off between the potential monetary rewards against the possibility of losses (Cui, 2022). The nature of this trade-off varies significantly depending on the stakes associated with the decision, with high stakes decisions involving serious risk if there is no success (Cambridge Dictionary, 2023). Research into the use of algorithms in financial decisions has focused mainly on self-reported attitudes or no-stakes forecasting tasks (Castelo et al., 2019; Filiz et al., 2021; Önkal et al., 2009). However, financial decisions predominately hold consequences in real-world settings (Greenberg & Hershfield, 2019). When considering that algorithm aversion is influenced by the perceived consequentiality of a task (Castelo et al., 2019), it becomes crucial to investigate how different types of potential outcomes may influence individuals' acceptance of algorithms in financial decisions.

Crucially, if individuals are more accepting of AI in low stakes decisions, this may support the longer-term adoption of AI in high stakes contexts. According to the *risk-return model* (Merton, 1973), greater risk should be compensated with proportionally higher returns. Applying this model to innovation acceptance (Sinfield & Solis, 2016), the monetary risk of algorithmic failures are small in low stakes decisions. However, in high-stakes decisions, the risk of relying on algorithms is greater as the cost of error is higher. Therefore, the likelihood of adoption is greater in low stakes contexts where the benefits of such services are coupled with minimal risk. Furthermore, as people become more familiar with an innovation, it increases their likelihood of adopting it (Hengstler et al., 2016). Hence, if people gain experience with AI in low stakes decisions, through usage they may incrementally become more trusting of this technology in decisions with increasing significance.

In high stakes decisions, individuals tend to employ simple, non-compensatory decision rules, evaluating options based on single attributes (Kahn & Baron, 1995). This stands in contrast to utilising compensatory decision rules, which assess options based on multiple attributes to arrive at a decision. Algorithms, on the other hand, excel at rapidly processing vast volumes of data across various attributes, irrespective of the complexity of the decision environment (Sahoh & Choksuriwong, 2023). This capability positions algorithms as a valuable decision tool in high stakes decision environments, overcoming simplistic decision strategies enlisted by humans that fail to incorporate the breadth of information algorithms offer.

However, theoretical perspectives suggest people may exhibit greater aversion to algorithms in higher versus lower stakes decisions. One of the key benefits of advice taking is shared responsibility (Bonaccio & Dalal, 2006). In algorithmic decisions, holding a machine accountable for adverse outcomes becomes challenging (Bonaccio & Dalal, 2006). As a result, individuals tend to attribute more blame and accountability to human advisors than to automated advisors (Renier et al., 2021). Promberger and Baron (2006) found that individuals' tendency to follow human advice is partly mediated by the difference in perceived responsibility when acting on versus not acting on the advice. Moreover, the severity of the outcome of an event is directly related to the responsibility attributed to the perpetrator (Robbennolt, 2000). Consequently, in high-stakes decisions where the potential consequences carry greater significance, the focus on responsibility is proposed to be more salient. In such situations, individuals may prefer human advisors who they can share the responsibility of the decision with.

Accordingly, existing evidence supports this proposition. Individuals report a stronger aversion to using algorithms in high stakes decisions with potentially serious consequences (Ashoori & Weisz, 2019; Grzymek & Puntschuh, 2020). Filiz et al. (2023) presented participants with decision scenarios ranging from low stakes decisions involving algorithms in recipe selection and matchmaking to high stakes decisions concerning their use in driving autonomous vehicles and disease diagnosis. The algorithm was framed with a 70% success rate compared to a human expert with a 60% success rate. Participants were informed that they would receive a payment for a successful decision. An economically rational agent, or *homo economicus*, is expected to select the algorithm in all scenarios to maximise its financial utility. However, algorithm aversion increased in line with the perceived gravity of the decision, depicting a willingness to override one's economic self-interest to limit the use of algorithms in high stakes contexts.

Critically, prior research has compared the influence of decision stakes on attitudes towards algorithms across different contexts (Ashoori & Weisz, 2019; Filiz et al., 2023; Grzymek & Puntschuh, 2020). In Filiz et al. (2013) study, for example, the matchmaking and disease diagnosis scenarios likely vary on several dimensions other than exclusively the perceived gravity of the decision. Attitudes towards algorithms have been shown to vary depending on whether the decision outcome is viewed as hedonic versus utilitarian (Longoni & Cian, 2022) or the perceived subjectivity versus objectivity of the decision (Castelo et al., 2019). Arguably, both factors may have varied across the scenarios used in prior research, raising valid concerns regarding the establishment of causality.

Within a singular domain, Longoni et al. (2019) compared low and high stakes medical decisions. Participants were found to prefer a human to an AI healthcare provider in both scenarios. Although, aversion to AI was greater in high stakes compared to low stakes medical scenarios. Therefore, the evidence suggests that algorithm aversion will be more pronounced in higher stakes decisions. However, further research is needed to explore whether this can extend to a financial context. This is especially important when considering that the extent of algorithm aversion has been shown to vary between the medical and financial domains (Larkin et al., 2022).

In a financial context, research has been centred on no stakes decisions (Castelo et al., 2019; Filiz et al., 2021; Önkal et al., 2009) or high stakes investment decisions (Larkin et al., 2022; Niszczota & Kaszás, 2020; Zhang et al., 2021), all of which have found algorithm aversion. However, to our knowledge, no study has investigated whether the extent of this aversion differs between low and high stakes decisions. Hence, a research gap emerges where the influence of decision stakes on the uptake of algorithmic advice within financial decisions has not been investigated.

Decision Perspective

As highlighted by Castelo et al. (2019), Logg et al.'s (Study 1C, 2019) finding of algorithm appreciation utilised scenarios where the participant made a decision in which the consequences would impact an unknown other. In contrast, several instances of aversion have been found in decisions with personally relevant consequences (e.g., Larkin et al., 2022; Longoni et al., 2019). Therefore, this suggests that the decision perspective could underlie such differences.

Several streams of research support the proposition that decision perspective may influence the use of algorithms. Across a large body of literature, it has been shown that decision-making is influenced by whether the individual decides for someone else (i.e., *proxy decision-makers*) in comparison to individuals who decide for the self (i.e., *personal decision-makers*) (Polman, 2012). Information seeking (Jonas et al., 2005; Kray, 2000), omission bias (Zikmund-Fisher et al., 2006), and decision aversion (Beattie et al., 1994) all vary systematically with decision perspective. Therefore, self other decision-making asymmetries demonstrate that perspective is a key decision criterion that shapes the choices that individuals make.

Furthermore, *construal level theory (CLT)* outlines that psychological distance significantly shapes people's thoughts and behaviour (Trope & Liberman, 2010, 2012). Psychological distance is "a subjective experience that something is close or far away from the self, here, and now," (Trope & Liberman, 2010, p.1). Social distance, a component of psychological distance, represents the perceived psychological gap between the self and others (Liberman et al., 2007). Social distance influences decision-making such that psychological distance increases when deciding for someone else versus the self (Trope & Liberman, 2010).

As psychological distance increases, people predominately use high-level construals over low-level construals (Trope & Liberman, 2010, 2012). High-level construals are decontextualised, abstract mental representations. In contrast, low-level construals are contextualised, concrete mental representations (Polman & Emich, 2011). As argued by Castelo et al. (2019), algorithms primarily focus on patterns, trends, and generalisations, aligning with high-level construals. In contrast, humans tend to rely more on contextual cues and specific situational factors, aligning more with low-level construals. Consequently, it could be expected that when choosing for others, high-level construals are activated, prompting a greater reliance on algorithms (Castelo et al., 2019).

Furthermore, people report feeling more similar to human advisors than virtual advisors, even in the absence of interpersonal contact (Prahl & Van Swol, 2017). Individuals place more weight on advice from similar advisors when making judgments relevant to themselves. However, when making judgements about unknown individuals, they rely more on advice from dissimilar advisors (Gino et al., 2009). Moreover, proxy decision-makers have been demonstrated to be more likely to shift from the status quo (Lu & Xie, 2014). Therefore, it would be expected that individuals will be more likely to prefer novel, dissimilar automated advisors when making decisions that impact others versus the self.

Critically, within the financial domain, algorithm aversion has been found in consequential decisions made for the self (Larkin et al., 2022) and someone else (Zhang et al., 2021). However, it remains unclear whether the extent of this algorithm aversion may differ depending on the decision perspective. Within the context of automated financial advisory, receiving and acting on financial advice predominately impacts the decision-maker. Therefore, research that focuses on making decisions for others may lack generalisability when applied to real-life financial decisions.

To our awareness, only one study has investigated the influence of decision perspective on algorithm acceptance. Across several moral decision scenarios, Utz et al. (2021) found a preference for algorithms was significantly lower for personal compared to proxy decision makers, but only within the highest-stakes scenario. Therefore, this points not only to an influence of decision perspective on the uptake of algorithmic advice but potentially an interaction between decision stakes and perspective. However, to increase the generalisability of the findings, further research is needed to determine whether this effect extends to a financial context. This is especially important when considering that self other decision making differences have been shown to vary across different domains (Stone & Allgaier, 2008). Hence, we aim to fill this research gap by investigating the influence of decision perspective within a financial context.

The present research

The current work aims to replicate and extend the literature on the uptake of algorithmic advice by investigating the influence of decision stakes and perspective within financial decisions. Simultaneously testing these factors allows us to assess their relative, independent, and combined influence on the use of algorithmic advice. Based on the findings across existing literature the following hypotheses were developed:

$\boldsymbol{H_1}$**:** Individuals will place a significantly greater weight on human advice compared to algorithmic advice across all decisions.

$\boldsymbol{H_2}$**:** Individuals will place a significantly greater weight on algorithmic advice in low stakes compared to high stakes decisions.

$\boldsymbol{H_3}$**:** Individuals will place a significantly greater weight on algorithmic advice in decisions which directly impact someone else compared to decisions which directly impact the self.

Method

Pre-test

The scenarios used in the current work involved making investment decisions in line with existing research (Larkin et al., 2022; Zhang et al., 2021). As the vignette scenarios used in the present study were specifically designed for this research, a pre-test was conducted to support the validity of the scenarios. Based on the minimum recommended pre-test sample size to be reasonably powered to identify fairly prevalent issues with a new measure (Perneger et al., 2015), 30 participants were recruited via a convenience sample of the researcher.

Drawing inspiration from Wang et al. (2023), the pre-test measured the comprehension, perceived stakes, and applicability of the decision perspective of the scenarios. Participants were asked, "*How easy is it to understand the scenario?*" with answers being given on a scale of 1 (*very difficult to understand*) to 7 (*very easy to understand*). The average comprehension scores were high: 6.10 (SD = 1.30) in the low stakes scenario and 6.00 (SD = 1.25) in the high stakes scenario.

Furthermore, participants rated the stakes of the decision from 1 (*very low stakes*) to 7 (*very high stakes*). As expected, the stakes were rated higher in the high stakes scenarios (M = 5.86, SD = 0.95) compared to the low stakes scenario (M = 2.21, SD = 1.05), a statistically significant difference of 3.65 (95% CI [3.01, 4.30], $t(28) = 11.61$, $p < .001$). Additionally, participants were asked if their decision would be affected by whether they were making the decision for themselves or someone else, responding on a scale of 1 (*not at all affected*) to 7 (*very affected*). The scores were 3.73 and 4.93 in the low and high stakes decisions, respectively, indicating that the scenarios were appropriate to investigate the influence of decision perspective on decision-making (Wang et al., 2023). Qualitative feedback was also requested, with small adjustments to the format and visual presentation of the scenarios being made accordingly.

Participants

Power analysis

Based on *a priori* power analysis conducted in G*Power 3.1 (Faul et al., 2007), it was determined that a minimum sample of 387 participants was required for an 80% probability of detecting a small effect (partial $\eta^2 = .020$) given a conventional level of significance ($\alpha = 0.05$) (see Appendix A).

Recruitment

394 participants were recruited via *Prolific,*[1] an online crowdsourcing platform demonstrated to yield high-quality data (Peer et al., 2022). Participants were pre-screened to confirm they were from the UK, fluent in English, and over 18. Participants were reimbursed according to the recommended compensation on Prolific in return for completion.

Design

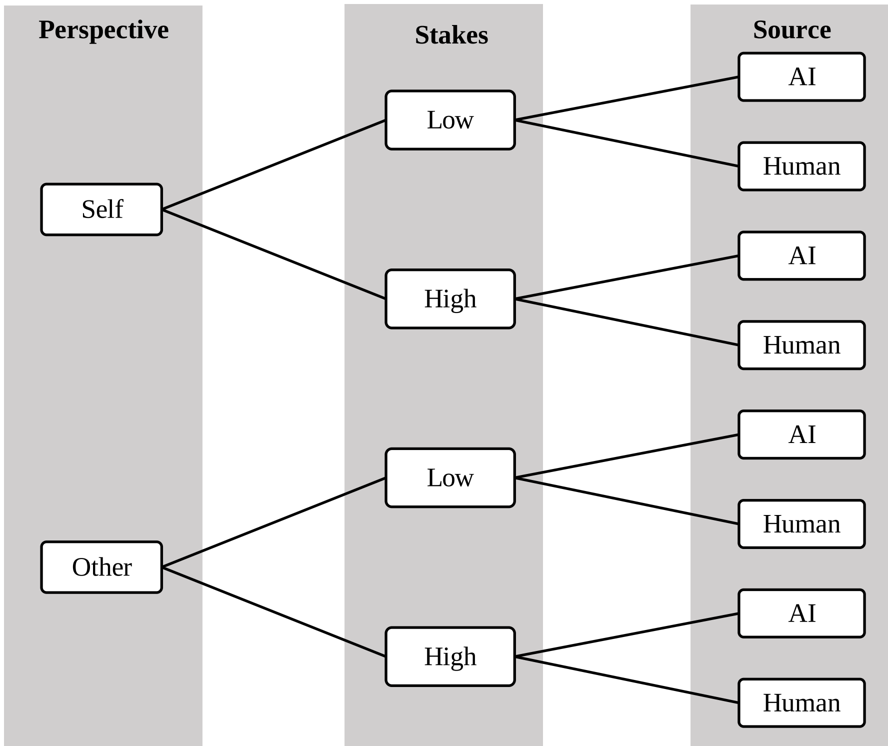
The study utilised a 2x2x2 between-subjects design (see Figure 1). The three dichotomous independent variables were decision stakes (high versus low), decision perspective (self versus other), and source of advice (AI versus human). Participants were randomly assigned to one of four vignette scenarios developed from the pre-test (see Appendix B). The low and high stakes scenarios differed in terms of the risk involved and the potential reward, with higher stakes scenarios involving a higher risk of loss coupled with a higher potential reward. In the self-condition, participants were tasked with investing their own money. In the other condition, they were tasked with investing someone else's money.

Across prior research, the terminology used to frame the human versus non-human advice source has varied, with non-human advice largely described as originating from 'an algorithm' (e.g., Filiz et al., 2023; Logg et al., 2019) or 'AI' (e.g., Longoni et al., 2019). In agreement with Larkin et al. (2022), the non-human advice was framed as coming from AI, as it is likely how these types of systems will typically be presented to the general public. Consequently, participants were randomly assigned to advice framed as coming from a 'human financial advisor' or an 'automated financial advisor powered by artificial intelligence'.

[1] https://www.prolific.co/

Figure 1

Study Design Overview



Procedure

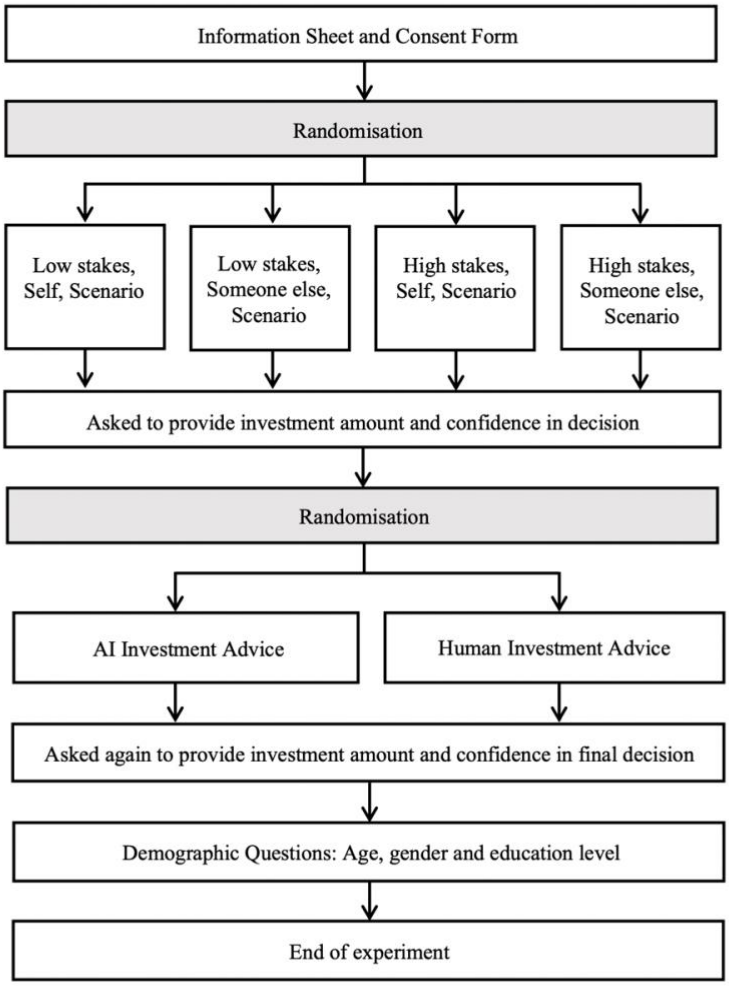
The study followed the *Judge Advisor System* (JAS) paradigm (Sniezek & Buckley, 1995), which is commonly employed to measure advice utilisation by measuring how individuals change their initial judgement after receiving advice. In the JAS paradigm, participants are initially asked to provide a judgment in response to a particular question. Afterwards, they are given advice related to the decision. Following receipt of the advice, participants can revise their original estimate based on the information provided by the advisor.

The study was conducted online via *Qualtrics*[2]. See Figure 2 for an overview of the procedure. Participants were told that the study would investigate financial decision-making. Before taking part, participants were asked to read the information sheet, provide consent (see Appendix C), and commit to providing thoughtful responses.

[2] https://www.qualtrics.com/uk/

Figure 2

Experimental Flow Diagram



Participants were tasked with reading one investment scenario. After reading the scenario, they were asked what percentage of their or someone else's savings they would like to invest and to provide a rating of confidence in their decision, both of which they responded to on a scale of 0%-100%. Investing a relative proportion of the participant's savings rather than a fixed investment amount was used as it provides an estimate relative to the participant's income, helping to account for differences in income levels across the sample.

Participants were asked to consider the following advice: "*An automated financial advisor powered by artificial intelligence (AI)/a human financial advisor has evaluated the present investment and recommends instead investing X% of your savings.".* Following receipt of this advice, participants were asked what proportion of their savings to invest and to rate their confidence in their decision. Lastly, participants answered several demographic questions before completing the study.

Measures and materials

Weight of advice

The dependent variable was the weight of advice (WOA), which measures how much an individual weighs the advice they receive, acting as a behavioural measure of trust (Prahl & Van Swol, 2017). WOA is a popular measure within the advice taking (e.g., Bonaccio & Dalal, 2006) and uptake of algorithmic advice literature (e.g., Logg et al., 2019). As a continuous measure, WOA is a more sensitive measure of advice utilisation than a categorical choice between humans and algorithms, as seen in much of the prior literature on the acceptance of algorithms (Logg et al., 2019). WOA is calculated as follows: $\mathrm{WOA} = \frac{[\text{final estimate} - \text{initial estimate}]}{[\text{advice} - \text{initial estimate}]}$. A WOA of 0 depicts that the participant has completely disregarded the advice (100% advice discounting). A WOA of 1 indicates that the participant ignored their initial judgement in favour of the advice (100% advice utilisation).

Confidence ratings

Participants may not respond to the advice by only changing their judgement; instead, advice may change the participant's confidence in the decision (Bonaccio & Dalal, 2006). Accordingly, advice utilisation has been shown to be positively related to decision confidence (Sniezek & Van Swol, 2001). Therefore, confidence ratings were recorded on a scale of 0% (*not at all confident*) to 100% (*very confident*) to enhance our understanding of the impact of the advice.

Investment advice

As investment advice is subjective, consistent with Hou and Jung (2021), the advice was a transformation of the participant's initial answer. Participants were randomly assigned to one condition: advice which *added* and advice which *subtracted* on a random constant between 6%-9% of their initial judgment. Implementing a custom JavaScript code on Qualtrics allowed us to manipulate the participants' initial judgment and present it back to them in the form of advice. If judgements were over 91% in the add condition or less than 9% in the subtract condition, the advice was instead subtracted or added to the initial judgment, respectively. This was to prevent extreme advice such as 0% or 100% influencing the results. Any participants reassigned to either condition due to their initial judgement were re-coded before analysis.

The reasons for manipulating the advice in this way are twofold. Firstly, a difference of 6%-9% of the initial judgment is close to the original answer, meaning it seems less outrageous to follow

(Hou & Jung, 2021). Secondly, in studies which use WOA, when advice is equal to the original estimate, the data cannot be used (Gino & Moore, 2007). By manipulating participants' original answers, we overcome this pitfall.

Data treatment

394 responses were collected. 4 incomplete responses were deleted. The WOA is argued to be well-defined if the final judgement falls within the range between the initial judgement and the advice received (Yaniv, 2004), which it did in approximately 92% of the cases. WOA is theoretically bounded between 0 and 1, with high sensitivity to outliers who fall outside this range (Hütter & Ache, 2016). Therefore, following the recommended practice in the literature (e.g., Gino, 2008; Gino & Moore, 2007; Soll & Larrick, 2009) and prior research into the uptake of algorithmic advice (e.g., Larkin et al., 2022; Logg et al., 2019), WOA values outside of this range were winsorized. WOA values over 1 (but not greater than 2) were changed to 1 (22 cases), and values under 0 (but greater than -1) were changed to 0 (3 cases). Values over 2 and less than -1 were removed from the analysis (6 cases) as moving away from the advice at this magnitude is considered to reflect participant inattention or lack of engagement with the task (Logg et al., 2019).

Data Analysis

The data was analysed using IBM SPSS Statistics (Version 27). The statistical significance level was set at $p < .05$. Visual inspection of the data using histograms and the Shapiro-Wilk's test of normality illustrated that the data violated the normality assumption ($p < .001$). While the ANOVA is generally known to tolerate deviations from normality (Blanca et al., 2017), bootstrapping was employed for all analysis of variance (ANOVA) and analysis of covariance (ANCOVA) tests to increase the robustness of the analysis (Mooney & Duval, 1993). Bootstrapping additionally addressed violations of the homogeneity of variance assumption found across some sections of the analysis (Zhang, 2015). Due to the non-normal data, the non-parametric Mann-Whitney U test was used. The analyses were broken into four sections outlined below.

The effect of decision stakes and perspective on investment amount prior to receiving advice

We determined the effectiveness of the manipulation in impacting investment behaviour, separate from its influence on the use of advice. A bootstrapped factorial ANOVA examined the effects of decision perspective and stakes on the initial investment amount.

The effect of decision stakes, perspective, and source of advice on the WOA

We directly tested the proposed hypotheses by examining whether decision perspective, stakes and the source of advice influenced how much weight participants gave to the advice. A bootstrapped factorial ANOVA assessed the effect of decision stakes, perspective, and the source of advice on the WOA. Specifically, we were interested in examining the main effect of the source of advice in addition to the interaction effects between the source of advice and decision perspective and stakes, respectively.

The effect of decision stakes, perspective, and source of advice on final confidence

To aid our understanding of the hypotheses tests, we assessed whether decision perspective, stakes and source of advice had an effect on decision confidence. In line with Bogert et al. (2022), an ANCOVA was deemed an appropriate analysis due to the linear relationship between initial and final confidence. Linearity was confirmed across all eight conditions by visually examining the scatter plots for each condition. By comparing the three-way ANCOVA model both with and without the interaction terms, the homogeneity of regression slopes was confirmed, $F(7, 368) = 0.823$, $p = .568$. There was homoscedasticity within each combination of groups, as confirmed by visual inspection of the graphs of the studentized residuals plotted against the predicted values for each condition. A bootstrapped ANCOVA analysed the influence of decision stakes, perspective, and source of advice on final confidence, with the initial confidence rating as the covariate.

Exploratory analyses on the effect of the type of advice on the WOA

As previous research has indicated that the distance between the initial judgment and advice can influence advice utilisation (Yaniv & Milyavsky, 2007), we examined whether advice which recommended a higher investment amount (add condition) versus a lower investment amount (subtract condition) influenced how participant's weighed the advice. Firstly, a Mann-Whitney U test was performed to see if the WOA significantly differed between the two conditions. Visual inspection of a population pyramid demonstrated that the two distributions were similarly shaped. Following this, subgroup analyses split by the advice condition were performed to further illuminate our understanding of any differences across the two forms of advice.

Results

See Appendix D For the SPSS syntax and output of the analyses reported below.

Demographics

The demographic characteristics of the sample can be seen in Table 1. A Pearson's two-tailed correlation test found no significant correlation between the variables of interest and demographic variables.

Table 1

Frequency distribution for participants' gender, age, and educational experience

Characteristic	Frequency	Percentage (%)
Gender		
Male	193	50.3
Female	188	49.0
Prefer not to say	3	0.7
Total	384	100
Age		
18-24	33	8.6
25-34	110	28.6
35-44	118	30.7
45-54	59	15.4
55-64	41	10.7
65+	23	6.0
Total	384	100
Education		
Some secondary	6	1.5
Completed secondary school	64	16.7
Vocational or similar	63	16.4
Some university but no degree	29	7.6
University bachelor's degree	143	37.2
Graduate or professional degree	79	20.6
Total	384	100

The effect of decision stakes and perspective on investment amount prior to receiving advice

A two-way bootstrapped ANOVA was conducted to determine whether decision stakes and perspective influenced the initial investment amount before receiving advice. The main effect of decision stakes was significant, $F(1, 380) = 56.38$, $p < .001$, partial $\eta^2 = .129$. Participants invested significantly more in the low stakes condition ($M = 41.97$, 95% *BootCI* [38.50, 45.54]) compared to the high stakes condition ($M = 25.38$, 95% *BootCI* [22.90, 27.95]).

The main effect of perspective was also significant, $F(1, 380) = 24.78$, $p < .001$, partial $\eta^2 =$ .061. When deciding to invest other people's money, participants invested significantly more ($M =$ 39.18, 95% *BootCI* [36.16, 42.40]) compared to when deciding to invest their own money ($M =$ 28.18, 95% *BootCI* [25.22, 31.31]). The interaction effect between decision stakes and perspective was non-significant, $F(1, 380) = 1.06$, $p = 0.303$, partial $\eta^2 = .003$.

The effect of decision stakes, perspective, and source of advice on the WOA

Table 2 illustrates the descriptive statistics for the WOA across the eight conditions. A three-way bootstrapped ANOVA was performed to evaluate the effects of decision stakes, perspective, and the source of advice on the WOA. The main effects of stakes ($F(1, 376) = 2.85\text{x}10^{-4}$, $p = .987$, partial $\eta^2 < .001$) and perspective were non-significant ($F(1, 376) = 1.52$, $p = 0.219$, partial $\eta^2 = .004$).

The main effect of the source of advice was significant, $F(1, 376) = 15.00$, $p < .001$, partial η^2 = .038. Participants placed significantly greater weight on advice framed as coming from a human (M = 0.61, 95% *BootCI* [0.55, 0.66]) compared to advice framed as coming from AI ($M = 0.45$, 95% *BootCI* [0.40, 0.51]). All two-way interactions were non-significant.

Table 2

Descriptive statistics for the WOA across the eight conditions

AI Advice					
			95% *BootCI*		
Condition	**Mean**	**S.D.**	**Lower bound**	**Upper bound**	***N***
Low stakes, Self	0.41	0.40	0.30	0.53	48
Low stakes, Other	0.51	0.41	0.39	0.63	46
High stakes, Self	0.45	0.41	0.34	0.57	47
High stakes, Other	0.43	0.40	0.31	0.54	47

Human Advice					
			95% *BootCI*		
Condition	**Mean**	**S.D.**	**Lower bound**	**Upper bound**	***N***
Low stakes, Self	0.64	0.40	0.52	0.75	48
Low stakes, Other	0.56	0.42	0.44	0.67	51
High stakes, Self	0.51	0.42	0.39	0.63	47
High stakes, Other	0.73	0.35	0.63	0.82	50

Total N = 384

The three-way interaction effect between the source of advice, decision stakes and perspective was significant, $F(1, 376) = 6.33$, $p = .012$, partial $\eta^2 = .017$. As illustrated in Figures 3 and 4, the effect of stakes and perspective on the WOA differs depending on whether the advice was framed as coming from AI versus a human.

Figure 3

Estimated Marginal Means of the WOA for the AI advice condition

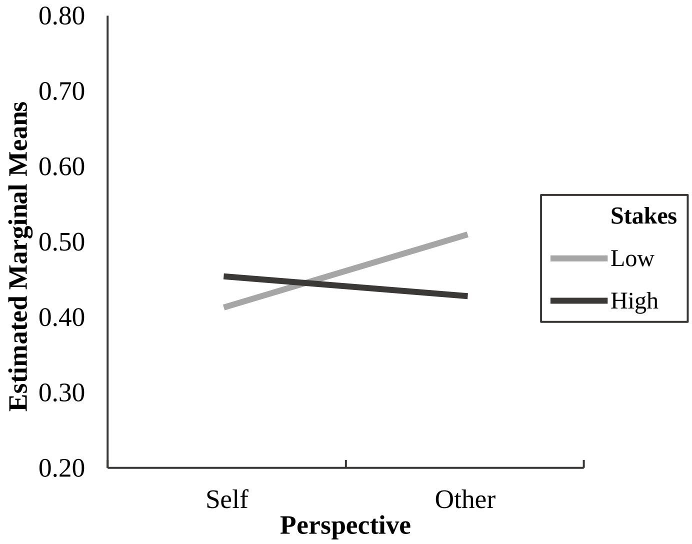
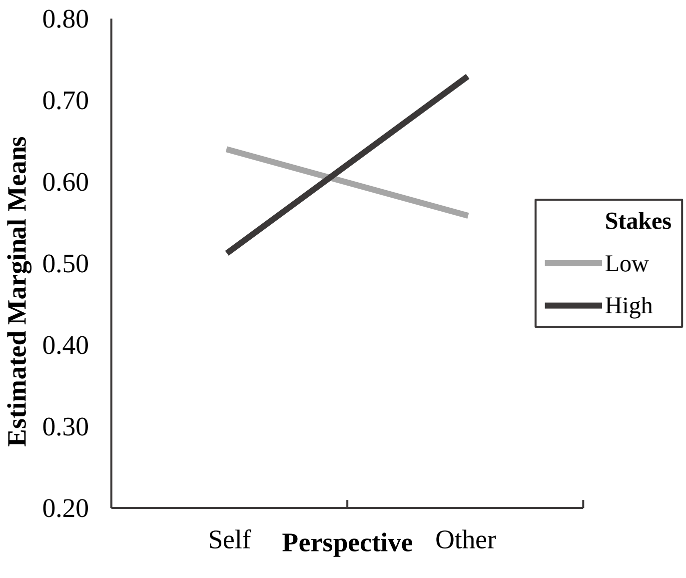


Figure 4

Estimated Marginal Means of the WOA for the human advice condition



To further explore the interaction between stakes and perspective at each level of the source of advice, follow-up analyses were performed to examine simple two-way interactions. Following the methodology outlined by Wickens and Keppel (2004), simple two-way interactions were examined, analogous to a two-way interaction in a traditional two-way ANOVA. However, the error term and degrees of freedom for these analyses were replaced with those from the initial three-way ANOVA by customizing the SPSS syntax (e.g., sum of squares error term = 60.58, *df* = 376, see Appendix D). Specifically, the dataset was split by source, and a two-way bootstrapped ANOVA was conducted with decision stakes and perspective as factors influencing the WOA.

There was a statistically significant simple two-way interaction between stakes and perspective when the advice was framed as coming from a human, $F(1, 376) = 6.50$, $p = .011$, partial $\eta^2 = .017$. However, the simple two-way interaction between stakes and perspective was non-significant when advice was framed as coming from AI, $F(1, 376) = 1.05$, $p = .305$, partial $\eta^2 = .003$. To follow up the statistically significant simple two-way interaction between stakes and perspective when advice is framed from a human, further analysis was used to analyse simple simple main effects (i.e., the simple main effects of the simple two-way interaction). Therefore, we examined the effect of perspective at both levels of stakes within the human advice condition. The file was split on the source of advice and decision stakes; then, a one-way bootstrapped ANOVA was conducted with perspective on the WOA with the error term and degrees of freedom from the three-way ANOVA substituted in.

The simple simple main effect of perspective within the human advice condition was non-significant in low stakes decisions: $F(1, 376) = 0.97$, $p = .325$, partial $\eta^2 = .003$. However, the simple simple main effect of perspective within the human advice condition was statistically significant for high stakes decisions: $F(1, 376) = 6.79$, $p = .010$, partial $\eta^2 = .018$. Specifically, when making high stakes decisions for others, individuals placed significantly greater weight on human advice (M = 0.73, 95% *BootCI* [0.63, 0.82]) compared to when making decisions for the self (M = 0.51, 95% *BootCI* [0.40, 0.63]). Overall, decision perspective influenced the weight placed on human-framed advice in high stakes decisions, but not low stakes decisions.

The effect of decision stakes, perspective, and source of advice on final confidence

A three-way bootstrapped ANCOVA was conducted to examine the influence of decision perspective, stakes, and the source of advice on participants' final confidence in their decision while controlling for initial confidence. As anticipated, the covariate of initial confidence had a significant and large effect on final confidence, $F(1, 375) = 745.20$, $p < .001$, partial $\eta^2 = .665$. After accounting for initial confidence, there were no significant main effects of decision perspective ($F(1, 375) = 2.76$, $p = .098$, partial $\eta^2 = .007$) or stakes ($F(1, 375) = 0.16$, $p = .687$, partial $\eta^2 < .001$) on participant's final confidence.

After accounting for initial confidence, the main effect of the source of advice on the final confidence ratings was significant, $F(1, 375) = 8.26$, $p = .004$, partial $\eta^2 = .022$. Participants reported significantly higher confidence in their final decision when receiving advice framed as coming from a human (M = 73.29, 95% *BootCI* [70.73, 75.72]), compared to advice framed as coming from AI (M = 69.53, 95% *BootCI* [66.77, 72.14]).

Exploratory analyses on the effect of the type of advice on the WOA

Mann-Whitney U test

A Mann-Whitney U test was conducted to determine whether there was a significant difference in the WOA between the add and subtract advice conditions. The median WOA scores significantly differed between the add and subtract conditions, U = 23002.50, z = 4.35, p < .001. The weight participants placed on advice was significantly greater in the subtract condition when the advice was lower than their initial judgement (*Mdn* = 0.71) than in the add condition when the advice was higher than their initial judgement (*Mdn* = 0.50). Due to this significant difference, the decision was taken to perform sub-group analyses by splitting the data into the add versus subtract conditions.

Subgroup Analysis: Add condition

A three-way bootstrapped ANOVA was performed to evaluate the effects of decision stakes, perspective, and the source of advice on the WOA within the add advice condition sample. The main effects of decision stakes ($F(1, 178) = 0.01$, p = .940, partial $\eta^2 < .001$), perspective ($F(1, 178) = 0.17$, p = 0.683, partial η^2 = 001), and the source of advice were non-significant ($F(1, 178) = 1.76$, p = 0.187, partial η^2 = .010). All two-way interactions were non-significant.

The three-way interaction effect between the source of advice, decision stakes and perspective was significant, $F(1, 178) = 4.69$, p = 0.032, partial η^2 = .026. As illustrated in Figures 5 and 6, the effect of stakes and perspective differs depending on whether the advice was framed as coming from AI versus a human.

Figure 5

Estimated Marginal Means of the WOA for the AI advice condition (Add Subgroup)

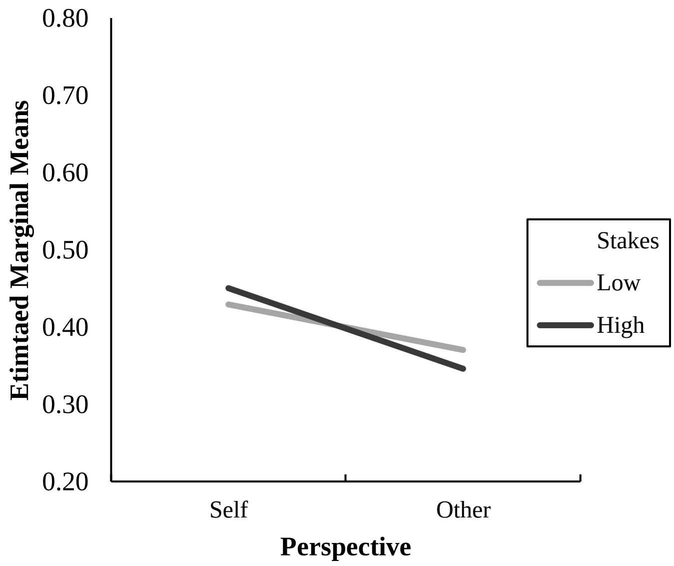
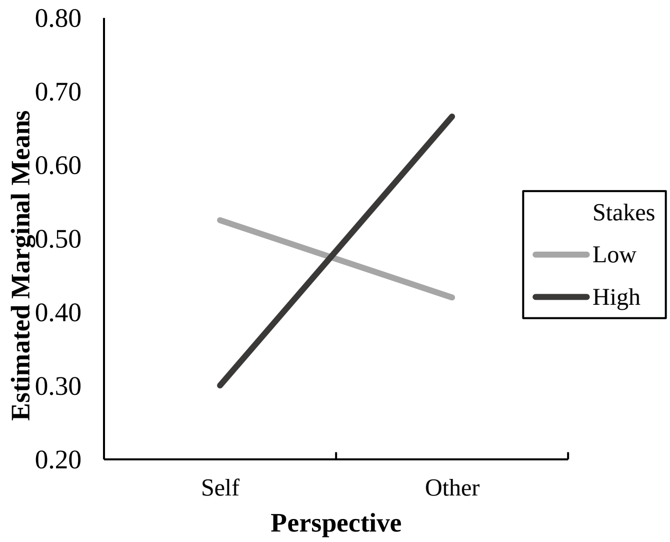


Figure 6

Estimated Marginal Means of the WOA for the human advice condition (Add Subgroup)



In the add condition sample, there was a statistically significant simple two-way interaction between stakes and perspective when the advice was framed as coming from a human, $F(1, 178) = 8.83$, $p = .003$, partial $\eta^2 = .047$. However, the simple two-way interaction was non-significant when advice was framed as coming from AI, $F(1, 178) = 0.07$, $p = .799$, partial $\eta^2 < .001$.

In the add condition subgroup, there was a statistically significant simple simple main effect of perspective in the human advice condition for high stakes decisions ($F(1, 178) = 10.54$, $p = .001$, partial $\eta^2 = .056$), but not for low stakes decisions, ($F(1, 178) = 0.89$, $p = .347$, partial $\eta^2 = .005$). When making high stakes decisions for others, individuals place significantly greater weight on human advice ($M = 0.67$, 95% *BootCI* [0.52, 0.81]) compared to when making decisions for the self ($M = 0.30$, 95% *BootCI* [0.16, 0.46]).

Subgroup Analysis: Subtract Condition

A three-way bootstrapped ANOVA was performed to evaluate the effects of decision stakes, perspective, and the source of advice on the WOA within the subtract advice condition sample. The main effects of stakes ($F(1, 190) = 0.02$, $p = .887$, partial $\eta^2 < .001$), and perspective were non-significant ($F(1, 190) = 0.81$, $p = .368$, partial $\eta^2 = .004$).

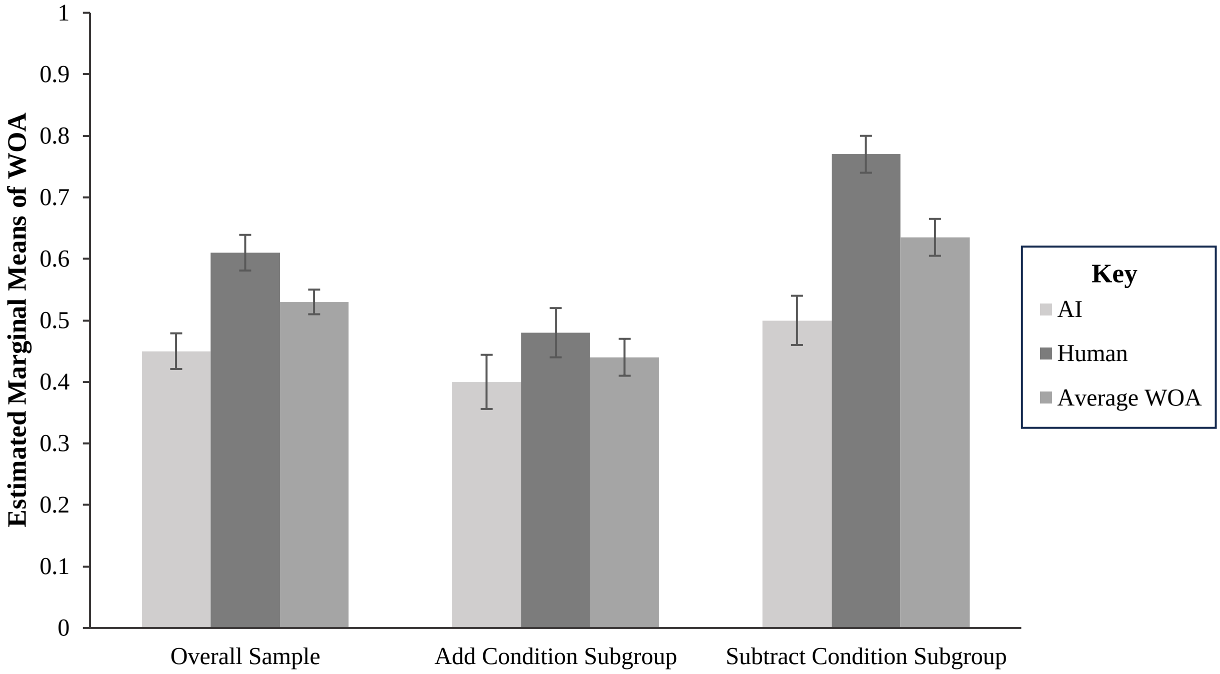
The main effect of the source of advice was significant, $F(1, 190) = 25.68$, $p < .001$, partial $\eta^2 = .119$. Participants placed significantly greater weight on advice framed as coming from a human ($M = 0.77$, 95% *BootCI* [0.70, 0.83]) compared to advice framed as coming from AI ($M = 0.50$, 95% *BootCI* [0.42, 0.58]). All two-way interaction effects and the three-way-interaction effect between the source of advice, decision stakes and perspective were non-significant.

Cross Group Comparisons

As shown in Figure 7, the average WOA is greatest in the subtract condition, followed by the overall sample and then the add condition. Furthermore, the main effect of the source of advice, which demonstrated a preference for human over algorithmic advice found in the overall sample, only emerged within the subtract advice condition. When individuals are advised to invest more than their initial judgement, there was no significant difference between the weight placed on human versus AI framed advice. Therefore, the effect of the source of advice depended on whether the advice was to invest an amount smaller or greater than the individuals' original estimate.

Figure 7

Cross-group comparisons of the effect of source of advice on WOA



Note: Error bars represent the bootstrapped standard error.

Furthermore, the interaction effect between the source of advice, decision stakes and perspective on the WOA that emerged within the overall sample was only found within the add condition. The interaction was similar within the overall sample and add condition (as seen in Figures 3-6), with a simple two-way interaction emerging between decision stakes and perspective within the human but not the AI advice condition. However, the size of the three-way interaction effect was greater in the add condition (partial $\eta^2 = .026$) compared to the overall sample (partial $\eta^2 = .017$). In both the overall sample and add condition subgroup, when making high stakes decisions for others (versus the self), individuals placed significantly greater weight on human advice.

Discussion

The present study investigated the effect of decision stakes and perspective on the uptake of algorithmic advice within a financial decision-making context. Overall, the findings provided mixed support for the proposed hypotheses.

As hypothesised (H_1), individuals placed a significantly greater weight on human advice than algorithmic advice across all decisions. Participants also reported greater confidence in their decision after receiving human versus algorithmic advice. This is consistent with a large body of research depicting that humans are largely averse to algorithms (Dietvorst et al., 2015; Mahmud et al., 2022). Furthermore, this contributes to instances of algorithm aversion within the financial domain (e.g., Larkin et al., 2022; Önkal et al., 2009; Zhang et al., 2021). Financial services have traditionally been a "high-touch" sector characterised by significant human involvement (Bitner et al., 2000). However, it appears that despite the potential of AI to disrupt this industry, adoption lags behind technological progress.

The present findings contrast cases of algorithm appreciation (Logg et al., 2019). This is likely due to the consequentiality of the decisions (Castelo et al., 2019), the description of the human as an expert (Jussupow et al., 2020), and the risk involved in both decisions (Perkins et al., 2010) all of which have been shown to increase algorithm aversion. However, future research should continue to explore in what contexts people tend to reject versus utilise algorithms to deepen our understanding of adoption as the AI boom continues.

Despite participants' reluctance to use algorithms, several strategies can reduce algorithm aversion. Individuals are more accepting of algorithms if they can even slightly adjust its forecasts (Dietvorst et al., 2018) or are informed they can learn from experience (Berger et al., 2021). Furthermore, designing automated advisors to be more 'human-like' can increase trust in algorithms in a financial context (Hodge et al., 2021). Additionally, the utilisation of advice can be seen as a trade-off between potential costs and benefits (Bonaccio & Dalal, 2006). As automated financial advisory usage is primarily predicted by price (Epperson et al., 2015), in a real-world context where the benefit of affordability is felt, the likelihood of adoption may increase.

Furthermore, it was found that although the advice appeared at the same range above or below the initial judgement, participants placed a greater weight on advice recommending investing an amount lower (versus higher) than their original investment. It is proposed that *risk aversion* underlies this finding. Financial decisions largely encompass decision-making under risk, as most financial decisions will not have a certain outcome (Cruciani, 2017). Risk is an influential decision criterion (Phung et al., 2021), with individuals tending to prefer certain or less risky investments over uncertain or more risky investments (Badarinza et al., 2016). This is despite the expected values of potential gains being equal (Rabin, 2013), deviating from what is predicted by neoclassical economic theory (DellaVigna, 2009).

An aversion to risk can be seen to be driven by *loss aversion*, as people are more affected by loss than gain of an equal magnitude (Köbberling & Wakker, 2005). Consequently, loss aversion encourages individuals to be more risk averse and prefer safer options in financial decisions. This is in a bid to avoid losses despite the potential for gains. Furthermore, *confirmation bias* depicts that individuals selectively favour information that aligns with their prior beliefs (Wason, 1960). As investing more money would have increased the risk of the investment, advice to invest a smaller amount aligns with a reduction in risk. Therefore, investment advice which fell 6%-9% lower than their original answer, was likely favoured as it supports an aversion to risk.

As attitudes towards risk have been demonstrated to depend on how the decision is framed (Kahneman & Tversky, 2013), the investment scenarios were deliberately kept neutral by equally emphasising both the possibility of loss and gain to limit the impact on risk behaviour. However, attitudes towards risk have been shown to vary depending on whether the investment money in the experiment is earned or given for experimental purposes. When money is earned, individuals exhibit a greater aversion to risk (Corgnet et al., 2015; Thaler & Johnson, 1990). In the present study, participants were asked to consider either their own savings or someone else's; money which is already earned. Hence, the experimental design of the study may have encouraged greater risk aversion.

Crucially, participants' preference for human over algorithmic advice depended on the nature of the investment advice. When the advice was smaller than the original investment amount, there was a significant and substantial preference for human advice (partial $\eta^2 = 0.120$). However, the difference between the weight placed on human versus algorithmic advice was not significant when the agent recommended a greater investment amount. This suggests that participants are generally reluctant to accept riskier advice, regardless of the advisor.

Overall, it is clear that attitudes towards risk shape attitudes towards algorithmic versus human advice within a financial context. The implications of the present study on automated financial advisory services are significant when considering that such service providers capitalise on risk-seeking behaviour (Cui, 2022). It is argued that personalising investment advice based on individuals' risk preferences will be crucial for successful adoption so that advice aligns with the investors' propensity for risk in order to promote advice reliance. Accordingly, this approach has already been adopted by several automated financial advisory service providers (Abraham et al., 2019). It is crucial that further research examines what factors underlie this effect as existing research into risk taking behaviour and algorithm acceptance is scant. Future work may benefit from assessing individual risk preferences and the role of perceived risk to help illuminate the present results.

Contrary to hypothesised (H_2), there was no significant difference between the weight placed on algorithmic advice in high stakes compared to low stakes financial decisions. This contrasts with Longoni et al. (2019), who found a greater aversion to AI in high stakes compared to low stakes medical scenarios. The present results suggest this difference does not extend to the financial domain, aligning with Larkin et al. (2022), who found that acceptance of algorithms differs across medical and financial decisions.

However, the present research contrasts with that of Filiz et al. (2023), who found that algorithm aversion increases with the perceived gravity of a decision. Filiz et al. (2023) examined the choice between delegating the task to be performed independently by an algorithm or a human expert. Implementing algorithms as a decision tool rather than the decision maker can reduce algorithm aversion (Burton et al., 2020; Dietvorst et al., 2018). Accordingly, in high stakes contexts, there is a more negative perception when algorithms make decisions independently rather than providing support (Grzymek & Puntschuh, 2020). Therefore, the extent of the algorithm's involvement may underly the differences observed.

Furthermore, prior research that found that acceptance of algorithms is lower in high stakes versus low stakes decisions has been compared across contexts (Ashoori & Weisz, 2019; Filiz et al., 2023; Grzymek & Puntschuh, 2020). In contrast, a strength of the present research was the ability to manipulate investment decisions to be both low and high stakes, minimising potential confounding variables. However, the financial sector is characterised by uncertainty and volatility (Cruciani, 2017), meaning that both investment scenarios may have been perceived as relatively high stakes regardless of the investment type (Szeli, 2020).

Moreover, this may have been exaggerated by the experimental design. Although the pre-test confirmed significant differences in the perceived stakes, the pre-test examined the scenarios independently of the investment amount. However, in the study, individuals had control over the investment amount. Interestingly, participants invested substantially more in the low stakes than the high stakes scenario (17% difference). Therefore, perceived stakes in the low stakes scenario likely inadvertently increased due to the higher amount of money involved contributing to the lack of an effect of decision stakes. Future research may benefit from investigating the impact of different approaches to frame the investment decision on the uptake of algorithmic advice.

No support was found for the hypothesis (H_3) that individuals would place a significantly greater weight on algorithmic advice in financial decisions framed as impacting someone else compared to the self. Individuals were more willing to invest a greater proportion of an unknown other's money over their own consistent with prior research (Trump et al., 2015). However, decision perspective had no influence on the uptake of algorithmic advice or decision confidence. Despite a vast literature of self-other decision-making asymmetries, such differences do not appear to extend to the decision to use algorithmic advice. Therefore, the present research suggests that differences in acceptance of algorithms are not driven by decision perspective.

The present findings contrast those of Utz et al. (2021), who found an influence of decision perspective on attitudes towards algorithmic input in high stakes moral decisions. Moral versus non-moral decisions largely differ in the degree they engage emotional processing, and these differences can influence decision-making (Garrigan et al., 2018; Greene et al., 2001). Furthermore, self-other decision-making differences have been shown to vary depending on the decision domain, with financial decisions showing less decision perspective asymmetry (Batteux et al., 2019; Polman & Wu, 2020; Stone & Allgaier, 2008). Therefore, existing literature suggests that moral and financial decisions largely differ in their processing and the degree of influence of decision perspective. Hence, the different decision domains may explain the differences between Utz et al. (2021) and the present study.

A three-way interaction was found, such that individuals placed greater weight on human (but not algorithmic) advice when making decisions for others versus the self. Notably, this pattern was exclusive to advice to invest more than the initial judgment. In high stakes decisions which incur greater consequences, individuals may particularly benefit from sharing the responsibility of the decision, something which is easier to do with a human advisor (Bonaccio & Dalal, 2006). When investing someone else's money, the focus on responsibility will likely be more salient. Moreover, an increased propensity to take risks with someone else's money aligns with a higher investment recommendation (Trump et al., 2015), helping to explain why the effect was exclusive to the add condition. Therefore, when investing for others, advice which aligns with greater risk taking may be favoured over more conservative advice.

Critically, due to the halved sample size in the subgroup analysis, a sensitivity power analysis revealed that in the add condition, the analysis was sensitive to have 80% probability to detect a minimum effect of a partial $\eta^2 = .041$ given a conventional level of significance ($\alpha = 0.05$) (see Appendix E). As the three-way interaction effect between decision stakes, perspective and the source of advice in the add condition was substantially smaller than this minimum (partial $\eta^2 = .026$), this finding should be interpreted cautiously. Further research is therefore required to support the present results.

Limitations and future directions

The present study had several limitations that offer potential avenues for future research. Firstly, no measure of financial literacy or previous investment experience was collected. Financial literacy has been shown to influence financial decision-making (Fong et al., 2021) and the uptake of financial advice (Stolper, 2018). Furthermore, higher perceived competence in a decision domain predicts a greater preference for algorithmic over human advice (Yalcin et al., 2019). Future research should ensure to control for these attributes to determine whether these factors influenced the present findings.

Moreover, the investment scenarios were hypothetical vignettes, a commonly employed method in research into the use of algorithms due to their capacity to maintain a high level of experimental control (Renier et al., 2021). Nevertheless, the widespread use of vignettes raises valid concerns regarding the external validity of the findings (Mahmud et al., 2022). Additionally, it is crucial to consider that psychological distance can not only be shaped by social distance but also by hypotheticality (Liberman & Trope, 2014). Hence, the use of hypothetical scenarios may have influenced the findings on the decision perspective. Conducting future research in real-world settings is essential to determine whether the present findings hold true when real money is at stake.

Consistent with most of the research into algorithmic acceptance, participants were recruited exclusively from a crowdsourcing platform (Mahmud et al., 2022). Individuals who frequently participate in online experiments may arguably hold a higher level of digital experience compared to the general population. As Hengstler et al. (2016) illustrates, familiarity with an innovation can influence adoption. Therefore, participants in this study, more accustomed to digital environments and technology, might have a more positive attitude towards new technologies such as AI. Exploring more diverse demographic groups is required to enhance the generalisability of the present findings.

Lastly, WOA values outside the theoretical bounds of 0 and 1 were winsorized or removed following the recommended protocol in the literature (e.g., Gino & Moore, 2007; Logg et al., 2019). This approach allowed for the clearest comparison between existing and present research. Critically, it is reasonable to assume that participants' departure from the advice (WOA<0) or overreliance on the advice (WOA>1) reflects a deliberate choice resulting from their experience with the advisor (Berger et al., 2021; Prahl & Van Swol, 2017). Therefore, this approach poses the risk of valid responses being manipulated or removed. Future research should investigate participants' motivations for choosing WOA values outside of this range to provide a better rationale for handling such responses.

Conclusion

Overall, the present study provided valuable insights into understanding the adoption of AI within financial decisions. Contrary to expectations, no evidence emerged supporting the notion that acceptance of algorithms varied based on decision stakes or perspective. However, individuals relied more on human over algorithmic financial advice. Crucially, the benefits of greater accessibility and financial inclusion that AI financial advisory offers will only be felt if users are willing to trust this technology. Therefore, the AI paradigm shift in financial services may be premature (Hildebrand & Bergner, 2021). Notably, empirical research into the willingness of users to adopt AI has not kept up with the technological advancements in the field (Larkin et al., 2022). The present findings underscore the need for this research as user adoption of AI remains complex. Only through investigating how people react to AI can we truly understand the potential this technology offers.

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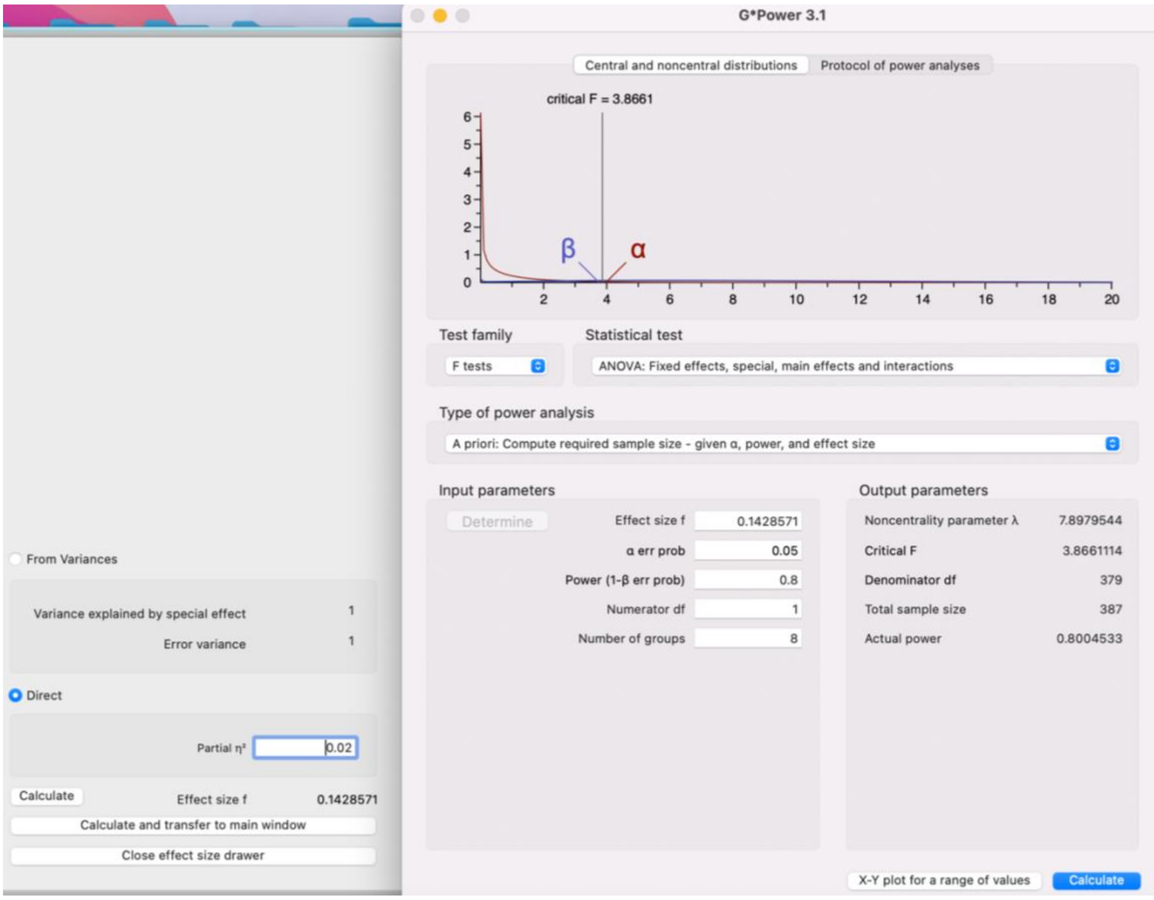
Appendix A

G*Power Priori Power Analysis



Note: The following *a priori* power analysis is for a 2x2x2 between subjects ANOVA. The input was determined as follows:
The number of groups:
2 (levels of Source) x 2 (levels of Perspective) x 2 (levels of Stakes) = 8 groups.
Numerator df:
(2 – 1) (2 – 1)(2 – 1) = 1
All calculations were conducted in accordance with G*Power 3.1 manual[3]

[3] Retrieved from: https://www.psychologie.hhu.de/fileadmin/redaktion/Fakultaeten/Mathematisch-Naturwissenschaftliche_Fakultaet/Psychologie/AAP/gpower/GPowerManual.pdf

Appendix B

Investment Decision Scenarios

Stakes	Perspective *Self*	*Other*
Low	Imagine you have the opportunity to invest a portion of your savings in a well-established food processing company. This company has a long-standing reputation in the industry, known for its stable growth over the years. The investment offers the potential for a moderate return on investment (ROI) of 7% within a five-year period. While the ROI may not be exceptionally high, it presents a reliable and steady opportunity for your finances to grow. Although the investment carries some level of risk, it is considered relatively low stakes. There is only a 1% chance of experiencing a complete loss of the investment. This means that while there is a slight possibility of losing the investment, the likelihood of this outcome is minimal. Considering the overall scenario, this investment offers a balanced approach to growing your savings without exposing you to significant risks. By carefully assessing the opportunity and understanding the low-stakes nature of the investment, you can make an informed decision about how much money to invest. The decision you make will directly impact your financial future, making it important to weigh the potential financial gains against the small chance of loss.	Imagine you have been entrusted with the responsibility of investing a portion of someone else's savings in a well-established food processing company. This company has a long-standing reputation in the industry, known for its stable growth over the years. The investment offers the potential for a moderate return on investment (ROI) of 7% within a five-year period. While the ROI may not be exceptionally high, it presents a reliable and steady opportunity for their finances to grow. Although the investment carries some level of risk, it is considered relatively low stakes. There is only a 1% chance of experiencing a complete loss of the investment. This means that while there is a slight possibility of losing the investment, the likelihood of this outcome is minimal. Considering the overall scenario, this investment offers a balanced approach to growing this individual’s savings without exposing them to significant risks. By carefully assessing the opportunity and understanding the low-stakes nature of the investment, you can make an informed decision of how much money to invest on behalf of this individual. You are responsible for the direct impact this investment decision will have on the financial future of this person, meaning it is important to weigh the potential financial gains against the small chance of loss.
High	Imagine you have the opportunity to invest a portion of your savings in a high-growth technology start-up. This start-up, although relatively new, has experienced rapid growth and is considered a frontrunner in the tech industry. The investment opportunity offers the potential for a high return on investment (ROI) of 150% within five years. The high ROI reflects the optimistic outlook for the start-up's growth trajectory. However, it's important to note that this investment carries a relatively high level of risk. There is a 34% chance of losing the entire investment.	Imagine you have been entrusted with the responsibility of investing a portion of someone else's savings in a high-growth technology start-up. This start-up, although relatively new, has experienced rapid growth and is considered a frontrunner in the tech industry. The investment opportunity offers the potential for a high return on investment (ROI) of 150% within five years. The high ROI reflects the optimistic outlook for the start-up's growth trajectory. However, it's important to note that this investment carries a relatively high level of risk. There is a 34% chance of losing the entire investment.

	Considering the overall scenario, this investment offers the possibility for large financial gain, but it exposes you to significant risks. By carefully assessing the opportunity and understanding the high-stakes nature of the investment, you must make an informed decision about how much money to invest. The decision you make will directly impact your financial future, meaning it is important to weigh the large potential financial gain against the substantial risk of loss.	Considering the overall scenario, this investment offers the possibility for large financial gain, but it exposes this individual to significant risks. By carefully assessing the opportunity and understanding the high-stakes nature of the investment, you must make an informed decision about how much money to invest on behalf of this individual. You are responsible for the direct impact this investment decision will have on the financial future of this person, meaning it is important to weigh the large potential financial gain against the substantial risk of loss.

Appendix C

Participant Information and Consent Form

You are being invited to take part in a research study. Before deciding to participate it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information. If there is anything which is not clear or any questions you have, feel free to ask. Take your time reading through the following information and don't feel rushed.

What is this research about?

The present research is investigating financial decision-making.

Who is conducting this research?

X X (X@lse.ac.uk) from the Department of Psychological and Behavioural Science at the London School of Economics.

What will participation involve?

The study will involve reading a short scenario and then answering questions based on this scenario. Demographic information will also be collected.

How long will participation take?

The study will take approximately 5 minutes to complete.

What about confidentiality?

Your privacy is guaranteed. We will not store or use any personally identifying information. The data which you enter into the online survey may be used in anonymised form in presentations or publications.

- If you feel that you have been given sufficient information about the research to enable you to decide whether or not to participate in the research,
- If you feel that you have had an opportunity to ask questions about the research,
- If you understand that your participation is voluntary, and that you are free to withdraw at any time, without giving a reason, and without penalty,
- If you are willing to take part in the research;

Then, please tick 'yes' in the box below.

I have read and understood the above consent form and desire of my own free will to participate in this study.

Yes [ ]
No [ ]

Appendix D

SPSS Syntax and Output of Analyses

The SPSS syntax below can be run on SPSS to produce the output which follows for each section of the analysis. The syntax and output of each test are included in the order in which they were reported in the text.

Pre-test

Syntax

Descriptive Statistics:

```
DESCRIPTIVES VARIABLES=S1_L_Comprehension S2_H_Comprehension S1_Stakes S2_Stakes
High_Perspective
    Low_Perspective
  /STATISTICS=MEAN STDDEV VARIANCE SEMEAN.
```

Paired sample t-test:

```
T-TEST PAIRS=S2_Stakes WITH S1_Stakes (PAIRED)
  /ES DISPLAY(TRUE) STANDARDIZER(SD)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.
```

Output

Descriptive Statistics

	N	Mean		Std. Deviation	Variance
	Statistic	Statistic	Std. Error	Statistic	Statistic
S1_L_Comprehension	30	6.100	.2366	1.2959	1.679
S2_H_Comprehension	29	6.00	.233	1.254	1.571
S1_Stakes	29	2.21	.195	1.048	1.099
S2_Stakes	30	5.80	.182	.997	.993
High_Perspective	30	4.93	.335	1.837	3.375
Low_Perspective	30	3.73	.395	2.164	4.685
Valid N (listwise)	28				

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	S2_Stakes	5.86	29	.953	.177
	S1_Stakes	2.21	29	1.048	.195

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	S2_Stakes & S1_Stakes	29	−.435	.018

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	S2_Stakes − S1_Stakes	3.655	1.696	.315	3.010	4.300	11.605	28	<.001

Effects of decision stakes and perspective on investment amount prior to receiving advice[4]

Syntax

2x2 bootstrapped ANOVA

```
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=Savings_1 INPUT=Stakes Persp
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA Savings_1 BY Stakes Persp
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /EMMEANS=TABLES(Stakes) COMPARE ADJ(LSD)
  /EMMEANS=TABLES(Persp) COMPARE ADJ(LSD)
  /PRINT ETASQ
  /CRITERIA=ALPHA(.05)
  /DESIGN=Stakes Persp Stakes*Persp.
```

Output

Between-Subjects Factors

		Value Label	N
Stakes	1	Low	193
	2	High	191
Persp	1	Self	190
	2	Other	194

Tests of Between-Subjects Effects

Dependent Variable: Savings_1

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	38442.872[a]	3	12814.291	27.350	<.001	.178
Intercept	435419.669	1	435419.669	929.323	<.001	.710
Stakes	26414.425	1	26414.425	56.377	<.001	.129
Persp	11609.767	1	11609.767	24.779	<.001	.061
Stakes * Persp	497.635	1	497.635	1.062	.303	.003
Error	178042.961	380	468.534			
Total	654426.000	384				
Corrected Total	216485.833	383				

a. R Squared = .178 (Adjusted R Squared = .171)

1. **Stakes**

Estimates

Dependent Variable: Savings_1

			95% Confidence Interval		Bootstrap for Mean[a]			
							95% Confidence Interval	
Stakes	Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	Lower	Upper
Low	41.971	1.558	38.907	45.034	.015	1.772	38.493	45.544
High	25.382	1.566	22.302	28.462	.009	1.300	22.899	27.952

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

[4] The variables were coded as follows: stakes (1 for low, 2 for high), perspective (1 for self, 2 for other), source of advice (1 for AI, 2 for human), and type of advice (1 for add, 2 for subtract) across all analyses.

Pairwise Comparisons

Dependent Variable: Savings_1

(I) Stakes	(J) Stakes	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
Low	High	16.589*	2.209	<.001	12.245	20.933
High	Low	-16.589*	2.209	<.001	-20.933	-12.245

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Bootstrap for Pairwise Comparisons

Dependent Variable: Savings_1

			Bootstrap[a]				
(I) Stakes	(J) Stakes	Mean Difference (I-J)	Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval Lower	Upper
Low	High	16.589	.006	2.188	<.001	12.271	20.890
High	Low	-16.589	-.006	2.188	<.001	-20.890	-12.271

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

Univariate Tests

Dependent Variable: Savings_1

	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Contrast	26414.425	1	26414.425	56.377	<.001	.129
Error	178042.961	380	468.534			

The F tests the effect of Stakes. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

2. Perspective

Estimates

Dependent Variable: Savings_1

			95% Confidence Interval		Bootstrap for Mean[a]			
Persp	Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	95% Confidence Interval Lower	Upper
Self	28.177	1.570	25.089	31.265	.017	1.550	25.219	31.308
Other	39.175	1.554	36.120	42.231	.007	1.585	36.156	42.397

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

Pairwise Comparisons

Dependent Variable: Savings_1

(I) Persp	(J) Persp	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
Self	Other	-10.998*	2.209	<.001	-15.342	-6.654
Other	Self	10.998*	2.209	<.001	6.654	15.342

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Bootstrap for Pairwise Comparisons

Dependent Variable: Savings_1

			Bootstrap[a]				
(I) Persp	(J) Persp	Mean Difference (I-J)	Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval Lower	Upper
Self	Other	-10.998	.010	2.226	<.001	-15.347	-6.574
Other	Self	10.998	-.010	2.226	<.001	6.574	15.347

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

Univariate Tests

Dependent Variable: Savings_1

	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Contrast	11609.767	1	11609.767	24.779	<.001	.061
Error	178042.961	380	468.534			

The F tests the effect of Persp. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

The effect of decision stakes, perspective, and source of advice on the WOA

Syntax

2x2x2 bootstrapped ANOVA

```
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=WOA INPUT=Stakes Persp Source
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA WOA BY Stakes Persp Source
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /PLOT=PROFILE(Persp*Stakes*Source) TYPE=LINE ERRORBAR=NO
MEANREFERENCE=NO
    YAXIS=AUTO
  /EMMEANS=TABLES(Source) COMPARE ADJ(LSD)
  /PRINT ETASQ DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=Stakes Persp Source Stakes*Persp Stakes*Source Persp*Source Stakes*Persp*Source.
```

Simple two-way interactions

```
SORT CASES  BY Source.
SPLIT FILE LAYERED BY Source.

BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=WOA INPUT=Stakes Persp
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA WOA BY Stakes Persp
  /METHOD=SSTYPE(3)
  /TEST=Persp*Stakes VS 60.579668 DF(376)
  /INTERCEPT=INCLUDE
  /PRINT ETASQ DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=Stakes Persp Stakes*Persp.
```

Note: As seen in the line '/TEST=Persp*Stakes VS 60.579668 DF(376)', the error term and degrees of freedom were replaced with those from the three way ANOVA

Simple simple main effects

SORT CASES BY Stakes Source.
SPLIT FILE LAYERED BY Stakes Source.

```
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=WOA INPUT=Persp
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA WOA BY Persp
```

```
/METHOD=SSTYPE(3)
/TEST=Persp VS 60.579668 DF(376)
/INTERCEPT=INCLUDE
/PRINT ETASQ DESCRIPTIVE
/CRITERIA=ALPHA(.05)
/DESIGN=Persp.
```

Note: As seen in the line '/TEST=Persp VS 60.579668 DF(376)', the error term and degrees of freedom were again replaced with those from the three way ANOVA

SPLIT FILE OFF.

Output

2x2x2 bootstrapped ANOVA: stakes, perspective and source on WOA

Between-Subjects Factors

		Value Label	N
Stakes	1	Low	193
	2	High	191
Persp	1	Self	190
	2	Other	194
Source	1	AI	188
	2	Human	196

Tests of Between-Subjects Effects

Dependent Variable: WOA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3.990[a]	7	.570	3.538	.001	.062
Intercept	107.968	1	107.968	670.123	<.001	.641
Stakes	4.595E-5	1	4.595E-5	.000	.987	.000
Persp	.244	1	.244	1.517	.219	.004
Source	2.418	1	2.418	15.006	<.001	.038
Stakes * Persp	.177	1	.177	1.099	.295	.003
Stakes * Source	.042	1	.042	.262	.609	.001
Persp * Source	.025	1	.025	.152	.697	.000
Stakes * Persp * Source	1.019	1	1.019	6.326	.012	.017
Error	60.580	376	.161			
Total	173.415	384				
Corrected Total	64.570	383				

a. R Squared = .062 (Adjusted R Squared = .044)

Source

Estimates

Dependent Variable: WOA

			95% Confidence Interval		Bootstrap for Mean[a]			
							95% Confidence Interval	
Source	Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	Lower	Upper
AI	.451	.029	.394	.509	.000	.029	.395	.509
Human	.610	.029	.554	.666	.000	.029	.553	.666

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

Pairwise Comparisons

Dependent Variable: WOA

(I) Source	(J) Source	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
AI	Human	-.159*	.041	<.001	-.239	-.078
Human	AI	.159*	.041	<.001	.078	.239

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Bootstrap for Pairwise Comparisons

Dependent Variable: WOA

			Bootstrap[a]				
(I) Source	(J) Source	Mean Difference (I-J)	Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval Lower	Upper
AI	Human	-.159	7.440E-5	.041	<.001	-.239	-.080
Human	AI	.159	-7.440E-5	.041	<.001	.080	.239

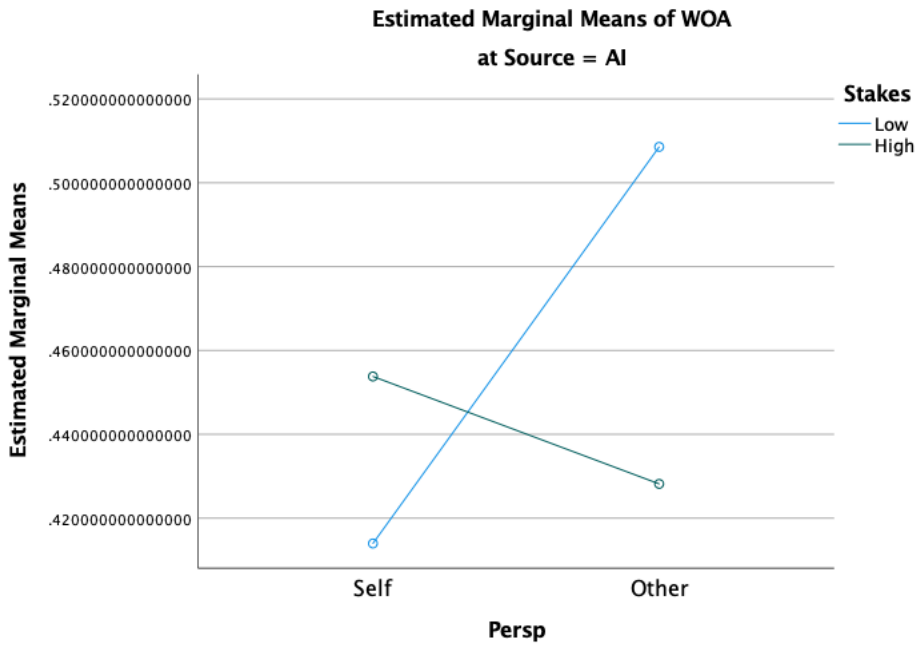
a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

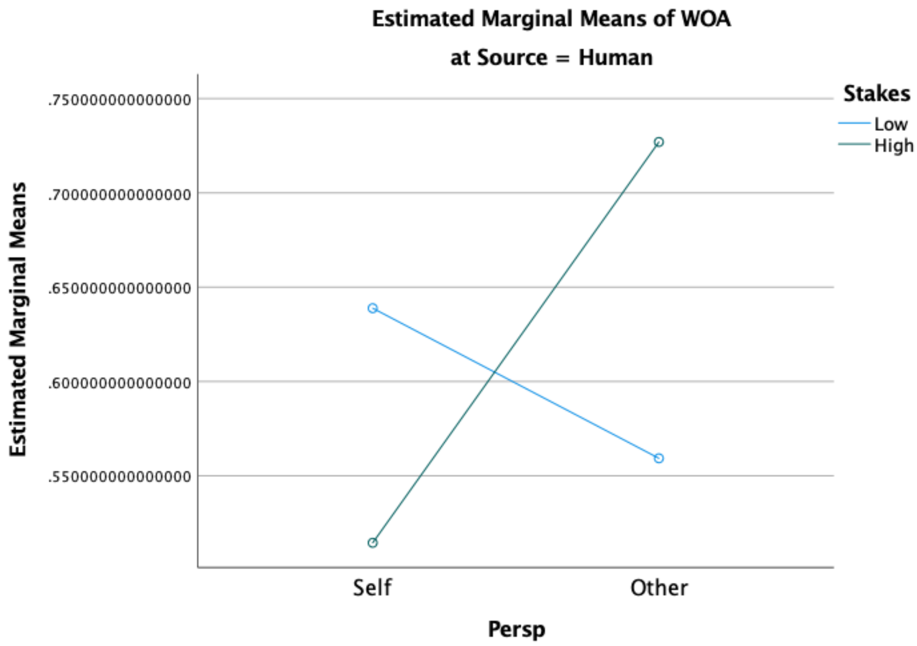
Univariate Tests

Dependent Variable: WOA

	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Contrast	2.418	1	2.418	15.006	<.001	.038
Error	60.580	376	.161			

The F tests the effect of Source. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.





Simple two-way interaction effects

Between-Subjects Factors

Source			Value Label	N
AI	Stakes	1	Low	94
		2	High	94
	Persp	1	Self	95
		2	Other	93
Human	Stakes	1	Low	99
		2	High	97
	Persp	1	Self	95
		2	Other	101

Tests of Between-Subjects Effects

Dependent Variable: WOA

Source	Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
AI	Corrected Model	.243[a]	3	.081	.491	.689	.008
	Intercept	38.255	1	38.255	231.960	<.001	.558
	Stakes	.019	1	.019	.117	.733	.001
	Persp	.056	1	.056	.339	.561	.002
	Stakes * Persp	.170	1	.170	1.030	.312	.006
	Error	30.345	184	.165			
	Total	68.767	188				
	Corrected Total	30.589	187				
Human	Corrected Model	1.285[b]	3	.428	2.719	.046	.041
	Intercept	72.837	1	72.837	462.543	<.001	.707
	Stakes	.023	1	.023	.146	.703	.001
	Persp	.216	1	.216	1.374	.243	.007
	Stakes * Persp	1.044	1	1.044	6.632	.011	.033
	Error	30.234	192	.157			
	Total	104.649	196				
	Corrected Total	31.519	195				

a. R Squared = .008 (Adjusted R Squared = −.008)

b. R Squared = .041 (Adjusted R Squared = .026)

Custom Hypothesis Tests

Test Results

Dependent Variable: WOA

Source	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
AI	Contrast	.170	1	.170	1.054	.305	.003
	Error	60.580[a]	376[a]	.161			
Human	Contrast	1.044	1	1.044	6.482	.011	.017
	Error	60.580[a]	376[a]	.161			

a. User specified.

Simple simple main effects

Between-Subjects Factors

Source	Stakes			Value Label	N
AI	Low	Persp	1	Self	48
			2	Other	46
	High	Persp	1	Self	47
			2	Other	47
Human	Low	Persp	1	Self	48
			2	Other	51
	High	Persp	1	Self	47
			2	Other	50

Tests of Between-Subjects Effects

Dependent Variable: WOA

Source	Stakes	Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
AI	Low	Corrected Model	.210[a]	1	.210	1.274	.262	.014
		Intercept	19.992	1	19.992	121.182	<.001	.568
		Persp	.210	1	.210	1.274	.262	.014
		Error	15.178	92	.165			
		Total	35.302	94				
		Corrected Total	15.388	93				
	High	Corrected Model	.015[b]	1	.015	.094	.760	.001
		Intercept	18.282	1	18.282	110.889	<.001	.547
		Persp	.015	1	.015	.094	.760	.001
		Error	15.167	92	.165			
		Total	33.464	94				
		Corrected Total	15.183	93				
Human	Low	Corrected Model	.157[c]	1	.157	.942	.334	.010
		Intercept	35.499	1	35.499	213.348	<.001	.687
		Persp	.157	1	.157	.942	.334	.010
		Error	16.140	97	.166			
		Total	51.686	99				
		Corrected Total	16.297	98				
	High	Corrected Model	1.094[d]	1	1.094	7.377	.008	.072
		Intercept	37.342	1	37.342	251.694	<.001	.726
		Persp	1.094	1	1.094	7.377	.008	.072
		Error	14.094	95	.148			
		Total	52.963	97				
		Corrected Total	15.189	96				

a. R Squared = .014 (Adjusted R Squared = .003)

b. R Squared = .001 (Adjusted R Squared = -.010)

c. R Squared = .010 (Adjusted R Squared = -.001)

d. R Squared = .072 (Adjusted R Squared = .062)

Custom Hypothesis Tests

Test Results

Dependent Variable: WOA

Source	Stakes	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
AI	Low	Contrast	.210	1	.210	1.305	.254	.003
		Error	60.580[a]	376[a]	.161			
	High	Contrast	.015	1	.015	.096	.757	.000
		Error	60.580[a]	376[a]	.161			
Human	Low	Contrast	.157	1	.157	.972	.325	.003
		Error	60.580[a]	376[a]	.161			
	High	Contrast	1.094	1	1.094	6.793	.010	.018
		Error	60.580[a]	376[a]	.161			

a. User specified.

Estimates

Dependent Variable: WOA

					95% Confidence Interval		Bootstrap for Mean[a]			
									95% Confidence Interval	
Source	Stakes	Persp	Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	Lower	Upper
AI	Low	Self	.414	.058	.300	.528	.001	.057	.307	.528
		Other	.509	.059	.392	.625	-.002	.059	.390	.620
	High	Self	.454	.059	.339	.569	.000	.059	.341	.571
		Other	.428	.059	.313	.543	.000	.058	.316	.544
Human	Low	Self	.639	.058	.525	.753	.001	.058	.523	.751
		Other	.559	.056	.449	.670	8.093E-5	.057	.446	.675
	High	Self	.514	.059	.399	.630	-.001	.062	.392	.634
		Other	.727	.057	.615	.839	.001	.049	.628	.819

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

The effect of decision stakes, perspective, and source of advice on confidence

Syntax

2x2x2 bootstrapped ANCOVA

```
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=Confidence_2 INPUT=Source Stakes Persp Confidence_1
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA Confidence_2 BY Source Stakes Persp WITH Confidence_1
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /SAVE=PRED RESID SRESID COOK LEVER
  /EMMEANS=TABLES(Source) WITH(Confidence_1=MEAN) COMPARE ADJ(LSD)
  /PRINT ETASQ DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=Confidence_1 Source Stakes Persp Source*Stakes Source*Persp Stakes*Persp
    Source*Stakes*Persp.
```

Output

Between-Subjects Factors

		Value Label	N
Source	1	AI	188
	2	Human	196
Stakes	1	Low	193
	2	High	191
Persp	1	Self	190
	2	Other	194

Tests of Between-Subjects Effects

Dependent Variable: Confidence_2

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	132430.34[a]	8	16553.792	101.239	<.001	.684
Intercept	27957.741	1	27957.741	170.984	<.001	.313
Confidence_1	121849.211	1	121849.211	745.204	<.001	.665
Source	1350.213	1	1350.213	8.258	.004	.022
Stakes	26.642	1	26.642	.163	.687	.000
Persp	450.733	1	450.733	2.757	.098	.007
Source * Stakes	17.244	1	17.244	.105	.746	.000
Source * Persp	25.600	1	25.600	.157	.693	.000
Stakes * Persp	21.691	1	21.691	.133	.716	.000
Source * Stakes * Persp	48.134	1	48.134	.294	.588	.001
Error	61316.723	375	163.511			
Total	2154135.00	384				
Corrected Total	193747.060	383				

a. R Squared = .684 (Adjusted R Squared = .677)

Estimated Marginal Means
Source

Estimates

Dependent Variable: Confidence_2

			95% Confidence Interval		Bootstrap for Mean[fkh]			
							95% Confidence Interval	
Source	Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	Lower	Upper
AI	69.528[a]	.934	67.692	71.364	-.015	1.379	66.770	72.139
Human	73.287[a]	.915	71.488	75.085	-.009	1.265	70.733	75.718

a. Covariates appearing in the model are evaluated at the following values: Confidence_1 = 64.96.

fkh. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

Pairwise Comparisons

Dependent Variable: Confidence_2

					95% Confidence Interval for Difference[b]	
(I) Source	(J) Source	Mean Difference (I-J)	Std. Error	Sig.[b]	Lower Bound	Upper Bound
AI	Human	-3.759*	1.308	.004	-6.330	-1.187
Human	AI	3.759*	1.308	.004	1.187	6.330

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Bootstrap for Pairwise Comparisons

Dependent Variable: Confidence_2

			Bootstrap[a]				
						95% Confidence Interval	
(I) Source	(J) Source	Mean Difference (I-J)	Bias	Std. Error	Sig. (2-tailed)	Lower	Upper
AI	Human	-3.759	-.006	1.308	.005	-6.429	-1.222
Human	AI	3.759	.006	1.308	.005	1.222	6.429

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

Univariate Tests

Dependent Variable: Confidence_2

	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Contrast	1350.213	1	1350.213	8.258	.004	.022
Error	61316.723	375	163.511			

The F tests the effect of Source. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Mann Whitney U-test comparing across the add and subtract conditions

Syntax

```
DATASET ACTIVATE DataSet2.
*Nonparametric Tests: Independent Samples.
NPTESTS
  /INDEPENDENT TEST (WOA) GROUP (A_S)
  /MISSING SCOPE=ANALYSIS USERMISSING=EXCLUDE
  /CRITERIA ALPHA=0.05  CILEVEL=95.
MEANS TABLES=WOA BY A_S
  /CELLS=STDDEV MEDIAN.
```

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of WOA is the same across categories of A_S.	Independent-Samples Mann-Whitney U Test	<.001	Reject the null hypothesis.

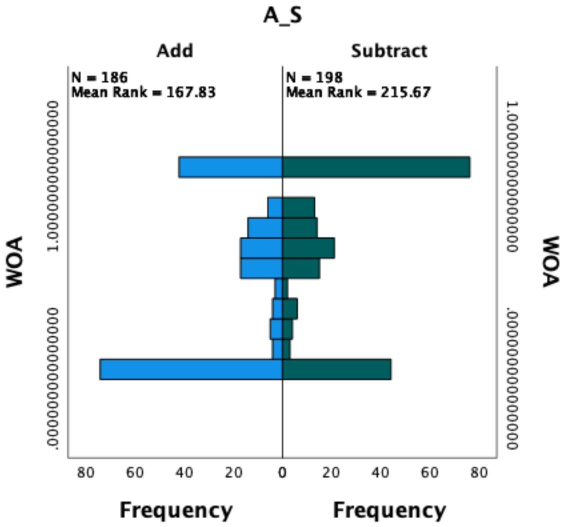
a. The significance level is .050.

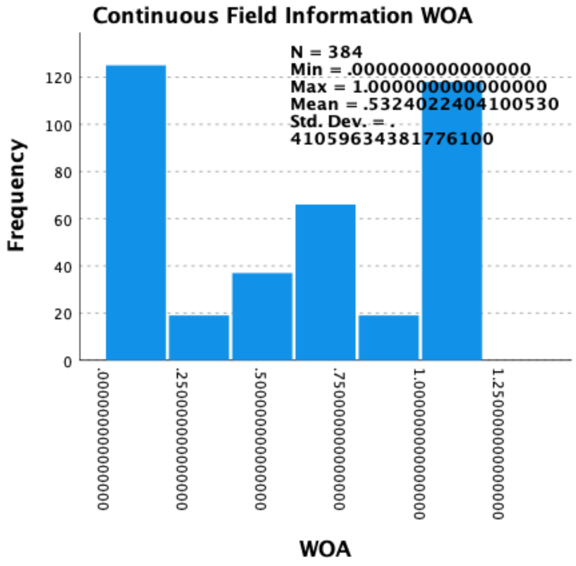
b. Asymptotic significance is displayed.

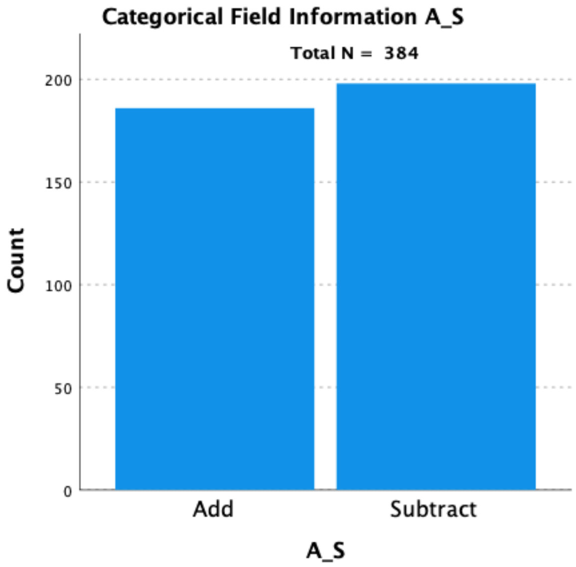
Independent-Samples Mann-Whitney U Test Summary

Total N	384
Mann-Whitney U	23002.500
Wilcoxon W	42703.500
Test Statistic	23002.500
Standard Error	1054.266
Standardized Test Statistic	4.352
Asymptotic Sig.(2-sided test)	<.001

Independent-Samples Mann-Whitney U Test







Report

WOA

A_S	Std. Deviation	Median
Add	.408800434	.500000000
Subtract	.393146814	.714285714
Total	.410596344	.625000000

Subgroup Analysis: Add condition

Selecting add condition responses only[5]

```
USE ALL.
COMPUTE filter_$=(A_S = 1).
VARIABLE LABELS filter_$ 'A_S = 1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.
```

2x2x2 bootstrapped ANOVA: source of advice, decision perspective and stakes on the WOA

```
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=WOA INPUT=Source Stakes Persp
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA WOA BY Source Stakes Persp
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /PLOT=PROFILE(Persp*Stakes*Source) TYPE=LINE ERRORBAR=NO
MEANREFERENCE=NO YAXIS=AUTO
  /EMMEANS=TABLES(Source)
  /EMMEANS=TABLES(Source*Stakes*Persp)
  /PRINT ETASQ DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=Source Stakes Persp Source*Stakes Source*Persp Stakes*Persp Source*Stakes*Persp.
```

Simple two-way interactions

```
SORT CASES  BY Source.
SPLIT FILE LAYERED BY Source.

BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=WOA INPUT=Stakes Persp
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA WOA BY Stakes Persp
  /METHOD=SSTYPE(3)
  /TEST=Persp*Stakes VS 28.662194 DF(178)
  /INTERCEPT=INCLUDE
  /PRINT ETASQ DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=Stakes Persp Stakes*Persp.
```

[5] The same syntax was run performed before the subtract subgroup analyses, but selecting the subtract condition responses only.

Simple simple main effects

```
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=WOA INPUT=Persp
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA WOA BY Persp
  /METHOD=SSTYPE(3)
  /TEST=Persp VS 28.662194 DF(178)
  /INTERCEPT=INCLUDE
  /PRINT ETASQ DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=Persp.
```

Output

2x2x2 ANOVA: Add condition subgroup

Between-Subjects Factors

		Value Label	N
Source	1	AI	83
	2	Human	103
Stakes	1	Low	97
	2	High	89
Persp	1	Self	92
	2	Other	94

Tests of Between-Subjects Effects

Dependent Variable: WOA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	2.255[a]	7	.322	2.000	.057	.073
Intercept	34.892	1	34.892	216.687	<.001	.549
Source	.283	1	.283	1.756	.187	.010
Stakes	.001	1	.001	.006	.940	.000
Persp	.027	1	.027	.167	.683	.001
Source * Stakes	.002	1	.002	.011	.918	.000
Source * Persp	.509	1	.509	3.162	.077	.017
Stakes * Persp	.513	1	.513	3.183	.076	.018
Source * Stakes * Persp	.755	1	.755	4.690	.032	.026
Error	28.662	178	.161			
Total	66.626	186				
Corrected Total	30.917	185				

a. R Squared = .073 (Adjusted R Squared = .036)

Estimated Marginal Means

1. Source

Dependent Variable: WOA

			95% Confidence Interval		Bootstrap for Mean[a]			
							95% Confidence Interval	
Source	Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	Lower	Upper
AI	.399	.045	.311	.487	-.001	.044	.310	.487
Human	.478	.040	.400	.556	.000	.040	.396	.554

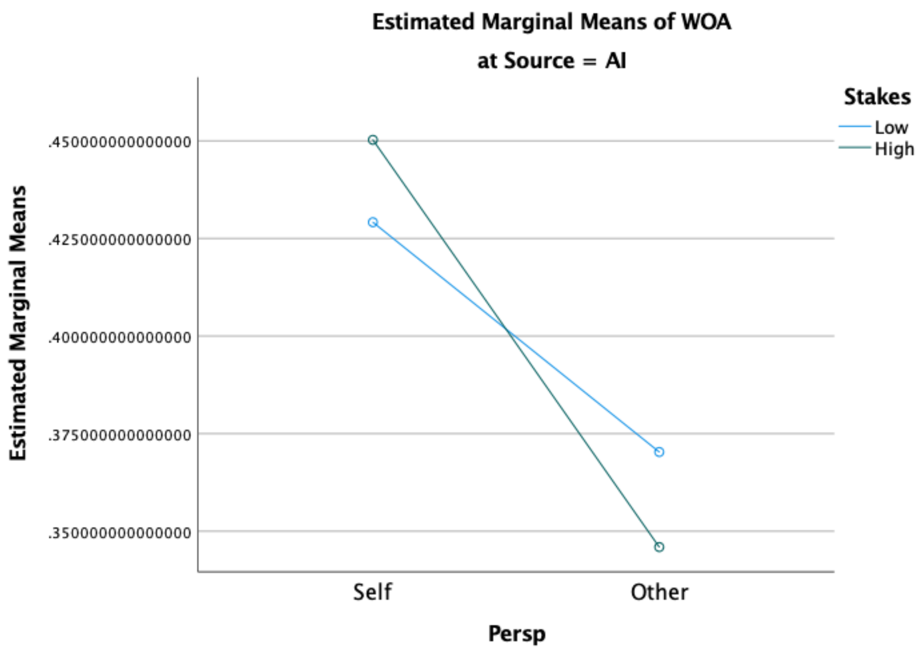
a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

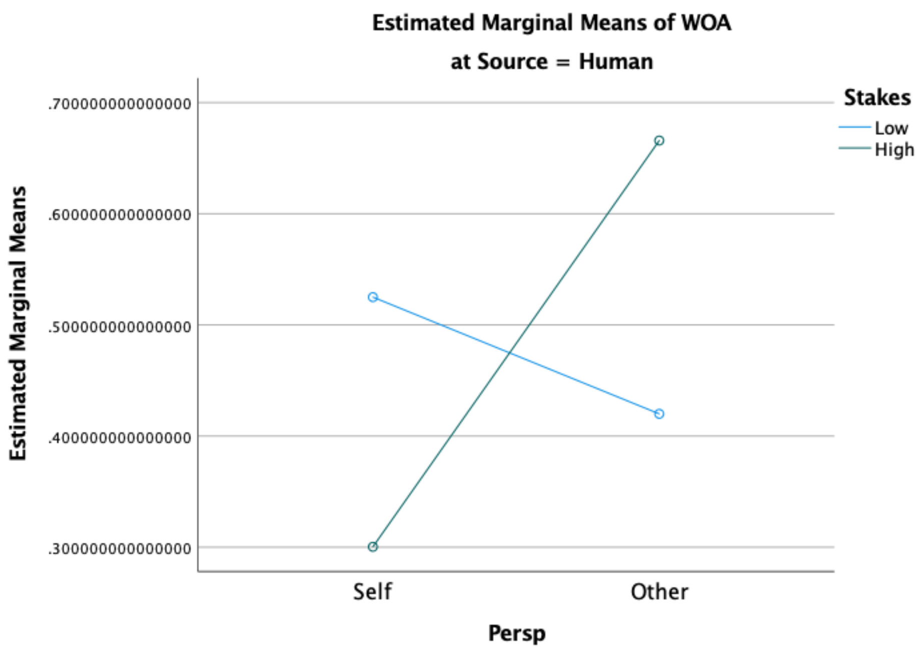
2. Source * Stakes * Persp

Dependent Variable: WOA

Source	Stakes	Persp	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Bootstrap for Mean[a] Bias	Bootstrap for Mean[a] Std. Error	Bootstrap 95% Confidence Interval Lower	Bootstrap 95% Confidence Interval Upper
AI	Low	Self	.429	.084	.264	.594	.001	.086	.263	.604
		Other	.370	.086	.201	.539	-.003	.086	.206	.540
	High	Self	.450	.100	.252	.648	-.003	.101	.245	.644
		Other	.346	.086	.177	.515	.000	.079	.193	.504
Human	Low	Self	.525	.079	.370	.680	-.001	.085	.357	.692
		Other	.420	.079	.265	.575	-.001	.084	.257	.588
	High	Self	.300	.077	.148	.453	.001	.076	.160	.459
		Other	.666	.082	.504	.828	.000	.075	.513	.807

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples





Simple two-way interaction effects

Between-Subjects Factors

Source			Value Label	N
AI	Stakes	1	Low	45
		2	High	38
	Persp	1	Self	39
		2	Other	44
Human	Stakes	1	Low	52
		2	High	51
	Persp	1	Self	53
		2	Other	50

Tests of Between-Subjects Effects

Dependent Variable: WOA

Source	Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
AI	Corrected Model	.142[a]	3	.047	.302	.824	.011
	Intercept	12.933	1	12.933	82.589	<.001	.511
	Stakes	5.375E-5	1	5.375E-5	.000	.985	.000
	Persp	.135	1	.135	.864	.356	.011
	Stakes * Persp	.010	1	.010	.067	.796	.001
	Error	12.371	79	.157			
	Total	25.501	83				
	Corrected Total	12.513	82				
Human	Corrected Model	1.841[b]	3	.614	3.729	.014	.102
	Intercept	23.475	1	23.475	142.656	<.001	.590
	Stakes	.003	1	.003	.018	.894	.000
	Persp	.436	1	.436	2.650	.107	.026
	Stakes * Persp	1.423	1	1.423	8.645	.004	.080
	Error	16.291	99	.165			
	Total	41.125	103				
	Corrected Total	18.132	102				

a. R Squared = .011 (Adjusted R Squared = -.026)

b. R Squared = .102 (Adjusted R Squared = .074)

Custom Hypothesis Tests

Test Results

Dependent Variable: WOA

Source	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
AI	Contrast	.010	1	.010	.065	.799	.000
	Error	28.662[a]	178[a]	.161			
Human	Contrast	1.423	1	1.423	8.834	.003	.047
	Error	28.662[a]	178[a]	.161			

a. User specified.

Simple simple main effects

Between-Subjects Factors

Stakes	Source			Value Label	N
Low	AI	Persp	1	Self	23
			2	Other	22
	Human	Persp	1	Self	26
			2	Other	26
High	AI	Persp	1	Self	16
			2	Other	22
	Human	Persp	1	Self	27
			2	Other	24

Tests of Between-Subjects Effects

Dependent Variable: WOA

Stakes	Source	Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Low	AI	Corrected Model	.039[a]	1	.039	.239	.628	.006
		Intercept	7.187	1	7.187	44.022	<.001	.506
		Persp	.039	1	.039	.239	.628	.006
		Error	7.020	43	.163			
		Total	14.274	45				
		Corrected Total	7.059	44				
	Human	Corrected Model	.143[b]	1	.143	.785	.380	.015
		Intercept	11.611	1	11.611	63.615	<.001	.560
		Persp	.143	1	.143	.785	.380	.015
		Error	9.126	50	.183			
		Total	20.880	52				
		Corrected Total	9.269	51				
High	AI	Corrected Model	.101[c]	1	.101	.678	.416	.018
		Intercept	5.873	1	5.873	39.515	<.001	.523
		Persp	.101	1	.101	.678	.416	.018
		Error	5.350	36	.149			
		Total	11.227	38				
		Corrected Total	5.451	37				
	Human	Corrected Model	1.697[d]	1	1.697	11.608	.001	.192
		Intercept	11.865	1	11.865	81.134	<.001	.623
		Persp	1.697	1	1.697	11.608	.001	.192
		Error	7.166	49	.146			
		Total	20.245	51				
		Corrected Total	8.863	50				

a. R Squared = .006 (Adjusted R Squared = −.018)

b. R Squared = .015 (Adjusted R Squared = −.004)

c. R Squared = .018 (Adjusted R Squared = −.009)

d. R Squared = .192 (Adjusted R Squared = .175)

Custom Hypothesis Tests

Test Results

Dependent Variable: WOA

Stakes	Source	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Low	AI	Contrast	.039	1	.039	.242	.623	.001
		Error	28.662[a]	178[a]	.161			
	Human	Contrast	.143	1	.143	.890	.347	.005
		Error	28.662[a]	178[a]	.161			
High	AI	Contrast	.101	1	.101	.626	.430	.004
		Error	28.662[a]	178[a]	.161			
	Human	Contrast	1.697	1	1.697	10.542	.001	.056
		Error	28.662[a]	178[a]	.161			

a. User specified.

Subgroup Analysis: Subtract condition

Syntax

2x2x2 bootstrapped ANOVA: source of advice, decision perspective and stakes on the WOA

```
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=WOA INPUT=Source Stakes Persp
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=5000
  /MISSING USERMISSING=EXCLUDE.
UNIANOVA WOA BY Source Stakes Persp
  /METHOD=SSTYPE(3)
```

```
 /INTERCEPT=INCLUDE
 /SAVE=PRED RESID SRESID COOK LEVER
 /PLOT=PROFILE(Persp*Stakes*Source) TYPE=LINE ERRORBAR=NO
MEANREFERENCE=NO YAXIS=AUTO
 /EMMEANS=TABLES(Source)
 /EMMEANS=TABLES(Source*Stakes*Persp)
 /PRINT ETASQ DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=Source Stakes Persp Source*Stakes Source*Persp Stakes*Persp Source*Stakes*Persp.
```

Output

Tests of Between-Subjects Effects

Dependent Variable: WOA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	4.472[a]	7	.639	4.673	<.001	.147
Intercept	77.974	1	77.974	570.317	<.001	.750
Source	3.511	1	3.511	25.683	<.001	.119
Stakes	.003	1	.003	.020	.887	.000
Persp	.111	1	.111	.813	.368	.004
Source * Stakes	.108	1	.108	.792	.375	.004
Source * Persp	.417	1	.417	3.048	.082	.016
Stakes * Persp	.061	1	.061	.444	.506	.002
Source * Stakes * Persp	.175	1	.175	1.282	.259	.007
Error	25.977	190	.137			
Total	106.789	198				
Corrected Total	30.449	197				

a. R Squared = .147 (Adjusted R Squared = .115)

Estimated Marginal Means

1. Source

Dependent Variable: WOA

			95% Confidence Interval		Bootstrap for Mean[a]			
							95% Confidence Interval	
Source	Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	Lower	Upper
AI	.498	.036	.426	.569	.001	.040	.420	.577
Human	.766	.039	.690	.842	.001	.032	.702	.830

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

2. Source * Stakes * Persp

Dependent Variable: WOA

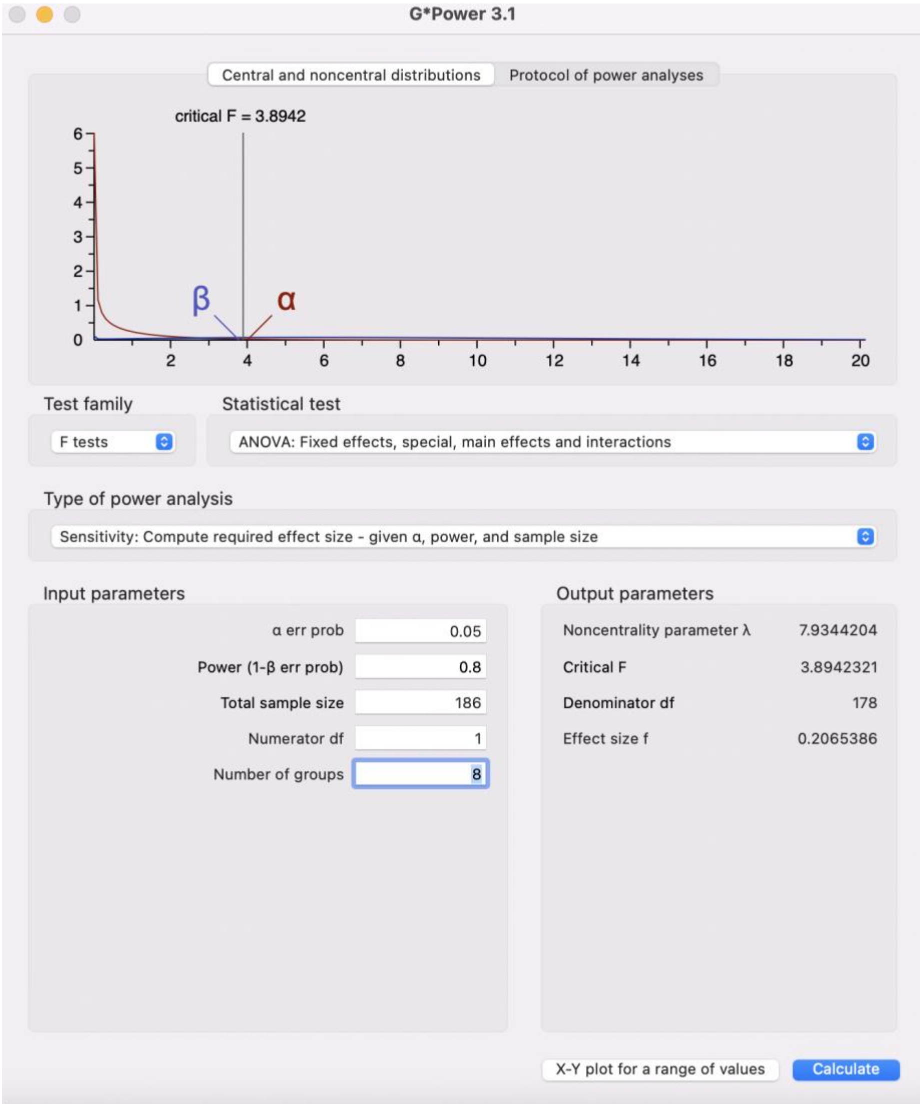
					95% Confidence Interval		Bootstrap for Mean[a]			
									95% Confidence Interval	
Source	Stakes	Persp	Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	Lower	Upper
AI	Low	Self	.400	.074	.254	.546	-.002	.083	.243	.567
		Other	.635	.075	.486	.784	.003	.076	.484	.780
	High	Self	.456	.066	.325	.587	.001	.077	.309	.608
		Other	.501	.074	.355	.646	.000	.081	.342	.665
Human	Low	Self	.773	.079	.618	.929	.000	.066	.636	.893
		Other	.704	.074	.558	.850	.002	.072	.563	.841
	High	Self	.803	.083	.640	.967	.001	.059	.681	.914
		Other	.783	.073	.640	.926	.003	.062	.655	.900

a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples

Appendix E

G*Power Subgroup Sensitivity Power Analyses

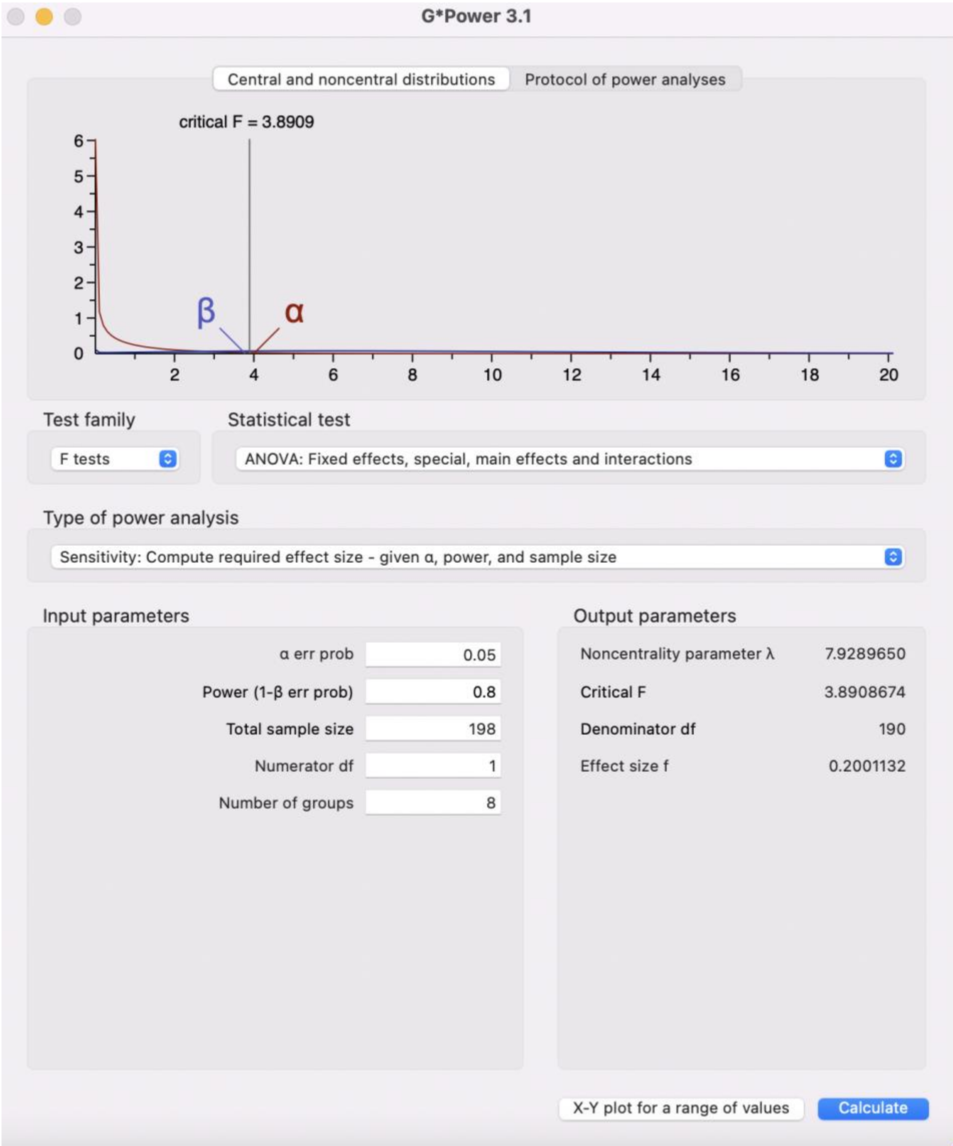
Add Condition



Partial η^2 was then obtained from Cohen's f using the following formula: $eta^2 = f^2 / (1 + f^2)$[6]. Therefore, the analysis was sensitive to detect an effect of partial η^2 = .041 (3.d.p.)

[6] Formula obtained from https://www.ibm.com/support/pages/effect-size-relationship-between-partial-eta-squared-cohens-f-and-cohens-d

Subtract Condition



After converting Cohen's f to partial $\eta^{2,}$ it was revealed that the analysis was sensitive to detect an effect of partial $\eta^2 = 0.039$ (3.d.p.)