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I'm special but A.I. doesn't get it

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I hereby declare that this dissertation is my original work and has been written by me in its entirety. I have duly acknowledged all the sources of information used in this dissertation..

This dissertation has also not been submitted for any degree in any university previously.

Laurel H. Teo

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Abstract

A growing body of management research on artificial intelligence (AI) has consistently shown that people innately distrust decisions made by AI and find such decision processes simply less fair compared to decisions made by humans. My dissertation adopts a different perspective to propose that aside from fairness concerns, AI decision methods trigger perceptions in people that their individual uniqueness has not be adequately considered and this has negative consequences for their psychological or subjective well-being.

By combining theories of uniqueness, individuality, power, and well-being, I develop five studies to provide empirical evidence that aversion to AI-mediated decisions also operates through uniqueness neglect particularly in high-stakes contexts, and this mechanism predicts significant incremental variance above other mechanisms identified in existing research. I also extend the consequences of AI decision methods beyond resistance/acceptance of the technology, linking it to subjective well-being, a critical individual outcome that predicts other important employee attitudes and behaviors such as turnover intentions and job performance.

Finally, I explore the implications of decision role on AI decision methods to examine responses of decision *makers* and decision *recipients* and identify the contexts in which uniqueness neglect is relevant for these different groups of decision stakeholders. In doing so I provide a more comprehensive understanding of the impact of AI decision methods on different stakeholders in organizations.

Keywords: artificial intelligence (AI), algorithms, decision-making, uniqueness neglect, power, subjective well-being

Contents

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I May, I Might, I Must

If you will tell me why the fen
appears impassable, I then
will tell you why I think that I can get across it if I try.

— Marianne Moore

When the idea of doing a PhD first occurred to me, almost everyone who could speak on this with authority warned me it would not be easy. Still I thought I'd attempt the impassable.

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CHAPTER 1 INTRODUCTION

> "I'm David. I'm David. I'm David. I'm David. I'm David. I'm David. I'm David. I'm David. I'm special! I'm unique! I'm David!"
>
> "My mommy doesn't hate me. Because I'm special! And unique! Because there's never been anyone like me before, ever!"
>
> — David, the android protagonist in *A.I. Artificial Intelligence*
>
> (Spielberg, 2001, 1:40:14, 1:31:39)

In Steven Spielberg's 2001 movie *A.I. Artificial Intelligence*, an android child David is reared by a human family who got him as a substitute for their terminally ill son. Unexpectedly the son regains his health. David becomes redundant and is promptly abandoned by his human "mother". Desperate to find her and regain her love, David recalls the fairy tale *The Adventures of Pinocchio* and embarks on a quest to become "a real boy". But to his horror he stumbles upon a workshop packed with multiple replicas of himself, ready to be sold to the rest of the world. Crushed by the revelation that he is not a unique individual – and by implication that he can never become a real human boy, David destroys himself.

The question of what distinguishes real human beings from machines and the idea of AI androids or robots evolving their own unique personal identity are familiar tropes in science fiction. Such philosophical musings arguably reflect the value that people place on uniqueness as a fundamental part of a self-concept and the intrinsic need that people have to be recognized as individuals special in their own right (Lynn & Snyder, 2002; Snyder & Fromkin, 1980).

While the prospect of a self-aware android passing off as human is still far from reality (Korteling et al., 2021), many people by now would have had close encounters with Artificial Intelligence (AI) in some shape or form (Mims, 2021; Littman et al., 2021). Now increasingly and widely deployed, AI refers to a broad category of technologies such as machine learning (ML), computer vision, robotics, natural language processing (NLP) and Internet of Things (IoT) (Stone et al., 2016) that can perform tasks that normally require human intelligence and cognition, including adaptive decision-making (Gillath et al., 2021; Tambe et al., 2019). For instance, computer vision is used in self-driving cars and in facial recognition in surveillance systems; NLP is applied in translation tools and chatbots; while machine learning is applied in managerial and investment decisions as well as healthcare e.g. medical diagnostic aids and most recently to speed up COVID-related drug discovery (Gillath et al., 2021; Kaplan & Haenlein, 2019; Zhang et al., 2021). While many definitions of AI abound in the literature, most of them agree that an AI technology system gathers and interprets data from the environment to identify patterns, make predictions, and independently learn from these experiences to perform better on specific tasks or objectives (Brynjolfsson et al., 2018; Gillath et al., 2021; Glikson & Woolley, 2020; Haelein & Kaplan, 2019; Mahmud et al., 2022).

At the national level, more than 50 countries have either published or announced that they are developing AI strategies to foster the systematic development and adoption of AI in their economies (Zhang et al., 2021). At the organizational level, more than 50% of about 2,400 organizations surveyed globally by McKinsey in 2020 across multiple industries indicated that they had adopted AI in at least one business function, ranging from product enhancement and service-operations optimization to customer analytics, risk modelling, supply chain optimization, as well as human resources (HR) (Balakrishnan et al., 2020).

Without a doubt the adoption of AI technologies is set to permeate society, from private to public to organisational settings. It is thus important to understand the impact of these technologies on people, particularly in high-stakes HR considerations such as personnel selection and performance management that can be pivotal to people's careers and futures.

Specifically, AI applications in HR have been in the areas of talent and performance management, such as recruitment and selection decisions, training recommendations, turnover predictions, and even compensation and promotion decisions (Balakrishnan et al., 2020; De Cremer, 2020; Fisher, 2019). Organizations typically adopt AI in these functions to enhance efficiency, increase objectivity and reduce biases in decision-making – in short to achieve better objective performance and fairness outcomes (Kuncel et al., 2013; Leicht-Deobald et al., 2019; Polli, 2019). Recent research in the OBHR domains on psychological responses to AI have tended to adopt the perspective of people at the receiving end of these decisions. Thus far, findings indicate that despite the purported benefits, people actually resist assessments or decisions made on them by AI or algorithms[1]. A large body of these studies centre on trust and justice theories (e.g. Bankins et al., 2022; Glikson & Wolley, 2020; Hughes et al., 2019; Langer & Landers, 2021;

[1] In management and behavioural science, algorithmic decisions and AI decisions are often used to denote similar concepts (Langer & Landers, 2021). Chapter 2 discusses this in greater detail.

Mahmud et al., 2022; Ötting & Maier, 2018), examining how such resistance or aversion arises from an innate distrust of machine-mediated decisions and the perception that these processes are – ironically – less fair compared to decisions made by humans.

This dissertation offers an alternative interpretation. Drawing on theories of uniqueness, identity, well-being, and power, I propose that using AI to make decisions in certain contexts triggers a perception in people that their unique qualities and individual identities have not been adequately considered or addressed in the decision process. Such a neglect of their uniqueness is critical and significant enough to negatively influence psychological well-being or subjective well-being, which is linked to important employee outcomes including job satisfaction, organizational commitment, and turnover intentions.

Human beings have an intrinsic need for uniqueness (Snyder & Fromkin, 1980) and individuation, a concept described by Maslach and colleagues (1985) as "relative distinctiveness", whereby a person feels a degree of differentiation from other people and objects. Someone who is deindividuated feels "indistinguishable, to some degree, from other people and objects" (Maslach et al., 1985, p. 730). Bearing this in mind, existing research shows that people implicitly believe that AI, algorithms, statistical models and other computerized or automated processes cannot understand or capture the complexity of human characteristics as well as human intuition can (Haslam 2006; Highhouse, 2008; Longoni et al., 2019; Nissenbaum & Walker, 1998). This likely explains why people consistently prefer decisions and recommendations made by humans over those devised by computerized or automated methods (Diab et al., 2011; Dietvorst et al., 2015; Hausknecht et al., 2004), despite a rich body of evidence on the latter being more accurate and achieving superior objective outcomes (Meehl, 1954; Dawes et al., 1989; Kuncel et al., 2013). Taken together, this suggests that when people are served by AI and other computerized or automated methods, they are likely to feel that their individual distinctiveness or uniqueness has not been adequately understood or considered. In a sense they are deindividuated. This is supported in recent work in consumer literature, where Longoni and colleagues (2019) found that consumers resist medical services delivered by AI providers because of concerns that the AI will overlook their unique medical symptoms and circumstances, a condition the authors term “uniqueness neglect”.

My dissertation builds on this concept of uniqueness neglect to propose that in organizational contexts, people similarly perceive uniqueness neglect when decisions or assessments on them are made by AI rather than humans. The importance of being unique becomes especially salient in high-stakes contexts such as performance appraisals or recruitment/selection processes, which have considerable impact on one’s career (Tambe et al., 2019). In these high-stakes competitive contexts, employees and job applicants need to stand out – i.e. be positively different from and outperform their peers – to be successfully rewarded with a pay raise, promotion or job offer. In short, uniqueness becomes salient and a valued resource in the competition to outperform others.

Prior studies on uniqueness theory and deindividuation indicate that being too similar to others triggers negative emotions and behaviours (Diener, 1977; Lynn & Snyder, 2002). This suggests that a failure to address people’s needs and concerns about their individual uniqueness would have a negative impact on their subjective or psychological well-being, which my dissertation proposes and tests empirically. I further explore whether theoretically relevant individual differences such as a need for uniqueness, or characteristics of the decision (such as outcome valence – a decision in or against one's favour) moderate the effect of AI decision methods on perceptions of uniqueness neglect.

Finally, I examine the implications of decision role or stakeholder as well as decision contexts for reactions to AI-driven decisions. In any organizational decision, one key stakeholder group is of course people who are being assessed or subjected to the decision (i.e. decision *recipients*); another key stakeholder group would be people in the role of *making* or being responsible for these assessments and decisions (decision *makers*). Earlier research on AI and algorithmic decisions suggests that both decision *makers* as well as *recipients* resist the use of AI in making decision. General research (not specific to OBHR domains) indicates that decision *makers* prefer to use their own judgement over relying on AI or algorithms in making predictions (Dietvorst et al., 2015). While recent OBHR research suggests that decision *recipients* find such machine-aided methods unfair, there is little research on the psychological consequences for decision *makers* beyond their preference for their own (human) judgement over AI methods.

In Chapter 3, I explore the psychological mechanisms and theoretical underpinnings by which responses to AI-mediated decisions unfold and attempt to answer the questions: 1) what negative psychological impact – if any – might there be when decision *makers* use AI to formulate assessments and decisions? 2) under what circumstances and in what contexts might individual uniqueness be salient for decision *makers*,

Through five experiments I test my hypotheses on the indirect negative effect AI decision methods have on subjective well-being via perceptions of uniqueness neglect, then go on to unpack the different conditions under which this relationship might strengthen, weaken, or even be negated. Studies 1 & 2 test the proposed indirect relationship with perceptions of uniqueness neglect as the mediating mechanism.

Studies 2 and 3 explore potential moderators including those that have been dominant in the fairness perspective. Study 2 tests individual differences in people's need for uniqueness and how they perceive themselves to be unique from others (personal sense of uniqueness) as potential moderators, while Study 3 tests decision outcome valence as another potential moderator for this theoretical model.

Study 4 investigates the implications of decision context – decision roles and decision stakes – by running two separate experiments on participants. In the first experiment, the stakes are held constant for both decision *makers* and *recipients*. In the second experiment, the stakes are varied, with relatively high stakes for decision *recipients* but relatively low stakes for decision *makers*.

Study 5 drills deeper into the impact of AI on decision *makers*, examining that the specific conditions that trigger perceptions of uniqueness neglect in higher-status decision *makers* who have power over lower-status decision *recipients* (e.g. supervisors vs. subordinates).

In summary, my research makes three important contributions. First. I develop and provide empirical evidence for an alternative mechanism for why people are averse to AI decision methods in organizations, over and above other mechanisms that have been studied to date. Existing research on AI and management has largely focused on fairness perceptions (Acikgoz et al., 2020; Hughes et al., 2019; Newman et al., 2020) and trust theories (Glikson & Woolley, 2020; Kaplan et al., 2021; Lee, 2018;) to explain such aversive reactions. By combining theories of uniqueness, individuality, power, and well-being, and building on related research in consumer literature (Longoni et all, 2019), I show that aversion to AI-mediated decisions also operates through uniqueness neglect particularly in high-stakes contexts, and this mechanism predicts significant incremental variance above other mechanisms identified in existing research. Second, I extend the consequences of AI decision methods beyond resistance/acceptance of the technology, linking it to psychological or subjective well-being, a critical individual outcome that predicts other important employee attitudes and behaviors such as organizational commitment (Jain et al., 2009), turnover intentions (Wright & Bonett, 2007) and job performance (Wright & Cropanzano, 2000). Finally, I explore the implications of decision role, context and organizational status on AI decision methods to compare responses of decision *makers* and decision *recipients* and identify the contexts in which uniqueness neglect is relevant for these different groups of decision stakeholders. In doing so I provide a more comprehensive understanding of the impact of AI decision methods on different stakeholders in organizations.

CHAPTER 2 REVIEW OF MANAGEMENT RESEARCH ON AI

As discussed in Chapter 1, AI is used in a wide range of functions to perform a variety of tasks ranging from personal to professional, business, and industrial. For purposes of this dissertation, my focus is on the application of AI in analytics and decision-making. Within the research domain of automated decision-making, the terms AI and algorithms are often treated as similar concepts and used interchangeably (Langer & Landers, 2021). As such AI-decision making is also often referred to as "algorithmic decision-making" or "algorithmic management" (Bankins et al., 2022; Landers & Behrend, 2020; Lee, 2018; Tambe et al., 2019). For consistency my dissertation will refer only to "AI decision-making" in discussing and framing my original research. In discussing or citing literature by other researchers, I will use a mix of these terms depending on what is used in the original works.

Algorithms are the building blocks of AI technologies (Stone et al., 2016). At the basic level, algorithms are simply computing rules that follow specific steps to autonomously solve a defined problem (Cambridge, n.d.; Lee, 2018; Merriam-Webster, n.d.). A more scientific definition describes algorithms as "encoded procedures for transforming input data into a desired output, based on specified calculations" (Gillespie, 2014, p. 167). The main difference between basic algorithmic decision-making systems and AI systems (also described as "high-complexity predictive models", Landers & Behrend, 2022, p. 1) is that the former considers only decision factors that are pre-determined by humans, while the latter freely selects decision factors based on patterns that they discover in data from the environment (Mahmud et al., 2022). Over time, AI systems “learn independently…from data to discover patterns in the data and make better decisions” (Mahmud et al., 20022, p. 2).

In recent years, researchers have found that people far prefer using their own decisions or decision made by other humans over superior decisions made by algorithms, a tendency first conceptualized by Dietvorst and colleagues (2015) as “algorithm aversion” (Burton et al., 2019; Mahmud et al., 2022). Since then, there has been a growing body of literature investigating the impact of algorithmic or AI decisions on people and algorithm aversion. A 2021 review by Langer and Landers focusing on decision *recipients* and *observers* of decisions (described respectively by the authors as “second party” and “third party” stakeholders in decisions) found 61 relevant studies on AI vs. human decision-making at work and in medical or healthcare contexts. The authors excluded from the review studies that focused on decision *makers* (i.e. “first-party” stakeholders). A separate 2022 review by Mahmud and colleagues specifically on algorithmic aversion research yielded 80 relevant studies that met the selection criteria.

Across these studies, the two broad categories of a) trust and trustworthiness perceptions and b) fairness and justice perceptions were overwhelmingly the most studied psychological outcomes, although fairness and justice was the most prominent perspective examined overall (Langer & Landers, 2021; Mahmud et al., 2022).

Trust can be broadly defined as the willingness of one party to be vulnerable to another party based on positive expectations of the intentions or behaviors the other party (Dirks & Ferrin, 2001). Most papers investigating general trust levels found that automated decisions tended to be less trusted than human decisions (Langer & Landers, 2021; Mahmud et al., 2022). Some researchers found that trust levels also depended on the level of information provided about how the automated systems or algorithms work (Goodwin et al., 2013) and the specific dimensions of trust or trustworthiness being measured (Langer & Landers, 2021).

According to Mayer and colleagues' (1995) conceptualization of trust, the extent to which one party (the trustor) trusts another (the trustee) stems from three characteristics or dimensions of trustworthiness in the trustee, namely ability, benevolence, and integrity. Ability refers to the competence or knowledge of the trustee in a specific domain (Colquitt et al., 2007; Mayer et al., 1995;). Benevolence refers to the extent to which the trustee is believed to want to do good and "care" for the trustor apart from profit motives (Colquitt et al., 2007; Schoorman et al., 2007). Integrity refers to the extent to which the trustee complies with ethical principles and moral standards that align with those adhered to by the trustor (Colquitt et al., 2007; Mayer et al., 1995).

Studies on the trustworthiness of AI and algorithmic decision-making have largely focused on perceptions of ability and integrity. Results on ability appear to be inconclusive, although humans were generally rated to be better than AI or algorithms in adapting to dynamic circumstances (Höddinghaus et al., 2020). Results on integrity indicated that people largely perceive AI systems to be higher on integrity than humans as AI systems have less motivation for discrimination compared to humans (Bigman et al., 2020) and are less biased than human decision makers (Höddinghaus et al., 2020). Hardly any papers were found on benevolence perceptions of AI systems. Of the two papers reviewed that did, results showed that people did not believe computers or automated systems cared about their individual needs or desires, generally rating such systems to be lower in benevolence than human counterparts (Höddinghaus et al., 2020; Yokoi et al., 2021).

Fairness or justice perceptions in the organizational context refer broadly to employees' perceptions that decisions and procedures follow agreed-upon rules about equitable treatment (Newman et al, 2020). Often, organizational justice is examined or tested in its three component dimensions: distributive, procedural and interactional. *Distributive justice* is associated with the perceived fairness of outcomes consistent with allocation norms (e.g. need, equity or equality) (Colquitt 2011; Landers & Behrend, 2022). *Procedural justice* concerns the rules and processes used to determine decision outcomes, and is often associated with or measured by whether such processes demonstrate consistency, bias suppression, accuracy, correctability, representativeness and ethicality (Colquitt, 2001; Colquitt et al., 2005). *Interactional justice* is associated with the level of respect and sensitivity with which decision makers treat people, and whether the rationale for decisions have been explained thoroughly (Colquitt, 2001).

With few exceptions, studies on fairness perceptions toward AI or algorithmic decisions have yielded predominantly negative effects (Langer & Landers, 2021). For instance, Acikgoz and colleagues (2020) showed in two studies (N = 320, N = 225) that job applicants rated traditional face-to-face interviews with HR managers to be significantly superior to AI interviews (digital interview via webcam with an AI software) in one of three dimensions of procedural justice (chance to perform), with no significant difference for the other two dimensions (consistency of application, job-relatedness). Traditional interviews were also rated to be significantly superior to AI interviews in three out of four dimensions of interactional justice (openness, two-way communication, and treatment), with no significant difference for the dimension “information known” (Acikgoz et al., 2020). Overall, Acikgoz and colleagues (2020) argued that the lack of human contact and perceived limited opportunities for self-expression in an AI selection process could lead people to feel that AI selection decisions have lower procedural and interactional justice, although this was not explicitly tested in their studies. Another study by Bankins and colleagues (2022) on decision-making in HR management found participants experienced lower interactional justice when AI (rather than human judgement) was used in decision-making; participants also tended to view AI as an inappropriate decision maker.

Separately, Newman and colleagues (2020) found in four laboratory experiments (N = 798) and a randomized field experiment (N = 1,654) that layoff and promotion decisions made by algorithms, as well as job interviews evaluated by algorithms, were rated significantly less fair than those conducted by human managers. Their studies measured overall organizational justice perceptions rather than drilling down to separate dimensions of the organizational justice construct.

Lee (2018) argued that perceptions towards algorithmic decisions depends on the type of tasks or decisions being performed. In an online experiment, Lee (2018) found that decision tasks requiring greater subjective judgement and emotional capability were perceived to be less fair and less trustworthy when performed by algorithms rather than human. In comparison, there were no significant differences in perceived fairness and trustworthiness between algorithmic or human decisions in tasks requiring largely mechanical skills (Lee 2018). Qualitative responses from Lee's study (2018) indicated that people felt algorithms lack "human intuition" and that algorithmic decisions were less fair than human decisions specifically in situations involving non-quantifiable variables.

The concept of algorithms being dehumanising and inferior in evaluating qualitative or non-quantifiable factors was also explored by Newman and colleagues (2020). In their paper, they argued that people believe algorithms quantify information about humans by reducing them to "a number" ("quantification"), and this fails to adequately account for qualitative aspects and personal contexts specific to the individual ("decontextualization"). Such perceived reductionistic characteristics explain why people perceive algorithmic decisions to be less procedurally fair (Newman et al., 2020). A serial mediation analysis showed that algorithmic-driven decisions led to lower levels of fairness perceptions, mediated first by perceptions of quantification followed by perceptions of decontextualization (Newman et al., 2020).

Studies in consumer research support this line of reasoning. Qualitative responses from a mixed-method study by Binns and colleagues (2019) indicate that people perceive algorithmic decision-making to be unfair because it "reduces a human being to a percentage" and "there could've been other influencing factors" specific to each case that an algorithm would not have been able to account for. Longoni and colleagues (2019) found people to be less likely to adopt automated medical advice (vs. advice from human doctors) as they felt such advice neglected their unique individual conditions.

Taken together, existing research appears to suggest that aversive reactions to AI and algorithm decision methods stem from perceptions that these methods are procedurally unfair in part because they cannot accurately capture unique qualities of each individual. My dissertation does not dispute this. To the extent to which one's unique qualities are perceived to be insufficiently or inaccurately reflected in decision processes, uniqueness neglect may overlap with justice perceptions since perceived accuracy is one of several elements that make up procedural justice perceptions (the rest being consistency, bias suppression, correctability, representativeness and ethicality) (Colquitt, 2001; Colquitt et al., 2005).

But apart from justice perceptions, I make the case that aversive reactions additionally stem from a more fundamental discomfort that people feel with being too similar to others and being treated too similarly (i.e. being "deindividuated"). This negative response is separate from perceptions of unfairness or fairness being violated. Not to be confused with the need for warmth or empathy from interacting with a fellow human being, uniqueness neglect – a concern that one's unique characteristics, circumstances and case are overlooked – encapsulates an intrinsic need in human beings for uniqueness and to be special (Snyder & Fromkin, 1980), and as such should explain incremental variance in accounting for why people resist or respond negatively to AI decision methods, over and above justice perceptions.

In the following chapter I examine in detail the theoretical underpinnings for uniqueness neglect perceptions towards AI decision methods and the psychological outcomes linked to such perceptions.

CHAPTER 3 THEORY DEVELOPMENT AND HYPOTHESES

Uniqueness and Identity – Importance of Context

Human beings are social creatures who need to form stable social relationships with others (Baumeister & Leary, 1995) and they tend to prefer to associate with those similar to themselves in physical attributes (Berscheid & Walster, 1969; Walster et al., 1971), attitudes and beliefs (Allen & Wilder, 1975), social-cultural background (Buss & Barnes, 1986), and personality (Botwin et al. 1997; Klohnen & Luo, 2003). They also identify with and derive a sense of self from their ingroup – the group to which they belong ((Hogg & Terry, 2000; Tajfel & Turner, 1985). Being a member of the ingroup entails sharing defining attributes common to the rest of the group (e.g. ethnicity, gender, beliefs, etc) – i.e. being similar to other group members. (Hogg & Terry, 2000). Yet, when people are asked to describe themselves, they often highlight characteristics that distinguish themselves from others (McGuire et al., 1978). Prior studies have found that when people are manipulated to show higher degrees of similarity relative to others – i.e. when they are deprived of uniqueness – they tend to choose scarce experiences unavailable to other people (Fromkin, 1970), conform less to peer judgements (Duval, 1972), and choose self-concepts that reflect uniqueness more strongly (Markus & Kunda, 1986).

Uniqueness theory suggests that people are uncomfortable with either being extremely similar with or being extremely different from others – they seek to be moderately different in ways that do not evoke social disapproval (Snyder & Fromkin, 1977, 1980). The point of optimal distinction varies between individuals depending on personality and preferences (Lynn &

Harris, 1997; Lynn & Snyder, 2002; Maslach et al., 1985; Şimşek & Yalınçetin, 2010; Snyder & Fromkin 1980); it is also dependent on the social and situational contexts through a process of psychological salience (Brewer, 1991; Hogg, 2008; Markus & Kunda, 1986). For instance, when inter-group comparisons are being made, people define themselves and construe their identity at the group level, emphasizing their similarities (and solidarity) with ingroup members; but when intra-group comparisons are made between the self and other members in the group, then individuality becomes salient (Turner et al., 1987).

In line with research suggesting a universal positivity bias in self attributions (Mezulis et al., 2004; Taylor & Brown, 1988), self-serving attributions also manifest in the way people desire uniqueness. Studies have shown that people find positive information and feedback more applicable and specific to them than to the "average" other person, but perceive negative feedback to be common to all and not just unique to themselves in the sense that "it's not just me but everyone else too" (Snyder, 1977; Snyder & Shenkel, 1975; Markus & Kunda, 1986). In short, people desire to be unique when it is advantageous to be different and they consider themselves to be so ("illusion of uniqueness") whether it is the case objectively or not (Snyder, 1977). This is supported by research on individuation, which has found that people deliberately try to stand out (they individuate themselves) when they anticipate positive rewards in a situation (Maslach, 1974). Conversely, when negative consequences are on the horizon, they attempt to minimize their differences and appear to be more like everyone else (Maslach, 1974).

In organizations, HR decisions such as performance evaluation and personnel recruitment/selection pit individual employees against their peers (intra-group comparison), with the potential for significant reward in the form of a pay raise, bonus, promotion, or job offer for the handful that emerge top in what is essentially a high-stakes competitive race. In this high-stakes context, the value of individuality or uniqueness becomes highly salient; it is desirable, valuable, and important to be unique. In the race to the top, people would not want to be regarded or evaluated as average. They want to be regarded as special and distinctive in a positive light. In other words, people perceive individual uniqueness to be especially salient in high-stakes contexts.

AI and Uniqueness Neglect

A substantial body of literature has recorded how statistical models and other mechanized, computerized or automated methods consistently outperform human effort in similar tasks. In 1954, clinical psychologist Paul Meehl (1954) compared predictions generated by mechanical methods (through actuarial or algorithmic models) against forecasts based on human judgement (termed the clinical method) in domains ranging from academic performance to parole violations; in every case the mechanical method was found to be equal or superior in objective performance. Since then, other research has produced similar findings. Grove and Meehl (1996) published a report comparing mechanical or formal methods against informal or clinical methods of prediction across 136 studies. The mechanical method refers to "formal, algorithmic, objective procedure (e.g. equation) to reach the decision", while the clinical method refers to "subjective, impressionistic" human judgement “based on informal contemplation and sometimes, discussion with others (e.g. case conferences)” (Grove & Meehl, 1996, p. 293). Results show that mechanical methods were almost invariably equal to or superior in accuracy to the clinical method across the 136 studies, which range in predictive criteria from mental and medical diagnoses and treatment recommendations to personality description, and parole violence and violence (Grove & Meehl, 1996).

Similarly, Kuncel and colleagues (2013) examined data in academic admissions and employee selection decisions, comparing mechanical methods against holistic (clinical) methods in predicting a variety of performance criteria (e.g. grade point average, training performance, supervisor ratings of performance). They found that holistic methods consistently resulted in substantial loss of validity; in the case of job performance the difference between the two methods was more than 50% (Kuncel et al., 2013). Similar results were found in other studies comparing data on human health and behavior (Grove et al., 2000), parole violations (Kleinberg et al., 2018), sales forecasts (Sanders & Mandrodt, 2003).

Yet despite their superior results, mechanical or automated methods have been consistently spurned over the past decades, as people invariably prefer human judgement and intuition. In a study by Önkal and colleagues (2009), participants adjusted their initial stock price forecasts more closely to match forecast advice from a financial expert compared to advice from a statistical model, even though the advice was identical. They also indicated a significantly higher level of trust in advice from the human expert than the statistical technique (Önkal et al., 2009). Separately, Dietvorst and colleagues

(2015) found that people preferred forecasts based on human judgment over those made by or assisted by a sophisticated statistical algorithm, even after they saw how the algorithm performed better than a human forecaster. In personnel hiring, job applicants prefer job interviews and work samples over other selection tools that rely on analytical or statistical methods such as cognitive ability tests, personality tests, and biodata (Hausknecht et al., 2004). Likewise, employers and recruiters conducting personnel selection favour intuitive approaches such as unstructured interviews over decision aids that use analytical methods (Highhouse, 2008; Lievens et al., 2005).

Such aversion to mechanical or algorithmic methods appears to arise in part from implicit beliefs that mechanical methods cannot adequately account for unique features that could be unprecedented or extreme outliers specific to very rare individuals or events, otherwise termed as “broken leg cues” (Meehl, 1954; Highhouse, 2008). The term arises from the classic hypothetical example that a regression model predicting the likelihood of someone going for a movie on a specific day will probably include many standard predictors such as type of movie, weather condition and past behavior, but is unlikely to consider that a particular person may be trapped at home that day because of a broken leg (Meehl, 1954; Highhouse, 2008; Longoni et al, 2019). As Dawes and colleagues (1989) observed: “A common anti-actuarial argument, or misconception, is that group statistics do not apply to single individuals or events.” (p. 1672) Beyond assumptions about mechanical models missing out on low-probability occurrences, importantly, people also appear to hold implicit beliefs that a mechanical approach somehow “dehumanizes” the human subjects being assessed or treated (Dawes et al., 1989; Nissenbaum & Walker, 1998).

A qualitative study by Nissenbaum and Walker (1998) found that one of the main concerns regarding how using computers in schools could dehumanize education was that it could result in education becoming too standardized or formulaic. Specifically this concern was described as a "nightmare" that "schools would become 'McSchools'" (Nissenbaum & Walker, 1998). The study, which analysed content from interviews with students and educators as well as content from relevant published books and articles, noted that people felt that computers would "register only a matrix of numbers, a pattern of performance on pre-set objectives", such that they would not be capable of seeing each child for his or her unique identity nor encouraging the child to develop in the specific or unique way appropriate for the child (Nissenbaum & Walker, 1998, p. 260). In other words, people believe that computers operate on pre-programmed rules and do not have the adaptive flexibility to cater to individual cases or idiosyncrasies. The implied danger is that this could compromise the development of students' individuality. Building on this, Haslam (2006) in his conceptual framework on dehumanization notes that people implicitly believe that computers are rigid, inflexible, lacking in curiosity and individuality.

Given such implicit assumptions about the nature of computers and automated or mechanized decision processes, people are likely to also assume that AI, as a complex technology designed to mimic or automate human cognitive abilities, is similarly incapable of taking into consideration and catering to the uniqueness of each and every individual affected by the decision-making process. Even though AI models are far more complex than basic statistical or algorithmic models and are capable of adaptive learning, the fact that these models are trained on large data sets is likely to play into the entrenched misperception most lay people have that “group statistics do not apply to single individuals or events.” (Dawes et al., 1989, p. 1672).

As discussed earlier in Chapter 2, such implicit assumptions appear to be corroborated by results from studies by Binns and colleagues (2018), Lee (2018), and Newman and colleagues (2020), which found that people believe AI and algorithms lack human intuition and reduce human beings to a number. Likewise in consumer literature. Longoni and colleagues (2019) found that healthcare consumers tend to believe their individual medical conditions are unique and differ significantly from the norm (compared to average other persons); this causes them to be more reluctant to use AI medical services than services delivered by human providers. The authors contend that such reluctance stems from concerns about uniqueness neglect, defined as “a concern that one’s unique characteristics, circumstances, and symptoms will be neglected” (Longoni et al., 2019, p. 630).

My dissertation builds on this concept of uniqueness neglect to apply it in the context of organizational decisions such as performance evaluation and personnel selection. In such high-stakes decisions, uniqueness is highly salient to and critical for employees, who are likely to perceive it as a valued resource that can provide individual competitive advantage. However, if such decisions are made by AI (AI method) rather than a human manager (human method), this would trigger perceptions of uniqueness neglect in employees. Employees implicitly attribute characteristics of inflexibility assumed in automated processes to AI; thus they believe AI decision methods cannot adequately appreciate or consider their unique characteristics and circumstances. In contrast, they expect that human managers would be better able accommodate unique characteristics of different people and provide customized considerations for different individuals. As such, I propose the following hypothesis:

Hypothesis 1. Using AI methods (vs. human methods) to make decisions on employees triggers greater perceptions of uniqueness neglect in employees.

Uniqueness Neglect and Wellbeing

What are the consequences when people feel that their uniqueness has been neglected? Cues can be taken from empirical studies on uniqueness deprivation and uniqueness enhancement. Fromkin (1972) found that people who received fake feedback describing them to be highly similar to others in their personality, values and interests reported significantly less pleasant affect, compared to people who were told that they were moderately similar to others. Consistent with this finding, a separate study by Case & Rosen (1985) found that college students who received feedback that their performance on a personality test was either virtually identical or radically different from the performance of their peers (i.e. other college students) rated themselves respectively to be much more similar or much more different than others after receiving such uniqueness-depriving or uniqueness-enhancing feedback, and such uniqueness-relevant feedback was associated with significantly less positive moods, compared to participants who were given no feedback on whether their performance was similar.

Relatedly, Koydemir and colleagues (2020) found that people who feel a stronger sense of uniqueness feel happier. The authors argue that the more people accept their unique features, the more they would feel that their behaviors reflect their own choice and self-expression, enabling them to act consistently with their true self. Such congruence between experience and self-concept is also known as authentic living or authenticity, which researchers have found to be essential to psychological health and well-being (Ryan & Deci, 2004; Wood et al., 2008). Based on a survey of 152 people in Germany, Koydemir and colleagues (2020) found that people who reported a stronger personal sense of uniqueness also reported themselves to be happier (measured by subtracting self-reported scores in negative affect from positive affect), and that this positive relationship was mediated by perceptions of authenticity.

In line with these findings, research by Brewer and colleagues (1993) suggests that depriving people of their identity as unique individuals could have potential negative consequences. In a series of experiments, participants made to feel highly depersonalized (by being told that there is no value or interest in their responses as an individual person but only as a member of a large general category) consistently gave higher ratings to in-groups than to out-groups when they were assigned to a minority category, regardless of the status of the minority category. In contrast, participants who were depersonalized and assigned to a majority category did not demonstrate any preference for their in-group (i.e. no significant difference between in-group and out-group ratings). The results suggest that depersonalization enhances the value of distinctiveness in the form of membership in minority groups whilst leading people to devalue majority in-groups even when these groups were associated with high status (Brewer et al., 1993). Extending this, depersonalization in an organizational context could have negative implications for people's affiliation with the organization at large.

Taken together, these findings suggest that having one's distinct identity being overlooked or one's uniqueness being neglected is likely to be undesirable and associated with negative feelings or emotions. High levels of unpleasant emotions and moods reduce one's subjective well-being (SWB) (Diener, 2000), which is often interchangeably referred to as psychological well-being or personal well-being (Wright & Bonett, 2007). SWB is conceptualized as "people's cognitive and affective evaluations of their lives" (Diener, 2000) and is regarded as an important workplace outcome (Keyes, 2006). Increased levels in SWB are associated with better physical and mental health (Keyes, 2004) as well as other important employee outcomes such higher job performance and retention rates (Wright & Bonett, 2007; Wright & Cropanzano, 2000). As such I extend the criteria space to investigate employees' SWB as the focal outcome for perceptions of uniqueness neglect and AI decision methods.

Hypothesis 2. Higher levels of uniqueness neglect will be related to lower levels of employee SWB.

Accordingly, I hypothesize a theoretical model whereby AI decision methods are indirectly and negatively associated with employee SWB, mediated by perceptions of uniqueness neglect. Figure 1 illustrates the theoretical model for this main effect.

Hypothesis 3. Using AI methods (vs. human methods) to make decisions on employees leads to lower SWB in employees (*H3a*); this negative effect of AI decision methods on employee SWB is mediated by perceptions of uniqueness neglect (*H3b*).

Figure 1 illustrates the proposed main theoretical model.

The Role of Individual Differences

After determining the main relationship between AI decision methods and perceptions of uniqueness neglect and how it is in turn associated with SWB, I turn my attention to examining two of the most likely moderators – individual differences and decision outcome valence – based on prior findings in research on personality, individual differences, and justice perceptions:

According to uniqueness theory, people have a fundamental need to be unique and are happiest when they feel moderately distinctive from others around them, but the strength of this need differs from person to person (Snyder & Fromkin, 1980; Lynn & Snyder, 2002). Thus, someone who has a stronger need for uniqueness may be even more negatively affected when they are subjected to AI decision processes deemed to lack customized considerations, such that they feel greater perceptions of uniqueness neglect compared to others who have a lower need to be different. Similarly, people who believe themselves to be more unique and have more special characteristics than others (i.e. who have a stronger personal sense of uniqueness) (Şimşek & Yalınçetin, 2010) may also be even more negatively affected by AI decision processes. Such individual differences in the need for uniqueness and sense of uniqueness are also likely to moderate the indirect negative effect that AI decision methods have on SWB.

Hypothesis 4. Individual differences in the need for uniqueness and personal sense of uniqueness moderate the indirect negative effect of AI decision methods on employee SWB through perceptions of uniqueness neglect (first-stage moderated mediation), such that this indirect negative effect is amplified for employees who report a greater need for uniqueness and personal sense of uniqueness.

Figure 2 illustrates the theoretical model with the proposed main effect and moderators.

Decision Valence

Research in judgement and decision-making suggests that the valence of decision outcomes affects how people evaluate the quality of the decision and decision-maker. When outcomes are positive, decisions are judged to be more justified and the decision process superior (Lipshitz, 1989). Consistent with these findings, prior research in the justice literature indicates that decision valence or favourability moderates the relationship between fairness perceptions and people's reactions, such that a combination of unfair procedures and negative outcome elicits particularly negative reactions, while fair procedures and positive outcomes are associated with more favourable perceptions (Brockner & Wiesenfeld, 1996). This is because people do not expect negative outcomes and tend to attribute negative outcomes to the process and external factors, rather than to their own performance (Ababneh et al., 2014; Brockner & Wiesenfeld, 1996). To sum up, people tend to take personal credit for success but attribute failures to external, uncontrollable factors (Ployhart & Ployhart, 1997).

Interestingly, results from recent studies investigating outcome valence and fairness perceptions in AI decision-making appear to be mixed. In two online studies based on job selection scenarios, Acikgoz and colleagues (2020) hypothesized that negative outcomes would moderate the relationships between procedural as well as interactional justice perceptions and applicant reactions such as attraction to organization and job pursuit intentions. But their results were largely insignificant. Separately, Wang and colleagues (2020) found that crowdsource workers on MTurk who were given a negative performance rating ("fail") by a decision algorithm after completing a task rated the algorithm significantly lower in process fairness perceptions, compared to those who received a positive rating ("pass"). Bankins and colleagues (2022) tested the impact of decision valence on interactional justice perceptions and found that when valence was negative for HR management outcomes, there was no significance difference in perceived interactional justice of AI vs human decision makers. But when decision valence was positive, participants rated human decision makers more highly in interacted justice compared to AI decision makers (Bankins et al., 2022).

While I contend that perceptions of uniqueness neglect are largely distinct from justice perceptions, there exists potential for partial overlap with procedural justice perceptions to the extent to which people believe their uniqueness has not been accurately reflected or captured by AI decision processes. This is because perceptions of accuracy are a component of overall perceptions of procedural or process fairness (Colquitt, 2001). Given this potential partial overlap. it would be relevant to investigate outcome valence as a moderator in the proposed theoretical model. Based on earlier findings in the justice literature, I hypothesize the following:

Hypothesis 5. The valence of decision outcomes moderates the indirect negative effect of AI decision methods on employee SWB through perceptions of uniqueness neglect (first-stage moderated mediation) such that this indirect negative effect is amplified by negative decision outcomes (*H5a*); conversely this indirect negative effect is attenuated when decision outcomes are positive (*H5b*).

Decision Context – The Role of Decision Role & Stakes

Research on AI and algorithmic decision methods have separately examined their effects on decision *makers* and decision *recipients*. For purposes of this dissertation, I use the term "decision *makers*" to refer to people who are in the role of making decisions or being responsible for decisions (e.g. managers involved in personnel selection or overseeing performance reviews of subordinates). I use the term "decision *recipients*" to refer to people who are subjected to decisions and affected by decision outcomes (e.g. job applicants, employees undergoing performance appraisal). Most studies do not compare the responses of one group against the other or investigate whether aversive responses from both groups are similarly or differentially motivated. Responses to AI decision methods in organizational contexts have also largely been examined from the perspective of decision recipients (i.e. employee reactions)

What research that does exist on the perspective of decision *makers* shows that they also prefer their own judgement over recommendations from AI or algorithms (Dietvorst et al., 2015). A similar "algorithm aversion" reaction to that exhibited by recipients of AI decisions. However Logg and colleagues (2019) caution that such findings may not accurately reflect how people actually respond to algorithmic decision methods as it could stem from a general resistance to taking advice from others rather than AI or algorithms per se. The advice-giving and advice-taking literature has long shown that people routinely discount the advice of others and place more weight on their own opinion or judgment relative to that of others (Yaniv & Kleinberger, 2000). This could be because decision *makers* are privy to internal knowledge about how they arrive at their own judgment but lack access to other people's reasoning or rationale (Yaniv & Kleinberger, 2000). Discounting of advice from others could also be attributed to an egocentric bias that drives decision *makers* to believe that their own judgment is superior to that of others (Krueger, 2003). Indeed studies have shown that people tend to have an inflated confidence in their own abilities and judgement compared to those of others (Moore & Healy, 2008). Therefore, the fact that people prefer to utilize their own decisions rather than recommendations from AI or algorithms should not be attributed simply to a resistance to AI/algorithmic decision methods (Logg et al., 2019). Instead, it would be more meaningful to compare how decision *makers* respond to external recommendations from *other* humans vs. an AI or algorithm (Logg et al., 2019).

Evidence from a series of six experiments by Logg and colleagues (2019) corroborates with the advice literature. Results showed that lay people (with no domain expertise) were actually more likely to adopt advice from an algorithm versus advice from another human (a behavior the authors term "algorithm appreciation"), but this was not the case for experts with domain knowledge, who significantly discounted advice from external sources including algorithms (Logg et al., 2019). This is consistent with findings from the advice literature that decision *makers* exhibit less egocentric discounting of advice from others when they are less knowledgeable or have less expertise compared to the external advisors (Bonaccio & Dalal, 2006).

Notably however, the tasks presented to lay people participants in Logg and colleagues' (2019) studies involved relatively low stakes, e.g. estimating the weight of a person in a photograph, predicting the popularity of a song, and estimating which US state had the highest number of departing airline passengers. In comparison, the experts (who work in national security) in the same series of studies were asked to make geopolitical forecasts, a task that essentially tests their professional ability and is thus arguably higher in stakes. This is because people derive their self-concept and identity not just from personal traits but also from their professional roles (Ibarra et al., 2014), and they value their identities (Petriglieri, 2011). Hence they would care more about performing a task in their domain of expertise than one in random field.

Tambe and colleagues (2019) in their discussion on the challenges of using data science techniques in HR management noted resistance to such techniques in "high-stakes" contexts that "affect people's lives – or their careers" (p.33). Similarly, Landers and Behrend (2022) noted that most reservations and complaints about AI predictive models tend to be on their use in high-stakes decision making (e.g. in personnel selection, college admissions, or identifying people at risk of mental health issues). However, this is in reference largely to decision *recipients*.

Taken together, this suggests that "algorithm aversion" likely depends on decision contexts. In high-stakes context such as job interviews and performance evaluation, being unique is salient as it helps people to stand out from their competitors and win a job or a promotion. In such contexts people would desire even more strongly to be unique (rather than similar) – i.e. the point of optimal distinctiveness tilts towards being more distinctive. People would also consider themselves to be more unique (whether or not they are objectively so). In such contexts, if the decision-making process (e.g. via AI) is perceived to be unable to conduct customized evaluations for individuals, it would trigger stronger perceptions of uniqueness neglect in decision *recipients*. Being unique could also be highly salient when disadvantages are considerable for not being sufficiently unique, and when substantive loss or harm could be avoided if one's unique case is duly recognised. Medical situations provide one such example, where the stakes could be high if a patient's specific medical condition is not properly diagnosed and treated. Thus patients (decision *recipients*) are likely to perceive higher levels of uniqueness neglect when serviced by AI rather than medical providers (Longoni et al., 2019).

Building on this argument, decision *makers*, too, could be susceptible to perceptions of uniqueness neglect if they believe that using AI methods in their decision-making processes compromises their unique identity and causes them to lose out in a high-stakes situation. For instance, if decision *makers* who pride themselves on their professional competence (e.g. in making geopolitical forecasts or predicting stock prices) were asked to use an AI tool instead to perform such tasks in their area of expertise, they may feel that using the tool would not adequately showcase their unique talent, and may compromise their reputation or standing. This could trigger perceptions of uniqueness neglect.

Overall, I propose that in any given decision context, if the stakes are similarly high for both decision *makers* and decision *recipients*, regardless of roles, people are likely to perceive significantly higher perceptions of uniqueness neglect when AI instead of human decision methods are used, and there should be no significant differences in their perceptions of uniqueness neglect.

In some contexts, however, where the stakes may be higher for decision *recipients* than decision *makers*, then decision role may moderate perceptions of uniqueness neglect. For instance, in a performance appraisal, the stakes are likely to be much higher for the employee (decision *recipient*) being appraised than the supervisor (decision *maker*) conducting the appraisal, since it is the employee's salary and career prospects that are on the line. Furthermore, research on egocentrism suggests that people pay far greater attention to self-assessments than other-assessments; they are more sensitive to how the environment would affect themselves than others (Windschitl et al., 2003). For instance, if an organisation introduces a new system that uses AI to evaluate employee performance in place of the old system where evaluations are made by human (supervisors), all things being equal, those being evaluated (e.g. employees) would be far more concerned about this new system and how it affects them compared to those who are not under evaluation, e.g.

supervisors (assuming supervisors themselves are not being evaluated) Therefore, employees (decision *recipients*) would perceive significantly greater perceptions of uniqueness neglect with the new AI evaluation system compared to their supervisors (decision *makers*). Accordingly, I hypothesize:

Hypothesis 6. When AI (vs. human) decision methods are used, perceptions of uniqueness neglect would be significantly higher for both decision *makers* and *recipients* (*H6a*); but there would also be no significant difference in perceptions of uniqueness neglect if the stakes are similarly high for both groups *(H6b*). In decision contexts where the stakes are higher for decision *recipients* than decision *makers*, decision role moderates the indirect negative effect of AI decision methods on SWB through perceptions of uniqueness neglect (first-stage moderated mediation) such that this indirect negative effect is amplified for decision *recipients* (*H6c*).

Power, Identity & Uniqueness Neglect

In the previous section discussing implications of decision role and contexts, the assumption was that HR decision contexts such as performance appraisals are high stakes largely for decision *recipients* (employees) and much less so for decision *makers* (supervisors), such that the latter are less likely to experience uniqueness neglect when AI decision methods are used. But there could be circumstances that lead decision *makers* or supervisors to feel otherwise.

As leaders, supervisors hold power in organisations in that they have the ability to influence their subordinates and their subordinates' circumstances and behaviours (Podsakoff, 1982). The definition of power varies across an extensive body of research, but generally, interpersonal power refers to a person being able to act and influence his/her environment or other people, according to the person's will, and this often involves the person having an asymmetric control of valued resources (Sturm & Antonakis, 2015). Being able to evaluate subordinates' performance, influence their compensation and future career prospects are just some tasks that come with being a supervisor or a leader, and these constitute sources of power for supervisors, who can use them to reward (or punish) subordinates depending on their assessment of the latter's performance (Hinkin & Schriesheim, 1994).

If an AI tool takes over decision making from supervisors in leadership tasks (e.g. employee performance evaluation), it in effect removes a source of power from them and will likely cause supervisors to feel that they have less power. A loss in power for supervisors (decision *makers*) is arguably a high stakes context for them.

Management research has highlighted the "paradoxical tension" of AI which is used to both automate and augment work processes in organisations (De Cremer & Kasparov, 2021; Raisch & Krakowski, 2021). Conceptually, automation implies that machines replace humans in performing a task (Raisch & Krakowski, 2021); augmentation suggests that humans work in collaboration with machines, and that machines help to complement and enhance the overall ability or role of humans in the job (De Cremer & Kasparov, 2021; Raisch & Krakowski, 2021). Focusing on automation aspects of AI in managerial tasks would lead people to perceive machines as "adversaries" and trigger negative responses, whereas adopting an "augmentation strategy" and highlighting how AI can complement human talent would be much more productive (Raisch & Krakowski, 2021).

Building on this, I propose that if an AI tool is positioned as a tool that augments rather than replaces supervisors in their role as leaders, helping them to become more efficient and effective (by making better data-driven decisions, for instance), and serving as an additional leadership resource, this is likely to mitigate their negative perceptions about AI decision tools. They would be less likely to perceive the adoption of AI decision methods as a power loss.

Power and leadership also contribute to identity perceptions. People derive their self-concept from a combination of identities including their personal identity (individual traits), social identity (group membership and relationships with others), as well as professional and leader identities (Petriglieri, 2011). A leader identity is not just based on a formal position that people hold at work, but "evolves as a person internalizes and tailors a leader identity and is recognized by others as 'leader'" (Ibarra et al., 2014, p. 286). People establish their leadership identities by differentiating themselves from their subordinates and other leaders, and by building differentiated relationships with their subordinates (Ibarra et al., 2014). In short, being a leader can be an integral part of one's self-concept and how a person distinguishes himself or herself from others.

Losing leadership powers and influence (e.g. no longer being able to appraise employees' performance and influence their career) diminishes supervisors in their leadership role and can be seen as a threat to their leader identity.[2] It affects how they can enact their leadership role and may cause them to feel less differentiated not just from their subordinates but also from other leaders, as they have less opportunity to exercise their unique judgement as leaders. This is likely to affect their overall self-concept as an individual. In such instances, AI decision-making processes becomes high stakes for supervisors (decision *makers*) and are likely to trigger greater perceptions of uniqueness neglect. Accordingly, I hypothesize that in decision contexts where decision *makers* have power over decision *recipients*:

Hypothesis 7. Perceptions that AI methods replace (vs. augment) leaders in decision-making would lead to lower power perceptions in leaders (*H7a*); perceptions of AI methods replacing (vs. augmenting) leaders are also associated with greater perceptions of uniqueness neglect in leaders (*H7b*); and this association with perceptions of uniqueness neglect is mediated by power perceptions (*H7c*).

Figure 3 illustrates the relationships predicted in *Hypothesis* 7.

[2] Identity threats are defined as experiences "appraised as indicating potential harm to the value, meanings, or enactment of an identity" (Petriglieri, 2011).

CHAPTER 4 OVERVIEW OF METHOD

A total of 5 studies were conducted to test the hypotheses outlined in this dissertation. All studies employed a between-subjects design. Studies 1, 2, and 3 were experiments conducted online to test Hypotheses 1-3 on the main relationship between AI decision methods, uniqueness neglect, and subjective well-being, as well as Hypotheses 4 and 5 testing different potential moderators for this relationship. Participants for studies 1-3 were adult United States (US) nationals recruited from crowdsource survey platform Prolific, which was established to cater mainly to researchers and start-ups (Peer et al., 2017). Compensation fees of £2.50 were paid to each participant in these studies, which took about 15 minutes to complete.

Study 4 was designed as an experiment comprising two separate vignettes to test Hypothesis 6 (6a-c) on the implications of decision role, with participants recruited from a field sample of international investment and financial professionals through a combination of snowball, convenience and voluntary response sampling. Both vignettes were presented to all participants with the order of the vignettes presented in randomized order for counterbalancing. The survey was distributed online to participants (via email or social media messaging services) and required an estimated 20-25 minutes to complete. An honorarium of about US$7 was offered to each participant who submitted completed responses, although slightly over half of the final sample (51.85%) waived this payment.

Finally, Study 5 was another online experiment conducted to test the final set of Hypotheses (7a-c) on implications of AI decision methods on decision *makers* with power in organizations. Participants for this study were

US nationals employed as supervisors (who have at least one direct report) in their actual work life. Also recruited from Prolific, these participants were similarly paid £2.50 to complete the study, which was estimated to take about 15 minutes.

To prevent observations from being biased by participation in previous studies, candidates on Prolific were automatically screened out from recruitment if they had participated in other studies for this dissertation.

The sample size for each study was determined a priori by conducting power analyses (at 80% power) using G*Power 3.1 as well using empirical estimates developed by Fritz and MacKinnon (2007) for analyses for mediated effects. As far as possible effect size estimates were based on prior studies. Where no prior estimates or related estimates were available, I based assumptions relatively conservatively on smaller to medium effect sizes.

To establish causality, I used the experimental vignette methodology (EVM) for all five studies, which involved creating a realistic scenario as the manipulation for the predictors and measuring participants' responses to the hypothetical scenario. Prior research indicates that the EVM improves experimental realism to enhance both internal and external validity (Atzüller & Steiner, 2010; Hox et al., 1991). This method also allows the researcher to manipulate a high-stakes condition (in the case of this dissertation, employee performance evaluation, pay raise and promotion prospects, as well as investment portfolios) without running into an ethical dilemma (Aguinis & Bradley, 2014). The EVM was also the most common research design by far among studies on algorithmic decision-making and algorithm aversion (Langer & Landers, 2021).

The focal predictor in these studies was “AI decision” or “AI decision methods”. Rather than provide a technical definition of the technology behind AI (i.e. how it works), I chose instead to describe what tasks or functions this “AI decision tool” would perform (i.e. what it does) so that participants were clear about what the AI tool would be accomplishing or be responsible for in each scenario. In Study 5 I also provide more details of which stage of decision-making the AI model would be involved and where data would be drawn from. I chose not to provide explicit technical definitions because the study of AI in this dissertation rests on testing lay perceptions of AI. It is people’s assumptions about AI and their instinctive responses to the use of AI in automating decisions in specific contexts that my dissertation aims to unpack. Providing a detailed explanation of “how it works” might also be impractical as AI decision models are notoriously complex in how they generate predictions, with some models involving various permutations of up to thousands of variables (Landers & Behrend, 2022).

Participants were provided with a debrief at the end of each study. Sample sizes were set in advance for Studies 1-3 and Study 5, and there were no observations excluded except for those that failed manipulation and/or attention checks. All five studies were approved by the Singapore Management University Institutional Review Board. All studies were conducted virtually (i.e. online) as they took place largely during the COVID-19 pandemic when safe-distancing measures were enforced.

CHAPTER 5 STUDIES 1-3

Study 1

Sample and Procedure

Study 1 was designed to test the proposed causal relationship between AI decision methods, perceptions of uniqueness neglect, and employees' subjective well-being (SWB), outlined in Hypotheses 1-3. Participants were all United States (US) nationals currently residing in the US, aged at least 18 and above. A power analysis using G*Power 3.1 at 80% power suggested that a minimum sample size of 125 would be needed for an estimated effect size of .25. I recruited 160 participants initially from online research platform Prolific, giving an allowance of up to about 20% for invalid responses. In reality a total of 44 responses (27.5%) had to be excluded as they failed manipulation and attention checks in the study, yielding a final sample of only 116, suggesting that this study could be underpowered. Participants' ages ranged from 18 to 72 (M_{age} = 34.43, SD_{age} = 12.05), and they comprised 44.83% female, 53.45% male, 0.85% (1 person) who identified as bigender, with the remaining 0.85% (1 person) who declined to provide gender information.

Participants were presented with a vignette that asked them to imagine themselves as employees of a company called Smart Data. To increase realism, the vignette provided a brief description of the company, as well as participants' role and responsibilities within Smart Data. To maintain plausibility, the information for the role and responsibilities was modelled on information sourced online from major recruitment firms. Following this vignette, participants were asked to write a short paragraph (50-300 words) imagining what they would do and how they would feel on a typical day as a business development executive at Smart Data. This writing exercise was meant to help participants spend more time thinking about their imaginary role and to immerse themselves in the vignette. It also served as an additional attention check, as I excluded participants who had plagiarized content from internet websites.

After completing the paragraph, participants were asked to continue to imagine themselves as employees of Smart Data, and were presented with an email from the company's HR team about their annual performance appraisal. The email told participants that the company was introducing a new appraisal system and provided the evaluation criteria and method for their appraisal. The experimental manipulation was embedded in this email and involved two conditions: an AI condition and a control condition.

Participants were randomly assigned to one of these two conditions. In the AI condition (n = 60), participants were told that a new AI performance appraisal software would be analysing the data from the evaluation criteria described earlier (e.g. how much new business they had won for their accounts, customer satisfaction ratings, etc.). The AI would then compare their performance against their peers' performance and decide how much bonus and salary adjustment they would receive. In the control condition (n = 56), participants were told that their manager would be evaluating their performance, comparing them against their peers, and deciding on their bonus and salary adjustments. A sample of this vignette and instructions for participants is presented in Appendix A.

Immediately following the vignette, I ran four attention checks to ensure participants understood the scenario and were sufficiently immersed in it. These checks included items asking participants to identify – among one of three choices provided – the correct name of the company at which they were supposed to be employed (as described in the scenario), their role at the company, correctly identify a job requirement from three options provided, and a criterion included in their performance appraisal. Two more standard attention checks were interspersed in the rest of the study.

Manipulation Check & Measures

Manipulation check. As a manipulation check, after participants read the vignette, they were asked to respond to the question "Your performance over the past 12 months will be analysed by…", by selecting either "an AI performance appraisal software" or "Your manager" as their response. AI condition was coded as "1" for the variable Decision Method, while human or control condition was coded as "0".

Uniqueness neglect. Perceived uniqueness neglect was measured with a three-item scale adapted from Longoni and colleagues' 2019 study. The items are "how concerned would you be that Smart Data's appraisal procedures, in analysing your performance… would not recognize the uniqueness of your qualities and work / would not consider your unique circumstances / would not tailor the performance analysis to your unique case" (1 = *Not at all concerned* to 7 = *Extremely concerned*). These items demonstrated high internal reliability (α = .97).

Subjective well-being (SWB). SWB was operationalized and measured using two different scales: the PANAS measure (Watson et al., 1988) as well as the Perceived Stress Scale (Evans & Johnson, 2000), both of which are appropriate as state measures for SWB in a specific situation, rather than a general globalized measure. PANAS is a widely-used measure which has been applied in a number of studies on SWB (Anglim et al., 2020; Schmitt et al., 2014), including those that test the relationships between SWB and uniqueness (Koydemir et al., 2020). The PA scale includes 10 items such as "Interested", "Inspired", and "Enthusiastic", while the NA scale includes 10 items such as "Nervous", "Irritable" , and "Distressed". Participants were asked to rate the extent to which they experienced these feelings presently (1 = *Not at all* to 5 = *Extremely*). Alphas for PA and NA were .90 and .93 respectively. The Perceived Stress Scale comprised 7 items such as "Bothered", "Relaxed" (reversed scored) and "Frustrated", and showed high internal reliability (α = .91). Participants were asked to rate the extent to which they felt this way now (1 = *Not at all* to 5 = *Extremely*).

Control variables. I controlled for age because findings from some earlier studies on technology at work suggest that older workers find it more difficult to adapt to changes in the work environment, preferring to resort to familiar methods (Sharit & Czaja, 1994), and that younger workers, being more exposed to information technology at a younger age, tend to be more comfortable with and reliant on technology for work (Morris & Venkatesh, 2000). I also measured perceptions of procedural justice (PJ) on a 7-point scale by adapting six items from Colquitt's (2001) measure; items for this scale presented in Study 1 include: "I am able to express my views and feelings during these procedures", "These procedures are free of bias", "These procedures are based on accurate information". Controlling for PJ in the mediation analysis would indicate whether uniqueness neglect explains incremental variance beyond justice perceptions in accounting for resistance to AI decision methods.

Results

Descriptive statistics and correlations of the focal variables are presented in Table 1. Internal reliabilities for each scale are presented in parentheses along the diagonal from top left to bottom right of the correlation table. All correlations, descriptive statistics (mean, minimum and maximum values, S.D.), reliability, *T*-test and ANOVA analyses were conducted using STATA, while mediation analyses were conducted using both STATA (SEM) as well as SPSS and PROCESS.

Hypothesis 1 predicts that AI decision methods will trigger greater perceptions of uniqueness neglect in employees, compared to human decision methods. Independent sample *T*-tests conducted showed that participants in the AI condition (coded as "1") perceived significantly higher levels of uniqueness neglect (M_{AI} = 5.34, SD_{AI} = 1.36) compared to participants in the human or control condition (coded as "0") (M_H = 3.08, SD_H = 1.68, $t(114) = -7.80$, $p < .001$), providing initial support for Hypothesis 1. A between-subjects analysis of variance (ANOVA) showed that the effect of AI decision method was significant [F(1,114) = 63.94, $p < .001$]. I then regressed uniqueness neglect on decision method (controlling for age) and observed that AI decision method is significantly and positively associated with uniqueness neglect (*b* = 2.27, $p < .001$), providing further support for Hypothesis 1.

Hypothesis 2 predicts that higher levels of uniqueness neglect will be associated with lower levels of employee SWB. Controlling for age, robust regressions of the three measures for SWB (stress, NA, PA) separately on uniqueness neglect showed that uniqueness neglect was significantly and positively associated with perceived stress (b = .15, p = .001) and NA ((b = .11, p = .005), but not significantly associated with PA although there was a negative relationship ((b = − .15, p = .397) in the direction predicted. However, when I added PJ as a control variable, the relationships between uniqueness neglect and stress as well as uniqueness neglect and NA became insignificant (stress: b = .031, p = .523; NA: b = .072, p = .122), suggesting that uniqueness neglect may not provide incremental variance in explaining resistance to AI decision methods. Nevertheless, given the smaller-than expected sample size of 116, the lack of support could potentially be explained by study being under powered.

Hypotheses 3(a) and 3(b) predict respectively that AI decision methods would be associated with lower employee SWB, and this relationship is mediated by uniqueness neglect. Independent *T*-Test results for SWB showed that results for perceived stress were significant and in the direction predicted, with those in the AI condition feeling significantly more stressed (M_{AI} = 2.48, SD_{AI} = .85) than those in the control condition (M_H = 2.09, SD_H = .87, $t(114)$ = −2.43, p = .02). Results were weaker for the other two measures of SWB. While effects for PA and NA were consistent with the directions hypothesized, they were marginally significant. Participants in the AI condition felt lower PA (M_{AI} = 2.67, SD_{AI} = .78) and higher NA (M_{AI} = 1.79, SD_{AI} = .90) than those in the control condition (PA: M_H = 2.96, SD_H = .92, $t(114)$ = 1.82, p = .071;

NA: M_H = 1.50, SD_H = .69, t(114) = − 1.90, p = .060). These results indicate partial support for Hypothesis 3(a).

To test the mediation predicted in Hypothesis 3(b), I applied a bootstrapped indirect effect analysis with 5,000 bootstrap samples (Hayes, 2017) using PROCESS Model 4 for a single mediator and found partial support. Controlling only for age, the indirect effects from AI decisions to perceived stress and to NA were significant and in the direction predicted (Perceived Stress: *b* = .317, *SE* = .115, 95% CI [.094, .443]; NA: *b* = .237, SE = .099, 95% CI [.047, .435]), but no significant results were obtained for PA. When PJ was added as a control variable, however, the indirect effects from AI decisions to perceived stress and to NA became insignificant, although effect sizes were still in the directions predicted. A more robust test for Hypotheses 2 and 3 will be conducted with Study 2 with a larger sample size to increase power. Detailed results of the mediation analysis are presented in Table 2.

Study 2

Sample and Procedure

Study 2 was designed to test Hypothesis 4 predicting individual differences as potential moderators for the theoretical model. Hypothesis 4 proposes that the need for uniqueness (NfU) and personal sense of uniqueness (PSU) – two separate but related measures of individual traits – would moderate the indirect relationship between AI decisions methods and employees' SWB through their perceptions of uniqueness neglect. Specifically, employees who measure higher on each of these two traits would be significantly more influenced by AI decision methods such that they perceive significantly greater uniqueness neglect and lower SWB, compared to employees who measure lower on these traits.

A larger sample size was recruited for Study 2 to ensure sufficient power and provide more robust testing for Hypotheses 2 and 3. Initial power analyses suggested a minimum sample size of about 230 would be required for this study. Based on the experience from Study 1, I recruited an initial sample of 350 responses from Prolific, building in a more conservative estimate of about 30% for invalid responses. To obtain better quality responses and reduce the percentage of invalid data that would have to be excluded, I further specified in the recruitment requirements for Study 2 (and subsequent studies on Prolific) that only candidates with an approval rate of at least 95% can be invited to take part. A participant's approval rate refers to the percentage of studies on the survey platform for which his or her responses have been accepted and approved (i.e. not rejected for bad quality).

As with Study 1, all participants for Study 2 were United States (US) nationals currently residing in the US, aged at least 18 and above. After excluding 10 participants who failed manipulation checks and a further 65 participants who failed attention checks, the final sample of participants with valid responses stood at 275 (N = 275), indicating an exclusion or discard rate of about 21%. Participants' ages ranged from 19 to 76 (M_{age} = 32.48, SD_{age} = 11.08) and comprised 45.82% female, 53.45% male, and 0.73% who identified as binary gender.

Participants were presented with a vignette similar in design to the one used in Study 1. In addition to all the question items from Study 1, there were additional questions for two personality measures: the "Need for Uniqueness" (NfU) (Lynn & Harris, 1997; Lynn & Snyder, 2002) and the "Personal Sense of Uniqueness" (PSU) (Şimşek & Yalınçetin, 2010). According to Şimşek and Yalınçetin (2010), PSU differs from NfU in that it does not measure a positive striving for differentness which could be a defensive mechanism, but focuses instead on a more internal evaluation of one's uniqueness rather than assessing one's need to be different from other people (Şimşek & Yalınçetin, 2010).

Manipulation and Measures

Manipulation check. As described earlier, participants were requested to respond to a question on who would be appraising their performance. A total of 10 out of 350 initial participants (2.86%) failed the check (2 in the AI condition, 8 in the control condition). The final sample yielded an almost equal distribution of participants across the two conditions: 137 participants for the AI decision condition (coded "1"), and 138 for the human decision condition (coded "0").

Uniqueness Neglect, SWB. The same scales from Study 1 were administered in Study 2 to measure these variables. Alpha coefficients for these scales were .95 (uniqueness neglect), .92 (PA), .93 (NA), and .91 (Perceived Stress) respectively.

Need for Uniqueness (NfU). NfU was measured using a 4-item scale (Lynn & Harris, 1997; Lynn & Snyder, 2002). Sample items include "I prefer being different from other people", "Being distinctive is important to me". Participants were asked to rate the extent to which the statements reflect them

(1 = *Not at all* to 5 = *Extremely*). The items showed high internal reliability (α = .920).

Personal Sense of Uniqueness (PSU). PSU was measured using a 5-item scale (Şimşek & Yalınçetin, 2010). Sample items include “I feel unique”, “I cannot think of many special characteristics that distinguish me from others” (reverse coded), “I feel that some of my characteristics are completely unique to me”. Participants were asked to rate the extent to which the statements reflect them (1 = *Not at all* to 5 = *Very true of me*). The items showed high internal reliability (α = .83).

Control variables. As with Study 1, I controlled for age and procedural justice (using the same scale).

Results

Descriptive statistics and correlations for Study 2 are presented in Table 3. Internal reliabilities for each scale are presented in parentheses along the diagonal from top left to bottom right of the correlation table. All correlations, descriptive statistics (mean, minimum and maximum values, *SD*), reliability, *T*-test and ANOVA analyses were conducted using STATA, while moderated mediation analyses were conducted using SPSS and PROCESS.

Independent *T*-tests conducted replicated Study1’s support for Hypothesis 1. Participants who were assigned to the AI decision condition perceived significantly higher levels of uniqueness neglect (M_{AI} = 5.30, SD_{AI} = 1.54) compared to participants assigned to the human decision condition (M_H = 3.47, SD_H = 1.67, $t(273) = -8.08$, p <.001). A between-subjects analysis of variance (ANOVA) confirmed that the effect of AI decision methods on uniqueness neglect was significant [F(1,273) = 65.30, $p < .001$].

To test support for Hypothesis 2, I ran robust OLS regressions of the three measures for SWB (Perceived Stress, NA, PA) separately on uniqueness neglect, controlling for both age and PJ. Significant results in the direction predicted were obtained for both perceived stress ($b = .134$, $SE = .029$, $p < .001$) and NA ($b = .092$, $SE = .023$, $p < .001$), indicating that higher perceptions of uniqueness neglect were significantly associated with greater stress levels and negative affect in employers. Tests for PA yielded a very small effect size that was insignificant although in the direction predicted ($b = -.008$, $SE = .033$, $p = .805$). With a larger sample size providing sufficient power, Study 2 provided strong support for Hypothesis 2 with evidence that uniqueness neglect explains incremental variance for negative responses to AI decision methods.

Separate one-way ANOVAs showed that AI decision methods had significant effects on perceived stress [F(1,273) = 18.18, $p < .001$] and PA [F(1,273) = 13.98, $p < .001$] in the directions predicted, and marginally significant effects on NA [F(1,273) = 3.18, $p = .08$] in the direction predicted. This provided initial support for Hypothesis 3(a), which predicts that using AI decision methods leads to lower SWB in employees.

Mediation analysis using PROCESS Model 4 with 5,000 bootstrap samples (Hayes, 20017) showed that even after controlling for age and PJ, there was a significant negative indirect effect between AI decision methods and SWB mediated by uniqueness neglect (Perceived Stress: $b = .144$, $SE = .042$, 95% CI [.072, .237], NA: $b = .113$, $SE = .034$, 95% CI [.056, 188]).

Results for PA as a measure for SWB was insignificant for this mediation, although in the direction predicted ($b = -.001$, $SE = .038$, 95% CI [− .084, .069]). Taken together, results from Study 2 largely support Hypothesis 3.

To test whether individual traits (NfU and PSU) moderate the indirect negative effect of AI decision methods on SWB through uniqueness neglect, I ran a bootstrapped indirect effect analysis with 5,000 bootstrap samples using PROCESS Model 7 for moderated mediation (Hayes, 2017). This yielded insignificant results for the index of moderated mediation for both NfU and PSU as moderators, regardless of which of the three measures of the dependent variable SWB was used (Perceived Stress, NA, and PA). Detailed results of the moderated mediation analysis are presented in Table 4.

Figures 4 plots the effects of NfU (need for uniqueness) and AI decision methods on perceptions of uniqueness neglect, probing the interaction at three different levels of NfU (mean and +/− 1*SD*). Participants who measured higher on the trait Need for Uniqueness generally reported greater perceptions of uniqueness neglect – whether in the AI or control conditions, which was to be expected. However, the slopes for all three levels of NfU were almost parallel. This means that regardless of their individual needs for uniqueness, people were similarly affected by AI decision methods.

Measuring higher on NfU did not make people react more strongly to negative effects of AI decision methods. Figure 5 plots the effects of the other trait measure PSU (personal sense of uniqueness) and AI decision methods on perceptions of uniqueness. Probing the interaction at three different levels of PSU (mean and +/− 1*SD*) again yielded parallel slopes for all three levels.

Thus, as with NfU, measuring higher on PSU did not make people react more strongly either to the negative effects of AI decision methods. Therefore, Hypothesis 4 was not supported. One way to interpret this is that the effects of AI decision methods are so strong that individual differences matter less.

Supplementary analysis

One important premise of this dissertation is that perceptions of uniqueness neglect triggered in response to the use of AI decision making are separate from perceptions of unfairness, which has been to-date the dominant psychological mechanism proposed and studied on resistance to AI. Mediation analysis for Study 2 showed that as predicted, uniqueness neglect significantly mediated the indirect negative effect of AI decision on subjective well-being even after controlling for PJ. To supplement this analysis, I tested PJ in place of uniqueness neglect as a mediator. Controlling only for age, PJ significantly mediated the negative association between AI decision methods and SWB on all three measures of SWB (Perceived Stress: $b = .320$, $SE = .070$, 95% CI [.194, .468], NA: $b = .171$, $SE = .043$, 95% CI [.094, .263]; PA: $b = -.285$, $SE = .066$, 95% CI [− .423, . − 167]). This supports findings in previous studies by other researchers. The addition of uniqueness neglect as control variable, however, rendered the mediation effect of PJ insignificant across all three measures of SWB (Perceived stress: $b = .063$, $SE = .052$, 95% CI [− .031, .174], NA: $b = .029$, $SE = .025$, 95% CI [− .015, .086]; PA: $b = -.072$, $SE = .060$, 95% CI [− .196, .035]). This additional analysis supports my argument that uniqueness neglect serves as an alternate mechanism over and above justice perceptions in accounting resistance to AI decision methods.

Study 3

Sample and Procedure

Study 3 was designed to test Hypothesis 5 that decision outcome valence would moderate the indirect negative effect of AI decision methods on employee SWB through uniqueness neglect. A power analysis based on estimates from Fritz & Mackinnon (2007) for mediated testing suggested a minimum sample size of 396 was needed for 80% power. Based on experience from Studies 1 and 2 that between 20% and almost 30% of initial participant responses could be excluded from analysis due to poor quality, I used the 30% upper bound as a conservative estimate to determine an initial sample size of 560. Participants were recruited via the Prolific platform and were all US nationals currently residing in the US, aged at least 18 years and above. After excluding 23 people who failed manipulation checks and a further 21 people who failed attention checks, I obtained a final sample of 518 valid responses from participants whose ages ranged from 18 to 81 (M_{age} = 35.00, SD_{age} = 13.23). They were 52.70% female, 44.21% male, and 3.09 % who identified as binary gender.

Study 3 was in the format of a 2x2 factorial design with participants were randomly assigned to 1 of 4 conditions: AI decision method *and* favourable decision outcome (positive performance appraisal) (n = 135), AI decision method *and* unfavourable decision outcome (negative performance appraisal) (n = 126); human decision method *and* favourable decision outcome (positive performance appraisal (n = 125), and finally human decision method *and* unfavourable decision outcome (negative performance appraisal) (n = 132).

Participants were presented with an initial vignette similar in design to the one used in Studies 1 and 2, which included the manipulation for decision methods. Those assigned to the AI decision condition were told that a new AI performance appraisal software would be evaluating their performance data and giving them a performance rating. Those assigned to the human decision condition were told that their managers (humans) would be doing the evaluation and rating. To manipulate decision valence, I extended the vignette to include an additional “email from HR”. Participants in Study 3 were told that a month after the first email from HR about the new system, they receive a second email from HR informing them of their performance evaluation Those assigned to the condition of positive decision outcome were told” “You were given an overall rating of ‘Exceeded expectations’. Based on this rating, your performance merited a salary increment. The letter from HR confirms that your pay will increase from next month.” In contrast, those assigned to the condition of negative decision outcome were told: “You were given an overall rating of "Needs improvement". Based on this rating, your performance did not merit a salary increment. The letter from HR confirms that your pay will remain the same.”

Manipulation Checks and Measures

Decision method and decision valence manipulations. The manipulation check for decision method remained the same as for Studies 1 and 2 (question posed to participants on who would be appraising their performance – AI software or manager). For the manipulation check for decision valence, participants were requested to select out of three options which performance rating they received and a further question on whether their salary would increase or remain the same.

Uniqueness Neglect, Subjective well-being. The same scales from Studies 1 and 2 were administered in Study 2 to measure these focal variables. Alpha coefficients were .96 for uniqueness neglect, .92 (PA), .94 (NA), and .94 (Perceived Stress) respectively.

Control variables. As with Studies 1 and 2, I controlled for age and procedural justice.

Results

Descriptive statistics and correlations for Study 3 are presented in Table 6. As with Studies 1 and 2, all correlations, descriptive statistics (mean, minimum and maximum values, *SD*), reliability, *T*-test and ANOVA analyses were conducted using STATA, while moderated mediation analyses were conducted using SPSS and PROCESS.

Consistent with previous findings in Study 2, one-way ANOVAs confirmed AI decision methods had a significant effect on uniqueness neglect [$F(1, 516) = 60.98$, $p < .001$], and on two of the three measures for SWB [Perceived Stress: $F(1, 516) = 8.39$, $p = .004$, NA: $F(1, 516) = 3.29$, $p = .052$]. Although the effect was not significant for PA (which was also consistent with findings in previous studies), it was in the direction predicted [$F(1, 516) = 1.32$, $p = .25$]. These initial analyses continued to provide support for Hypotheses 1 and 3(a).

Robust regressions of Perceived Stress, NA and PA separately on uniqueness neglect (controlling for both age and PJ) yielded results and effect sizes very similar with those obtained in Study 2. As predicted, uniqueness neglect was positively associated with Perceived Stress (b = .144, SE = .025, p < .001) and NA (b = .097, SE = .022, p < .001), and negatively associated with PA with marginal significance (b = −.036, SE = .033, p = .109). These results replicated strong support for Hypothesis 2. A mediation analysis using PROCESS also largely replicated support for Hypothesis 3(b). Controlling for age and PJ, results showed that that AI decision methods were indirectly associated with significantly higher levels of Perceived Stress (b = .128, SE = .030, 95% CI [.032, .191]) and NA (b = .088, SE = .024, 95% CI [.044, .136]) through uniqueness neglect, though no significant results were found for PA.

A two-way ANOVA was run on the sample to examine the interaction effect of decision valence and AI decision method on perceived uniqueness neglect. No significant interaction effect was found [$F(1, 514) = .96$, $p = .33$], although AI decision methods [$F(1, 514) = 73.68$, $p < .001$] and decision valence [$F(1, 514) = 72.19$, $p <.001$] separately had significant effects on uniqueness neglect. Probing further on the interaction, I ran a bootstrapped indirect effect analysis with 5,000 bootstrap samples using PROCESS Model 7. This yielded an insignificant result for the index of moderated mediation for decision valence across all three measures of the dependent variable SWB. Detailed results of the moderated mediation analysis are presented in Table 7.

Figures 6 plots the effects of decision valence and AI decision methods on perceptions of uniqueness neglect, probing the interaction at both levels of decision valence (0 = negative, 1 = positive). As expected based on the two-way ANOVA analysis earlier, participants who received a negative decision outcome generally reported higher levels of uniqueness neglect and vice version for those who received a positive decision. But the slopes for the two different levels of decision valence were almost parallel. This means that regardless of decision valence, people were similarly affected by AI decision methods. Receiving a negative decision outcome from an AI software did not cause participants to respond more strongly and negatively to AI decision methods. Nor did participants who received a decision made by AI in their favour respond less negatively. Hence, there was no support for Hypothesis 5.

CHAPTER 6 STUDY 4

Study 4 was designed to test assumptions outlined in Hypotheses 6(a)-(c) on the potential moderating effect of decision role. Unlike in Studies 1-3 where participants were all adults from the general US population, Study 4 targeted field participants from a specific industry – investment management and financial services – but drawn from diverse geographical locations and cultures from around the world.

I chose this field setting for two main reasons. First, this an industry with one of the highest adoption rates of AI. A 2020 survey by McKinsey showed that about 60% of survey respondents in financial services reported AI adoption in their organizations, second only to those in the high tech or telecom industry (over 70%) (Balakrishnan et al., 2020). In particular the investment industry has increasingly adopted the use of algorithms and robo-advisory services to automate investment decisions (Uhl & Rohner, 2018; Zhang et al., 2021) – a trend that poses a direct challenge to human professionals in their domain of expertise. Thus, participants from this sector would be familiar with the use of AI in their own organizational or industry environment and would have formulated certain perceptions about the use of AI in making decisions at work. To these professionals, the use of AI in every-day work settings is not a far-fetched or hypothetical situation, but a real development unfolding right before their eyes.

Secondly, gathering data from field participants who are not crowdsourced from survey platforms and who are drawn from diverse geographies and cultures would help to establish generalizability and improve ecological validity of my findings.

Sample and Procedure

To recruit participants, I focused initially on members of a global professional association – CFA Institute – which has close to 200,000 members in local chapters or societies established across more than 160 cities and countries. Most of these members hold the professional designation of Chartered Financial Analyst®, which is awarded to candidates who have passed three levels of exams covering global investment and financial practices and have accrued at least four years of relevant professional experience in the industry. Specifically I contacted administrators of the local member societies in Singapore, Malaysia, Hong Kong and Australia, who together have an estimated membership of about 14,000. I secured their agreement to help publicize my survey link through their LinkedIn official pages, as well as through regular e-mail newsletters distributed to their members[3]. The survey was initially open only to CFA charterholders and candidates enrolled in the CFA program, i.e. professionals who are in the process of earning the CFA designation. The LinkedIn post and newsletter advertisement asked for volunteers to participate in a scientific survey on how financial professionals are reacting to recent technology disruptions.

After one week only about 50 volunteers responded. Due to the initial low response rate[4], as a CFA charterholder I expanded the survey distribution by sending direct messages on LinkedIn to CFA charterholders on my personal LinkedIn network and invited them to participate in the survey. I also

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[3] The e-mail newsletter recruitment drive for the survey was only in Singapore and Australia.
[4] According to local society administrators, internal surveys run by the associations themselves typically receive a response rate of about 1% to 2% over the entire survey period.

asked them to share the survey with others in their network, i.e. using snowball sampling. In addition I offered a modest incentive of SGD 10 (about USD 7) to be paid via PayPal to respondents who submit completed surveys. Finally I opened up the survey to financial professionals who were not CFA charterholders or candidate but were recommended to the survey by coworkers or friends who were CFA charterholders. The survey was open for 23 days and closed after no new responses were received for three consecutive days.

The survey was designed in the format of two separate vignettes – one was a scenario involving a wealth management team advising a client (Vignette 1), the other was a performance evaluation scenario similar to the HR setting used in Studies 1-3. Both vignettes were presented to all survey participants in randomized order to ensure counterbalancing. Observations for each vignette were analysed separately such that the vignettes were essentially two separate experiments.

My initial target was to achieve 300 to 400 responses, as prior power analyses recommended at least 250 to 300 valid observations. At the close of the survey I received a total of 334 submissions on Qualtrics, the survey platform on which the study was built. Of these only 231 were full responses as the rest of the participants had abandoned the survey before completing either Vignette 1 or Vignette 2. Because I treated Vignettes 1 and 2 as separate experiments, separate manipulation and attention checks were conducted for each vignette. I excluded observations from each vignette based only on responses to the checks specific to each vignette. So there were participants whose observations might have been included for Vignette 1 but not for Vignette 2, and vice-versa. A final total sample size of 216 was received across both Vignettes, with 196 valid observations for Vignette 1 and 178 valid observations for Vignette 2.

Of these, 45 (21.03%) were female, 167 (78.04%) were male, and 2 (0.93%) declined to specify their gender. Participants' ages ranged from 21 to 73 (M_{age} = 43.20, SD_{age} = 10.2), with 146 (67.59%) who were members of a CFA society (i.e. charterholders), 17 (7.87%) who were candidates on their way to earning a CFA charter, while the remaining 53 (24.53%) financial professionals were not part of the CFA network. Participants were drawn from 28 different nationalities across Asia (e.g. Singapore, Malaysia, Indonesia, Hong Kong, Bangladesh, India, Japan, South Korea), Australia, New Zealand and Oceania (Vanuatu), the Middle East (Bahrain, Lebanon, Saudi Arabia), Europe (Germany, France, Italy, UK, etc.), Africa (Mauritius, Yemen) and North America (Canada and US). I also asked participants for their primary country or territory of residence, and this was similarly distributed across 24 different countries. A full list of participants' nationalities and places of residence is provided in Appendix C.

Vignette 1

Vignette 1 was designed to test Hypotheses 6(a) and 6(b). The format was relatively short and in a 2x2 factorial design (decision method x decision role) with participants randomly assigned to 1 of 4 conditions: AI decision method and wealth manager (decision *maker*), AI decision method and client (decision *recipient*), Human decision method and wealth manager, Human decision method and client.

Participants were randomly assigned to imagine themselves either as a wealth manager employed at an investment firm called FairWell Advisors, or as a new client of the firm. They were given a description of the firm's investment policy and practices as well as procedures for handling new clients. They were then told that the firm had recently acquired a new AI investment tool that could perform invest portfolio allocations that matched the success rates of human wealth managers.

Half of the participants were told that in their case, FairWell's management had decided to deploy the new AI tool to perform portfolio allocations. They were then presented with portfolio allocations recommended by the AI tool. Among this group, participants assigned as "new clients" were asked to rate on a 7-point scale how likely they would follow this recommendation, while those assigned as "wealth managers" were asked to rate how much they would advise their client to follow this recommendation.

The other half of the survey participants were told that FairWell's management had decided to hold off on the AI tool. Instead, human wealth managers would continue to perform the allocation. They were then provided with identical information for the rest of the investment scenario. New clients were asked to rate how likely they would follow their wealth manager's recommendations while wealth managers were asked to rate how likely they would advise their clients to follow their (managers') own recommendation.

I then measured participants' level of concern that the investment system might neglect their uniqueness. While I did not manipulate decision stakes directly, the premise here is that the stakes would be similarly high for both decision *makers* (wealth managers) and decision *recipients* (clients). This is because for the former, their professional expertise and reputation are on the line and – in the case of those in the AI decision condition – challenged by a new automation technology. For the latter, their money or investment is at stake. As an attention check, participants were asked to identify from among three options the name of the firm they were assigned to in the scenario.

Manipulation Check and Measures

Manipulation check. After participants read the vignette, they were asked to respond to two questions: one asking them to indicate their role at the firm FairWell Advisors (from the options: “wealth manager”, “new client” or “founding partner”), the other asking them to indicate whether the portfolio allocation presented to them in the scenario was performed by an AI investment tool or a human manager (or “you and your team” for participants assigned to the wealth manager condition”). After excluding responses that had failed attention and manipulation checks, the number of responses distributed across the four conditions were as follows: Human decision method x wealth manager (52), human decision method x client (45), AI decision method x wealth manager (54), AI decision method x client (45). Coding-wise, for the predictor Decision Method, AI was coded “1” and Human method was coded “0; for the predictor Decision Role, wealth manager (decision *maker*) was coded “0” and client (“decision *recipient”*) was coded “1”.

Uniqueness neglect. Items measuring perceived uniqueness neglect were adapted from the 7-point scale used in Studies 1-3. Sample items for clients include “how concerned would you be that FairWell’s investment system… (1) will not recognize the uniqueness of your financial and investment situation; (2) will not consider your unique circumstances, and (3) will not tailor recommendations to your unique case". Items for wealth. managers were "how concerned would you be that FairWell's investment system (1) will not reflect the uniqueness of your skills and expertise; (2) will not accommodate or recognize your unique work circumstances and environment; (3) will not allow you to tailor the work in the specific or unique ways that you have in mind." These items demonstrated high internal reliability (α = .96).

Likelihood to endorse decision. Although I did not formulate any hypotheses on this outcome variable the theoretical model, I measured this out of interest for an idea of how receptive or resistant participants would be to the different decision methods. This was measured using the single-item question asking participants to rate on a 7-point scale "What is the extent to which you think you will follow this recommended portfolio allocation?" (for participants in the client role) or "What is the extent to which you think your new client should follow this recommended portfolio allocation?" (for those assigned to the wealth manager role).

Results

Descriptive statistics and correlations for Vignette 1 are presented in Table 8 and ANOVA summary findings presented in Table 9. All correlations, descriptive statistics, reliability, *T*-test and ANOVA analyses were conducted using STATA, while mediation analyses were conducted using both STATA (SEM) as well as SPSS and PROCESS.

Hypothesis 6(b) predicted that decision *makers* and *recipients* would not perceive significantly different levels of uniqueness neglect with the use of AI decision methods if stakes are high for both groups. Independent sample *T*-tests showed that in Vignette 1 (where stakes were designed to be similarly high for participants in both decision roles), decision *makers* (wealth managers) perceived slightly greater uniqueness neglect (M_M = 3.97, SD_M = 1.75) than decision *recipients* (clients) (M_R = 3.47, SD_R = 1.83, $t(194)$ = 1.37, p = .173) although the difference was not significant, providing indicative support for the prediction.

However, ANOVA results showed that AI decision methods did not have a significant main effect on perceptions of uniqueness neglect [$F(1, 192)$ = 1.55, p = .214], providing no support for Hypothesis 6(a). Further analysis showed that that AI decision methods had a significant simple main effect on people's likelihood to endorse decisions [$F(1, 192)$ = 14.38, p <.001]. There was also a significant interaction between decision method and role on people's likelihood to endorse decisions [$F(1, 192)$ = 8.11, p = .005]. Post-hoc regression analyses revealed that AI decision methods had a significant interaction with role such that decision *recipients* (clients, coded "1") were more likely than decision *makers* (wealth managers) to endorse decisions made by AI (b = .94, p = .005), suggesting that wealth managers resisted AI decision methods more than the clients.

For a more detailed analysis, I plotted the interaction of decision role (decision *makers* "wealth managers" vs. *recipients* "clients") and AI decision methods (x-axis) on perceptions of uniqueness neglect (y-axis). As depicted in Figure 7 the slopes for both decision *makers* and *recipients* were positive when decision methods changed from human (“0”) to AI (1”), indicating that people across both roles perceived greater uniqueness neglect with AI decision methods as predicted in Hypothesis 6(a) although the effect was not significant. The line slopes for wealth managers and clients also diverge, with the slope for wealth managers more sharply positive. This suggested that AI decision methods had a stronger negative effect on wealth managers (decision *makers*) than clients (decision *recipients)* although this effect was not significant based on the data collected. The difference – though not significant – points to the possibility that participants may not have perceived stakes to be at similar levels contrary to what the study design had intended.

Discussion

In hindsight the inconclusive findings for Vignette 1 can be attributed to two main issues. The first was a design flaw in the study. Instead of manipulating decision stakes directly to be constant across both decision roles and measuring stakes directly as a check, I had assumed that the stakes attributed to each role would be similarly high. Results showed that wealth managers perceived greater uniqueness neglect than clients under AI decision-making processes, indicating that the perceived stakes for wealth managers were probably higher. This could be because of the survey sample characteristics. As participants were largely financial professionals in their real work lives, they could have identified more closely with the wealth manager role and perceive the AI decision-making scenario as a reflection of the challenges they might be facing in their actual work environment. Also, as the scenario did not stipulate the specific size of the portfolio to be invested, the stakes were probably not as clear or high for those in the client role. I will need to address this design flaw in future studies.

Secondly, as a result of the higher percentage of data that had to be excluded due to incomplete or low-quality responses, there was a lack of sufficient power for Vignette 1 with responses unevenly distributed across the four conditions. For future field studies, I may consider partnering with a specific organization and getting the management's support to administer the study, rather than targeting the survey at individual volunteer participants.

Vignette 2

Vignette 2 was designed to test Hypotheses 6(a) and 6(c). The format for here was longer and more similar in design to the previous performance appraisal vignettes used in Studies 1-3. A 2x2 factorial design (decision method x decision role) was used with participants randomly assigned to 1 of 4 conditions: AI decision method and team leader (decision *maker*), AI decision method and team member (decision *recipient*), human decision method and team leader, human decision method and team member. The stakes were assumed to be high for those in the role of team member (decision *recipient*), and low for those in the role of team leader (decision *maker*). This is because in this context team members were the ones whose performances were under appraisal and whose pay would be affected by the appraisal process. Whereas team leaders were not under evaluation. A detailed discussion of this was outlined in Chapter 3 in the section "Decision Context".

Upon reading Vignette 2, participants were first randomly assigned to imagine themselves either as a team leader with direct reports, or as a member of a team, employed at an investment firm called Zenith Asset Management. They then received an "email" from Zenith's HR informing that that a new performance management system would be introduced and were given a detailed description of the new system's various features. These features were modelled on latest performance management systems in practice such as those implemented by IBM and Google, which are more data-driven and focus on real-time, continuous performance management (Schrage et al., 2019).

Half of the participants (assigned to "AI decision condition") were told that an AI evaluation tool would be performing a specific task in this system, namely analysing employee data to make a final performance appraisal and make salary recommendations. The other half (assigned to "human decision condition") were told that the team leader would be making the performance appraisal and salary recommendations.

Manipulation Check and Measures

Manipulation check. After participants read the vignette, they were asked to respond to two questions: one asking them to indicate their role at the firm (either "team leader" or "team member reporting directly to a team leader"); the other asking them to indicate which of two options would be evaluating employee performance under the new performance management system (either "An AI evaluation tool" or "You" for participants assigned to the team leader role/"Your team leader" for participants assigned to the team member role). Notably, a larger number of those assigned to the human decision condition failed the manipulation check (i.e. they assumed the evaluation would be performed by an AI tool even though they had been assigned otherwise), resulting in an uneven distribution of participants across the conditions.

After excluding responses that had failed attention and manipulation checks, the number of responses distributed across the four conditions were as follows: Human decision method x team leader (29), human decision method x team member (37), AI decision method x team leader (57), AI decision method x team member (55). Coding-wise, for the variable Decision Method, AI was coded "1" and Human method was coded "0; for the variable Decision Role, team leader (decision *maker*) was coded "0" and team member (decision *recipient*) was coded "1".

Uniqueness Neglect, SWB. Similar scales from earlier studies were administered in here to measure these variables. Alpha coefficients for these scales were .94 (uniqueness neglect), .913 (PA), .93 (NA), and .91 (Perceived Stress) respectively.

Control variables. As with Studies 1-3, I controlled for age and procedural justice, which was measured using the same scale used in previous studies.

Results

Descriptive statistics and correlations for Vignette 2 are presented in Table 10, ANOVA summary findings presented in Table 11, and moderated mediation analysis presented in Table 12. All correlations, descriptive statistics, reliability, and ANOVA analyses were conducted using STATA, while moderated mediation analyses were conducted using SPSS and PROCESS.

A two-way ANOVA was run to examine the effect of decision method (human coded “0” vs. AI coded “1”) and role (coded “0” for decision *makers* vs. “1” for decision *recipients*) on perceptions of uniqueness neglect. Results showed that AI decision methods had a significant main effect on perceptions of uniqueness neglect [$F(1, 161) = 18.49$, $p < .001$], providing support for Hypothesis 6(a) (and also Hypothesis 1). Post-hoc regression analysis showed that AI decision methods led to significantly higher perceptions of uniqueness neglect ($b = 1.39$, $p = .003$). However, there was no significant interaction between decision method and decision role on uniqueness neglect [$F(1, 161) = .48$, $p = .49$], indicating no support for Hypothesis 6(c).

For a more detailed analysis of the interaction, I ran a bootstrapped analysis with 5,000 bootstrap samples using PROCESS Model 7. I plotted the effects of decision role (team leaders vs. members) and AI methods (x-axis) on perceptions of uniqueness neglect (y-axis) (refer to Figure 8). The slopes for the line plots for leaders and members were both positive and almost parallel, with team members’ line minimally above leaders’ line, indicating that members and leaders were similarly and negatively influenced by AI decision methods. Results from the moderated mediation analysis on PROCESS (refer to Table 13) showed that controlling for age and PJ, AI decision methods were significant and indirectly associated with greater stress and NA for both leaders (stress: $b = .155$, $SE = .070$, 95% CI [.033, 309]; NA: $b = .070$, $SE = .040$, 95% CI [.006, 162];) and members (stress: $b = .143$, $SE = .071$, 95% CI [.017, .293]; NA: $b = .065$, $SE = .040$, 95% CI [.003, .153];), and this indirect effect operated through uniqueness neglect. This provided additional support for Hypotheses 3(a) and 3(b). But consistent with the

ANOVA results, the index of moderated mediation was insignificant across all measures of SWB (refer to Table 12), indicating that decision role did not moderate the indirect negative effect of AI methods on SWB.

Discussion

The results for Vignette 2 provide evidence that decision *makers* and decision *recipients* are both negatively affected by AI decision methods. Although I did not find support for Hypothesis 6(c) that decision role would moderate this negative effect, this was probably due again to the design flaw that plagued Study 4. Hypothesis 6(c) was formulated on the assumption that participants assigned as team members (decision *recipients*) would perceive significantly higher stakes than those assigned as team leaders (decision *makers*). Instead, going by the interaction plots, perceptions of decision stakes were likely to have been similarly high for participants in both decision roles .

This resulted in inconclusive findings that provided little clarity and support for Hypotheses 6(a)-(c). Nonetheless, the theory discussion in Chapter 3's section on “Power, Identity, and Uniqueness Neglect” did posit that team leaders could potentially perceive a performance appraisal context to be high stakes if they believed that having an AI tool replacing them in this task amounted to a loss in power for them. Study 5 was designed to test this.

CHAPTER 7 STUDY 5

Sample and Procedure

Study 5 was designed to test Hypotheses 7(a), 7(b) and 7(c) focusing on how AI decision methods influence decision *makers* with power and the effect of such methods on their perceptions of uniqueness neglect. I recruited 251 participants initially from online research platform Prolific, specifying for adult participants who were US nationals working as supervisors and had at least 1 subordinate reporting directly to them in their actual work lives. After excluding 8 responses that failed at least 1 attention check, I obtained a final sample of 243 participants, of whom 104 (44%) were female, 134 (55%) male, 1 (0.41%) who identified as genderqueer. Their ages ranged from 18 to 75 (M_{age} = 41.70, SD_{age} = 11.16).

Participants were asked to imagine themselves working at an imaginary firm, where they were a team leader managing a team of four subordinates. They read a description of their role and duties as a leader (including managing and setting goals for the team, evaluating team members' performance etc.). To help them immerse more deeply into their role, they were asked to write a short paragraph (50-250 words) imagining what it would be like to lead their team of four on a typical day as work.

Following the written exercise, they received an "email" from HR informing them of a new performance management system that the firm was introducing. They were provided with a list of the new system's key features including a new AI evaluation tool. Following this email, half the participants (randomly assigned) were told that the AI evaluation tool would replace them in evaluating their subordinate's performance "in a way that's much more efficient and effective" and that "we would no longer need you" to do so. Likewise, the AI tool will "take over your duty of recommending how much bonus and salary adjustment your team members should receive, and whether they should be promoted". The other half of the participants were told that this AI tool "enhances your role as a team leader" by "allowing you to be more efficient and effective" and that "you will no longer need to evaluate your team members' performance" to "focus your energy on other important tasks of team leadership". Details of this vignette are provided in Appendix E.

Manipulation Check & Measures

Manipulation Check. Overall participants were evenly distributed across the two conditions, with 122 participants were assigned to the high stakes or "Replace" condition (coded as "1") and 121 participants assigned to the low stakes or "Augment" condition (coded as "0"). As a manipulation check, participants were asked to respond to four questions. Two of them measured perceptions of how much the new AI tool "reduces my role as a team leader" and "replaces some of my leadership authority"; responses from these two items were combined to form a single measure for perceptions of replacement. The other two questions measured perceptions of how much the AI tool "enhances my role as a team leader" and "allows me to be more efficient and effective as a team leader", with responses for these two items combined to form a single measure for perceptions of enhancement or augmentation. A 7-point scale was used.

Independent *T*-test conducted showed that participants in the "Replace" condition reported significantly higher means for the two items measuring perceptions of replacement (M_R = 5.19, SD_R = 1.57) compared to participants assigned to the "Augment" condition (M_A = 3.97, SD_A = 1.63, $t(241) = 5.94$, $p < .001$). Conversely, participants assigned to the "Augment" reported significantly higher means for the two items measuring perceptions of enhancement (M_A = 5.16, SD_A = 1.41) compared to participants assigned to the "Replace condition" (M_R = 3.82, SD_R = 1.58, $t(241) = 6.94$, $p < .001$). These results suggest that the manipulation was effective.

Power. Perceived power was measured using a 10-item scale (Huang et al., 2011). Participants were asked to rate how powerful they felt after they read the vignette. Sample items include "To what extent do you feel you would have the ability to influence the appraisal process?", "How much do you feel in control?", "How powerful do you feel?", "How dependent do you feel?" (1 = *Not at all* to 11 = *Very much*). The items showed high internal reliability (α = .92)

Uniqueness Neglect, Subjective well-being. The same scales from previous studies were used to measure these variables. Alpha coefficients were .93 for uniqueness neglect, .92 (PA), .93 (NA), and .92 (Perceived Stress) respectively.

Control variables. As with earlier studies, I controlled for age. I also measured perceptions of procedural justice but did not control for PJ in the main analysis, although I did so later in supplementary analyses. This is because some items in the power scale (e.g. "how much do you feel in control of the processes" and "to what extent did you feel you would have the ability to influence the processes") overlap with items in the PJ scale, and the two measures were strongly correlated $r(241) = .61$, $p < .01$. Also in my theoretical model, PJ was a competing mechanism with uniqueness neglect (not power) in explaining people's resistance to AI decision methods. Given that Study 5 was set up to test the relationships between power and uniqueness neglect in decision *makers*, it was not necessary to control PJ as a test of Hypotheses 7(a) to 7 (c).

Results

Descriptive statistics and correlations for Study 5 are presented in Table 13 and mediation analysis presented in Table 14. All correlations, descriptive statistics, reliability, and ANOVA analyses were conducted using STATA, while mediation analyses were conducted using SPSS and PROCESS.

One-way ANOVAs confirmed that perceptions of AI "replaces" had a significant effect on perceived power [$F(1, 241) = 15.66$, $p < .001$] and uniqueness neglect [$F(1, 241) = 16.35$, $p < .001$]. Robust regressions conducted separately and controlling for age showed that perceptions of AI "replaces" had a significant negative effect on power ($b = -.998$, $SE = .254$, $p < .001$) and were also associated with significantly higher perceptions of uniqueness neglect ($b = .858$, $SE = .212$, $p < .001$). These findings support Hypotheses 7(a) and 7(b), which predict that leaders who perceive AI decision methods to be replacing them (vs. augmenting them) would have perceive lower levels of power and higher levels of uniqueness neglect.

As a test for the final Hypothesis 7(c), I ran a bootstrapped mediation analysis using PROCESS Model 4 for a single mediator and found that the indirect effect of perceptions of AI "replaces" (vs. "augments") on uniqueness neglect was significantly mediated by power perceptions (*b* = .488, *SE* = .132, 95% CI [.241, .759]. For a more conservative test I controlled for PJ (even though as discussed earlier this was not necessary theoretically) and this indirect effect was still significant (*b* = .156, *SE* = .068, 95% CI [.026, .292]. In conclusion, results for Study 5 provide full support for Hypotheses 7(a),7(b) and 7(c).

Supplementary Analysis

In my dissertation I did not theorize formally about the effects of perceptions of AI "replaces" (vs. augments) on subjective well-being, which was the focal dependent variable (DV) in the main theoretical model tested in Studies 1-4. Nonetheless as a supplementary analysis I extended the analyses in this study to include SWB as the ultimate DV. This involves a serial mediation (refer to Figure 9) which predicts that leader perceptions of AI method as "replace" (vs. "augment") are associated with lower SWB, mediated first through perceived power (first order mediator) followed by uniqueness neglect (second order mediator).

To test this model, I ran a bootstrapped mediation analysis using PROCESS Model 6 for two serial mediators. Results supported the serial mediation model. Controlling for age, the indirect effect of perceptions of AI "replaces" (vs. "augments) on SWB through power and uniqueness neglect was significant for measures of SWB using perceived stress (*b* = .115, *SE* = .037, 95% CI [.051, .197]) and NA (*b* = .057, *SE* = .022, 95% CI [.021, .108]. For a more conservative analysis I controlled for PJ and found significant indirect effects as well for both perceived stress and NA as measures of the DV, though effect sizes were reduced. No significant results were yielded for indirect effects on PA.

Details of the supplementary analysis are presented in Table 15.

CHAPTER 8 DISCUSSION & CONCLUSION

General Discussion

When I first embarked on researching AI, I reviewed the literature and found 185 studies discussing applications of AI at work or in organizational contexts published over the five decades spanning 1966 and 2018. More than half of these studies were published between 2016 and 2018, with the bulk of them in “tech-focused” journals. Now three years on as I conclude work on this dissertation, at least five review papers and one meta-analysis have been published recently in journals that are comparatively more mainstream, covering a growing body of work on people’s responses to the use of algorithms, robots, and generally AI.

No doubt this research field is fast expanding. One of the biggest concepts that have captivated researchers’ attention in recent years is “algorithm aversion”, which describes the tendency that people have to avoid decisions made for them or on them by algorithms, as opposed to decisions made using their own or other humans’ judgment (Dietvorst et al., 2015). Since Dietvorst and colleagues first published their paper in 2015 on algorithm aversion, an entire literature has emerged in management science to examine factors explaining this “aversion” and its associated outcomes, with fairness and justice perceptions being the most prominent perspective examined overall (Langer & Landers, 2021; Mahmud et al., 2021).

My dissertation adopts a different perspective by arguing that people’s resistance to AI decision methods stems from a fundamental need that human beings have to feel special and be somewhat different from others. When this need is not adequately met, perceptions of uniqueness neglect arise. I make the case that when AI decision methods are used instead of human judgement, people perceive uniqueness neglect because of implicit beliefs that machines – no matter how clever or adaptable – simply cannot match human intuition and adaptability in catering to individuals and their idiosyncrasies.

The research questions that I set out to address and the predictions I test in this dissertation can be organized into three clusters. The first core set of predictions centre on (1) demonstrating uniqueness neglect as an alternative psychological mechanism to other mechanisms identified in existing research that explain people's aversion to AI, and (2) demonstrating that such perceptions of uniqueness neglect are associated with lower levels of subjective well-being. These predictions are outlined in Hypotheses 1– 3.

The second cluster of predictions examine theoretically relevant moderators – individual differences (in the need for uniqueness and sense of uniqueness) and decision outcome valence – in my theoretical model. These predictions are outlined in Hypotheses 4 – 5.

The final cluster of predictions – set out in Hypotheses 6 – 7 investigate a contextual moderator –decision roles – as well as implications of AI decision methods on high-power decision *makers*. This final cluster aimed to investigate in particular implications of AI decision methods on decision *makers*, as prior studies on psychological mechanisms driving resistance to AI decision methods were largely based on perspectives from decision *recipients*.

Findings from all five studies I ran provided consistent and strong support for my core prediction that when AI decision methods are used rather than human decision methods, it leads people involved in the decision to perceive more acutely that their uniqueness has been neglected, and this is in turn associated with greater stress and negative affect. Results from these studies also largely support my prediction that uniqueness neglect accounts for incremental variance in explaining resistance to AI decision methods, over and above justice perceptions. This was shown in all studies with the exception of Study 1, which was under-powered because a large subset of poor-quality data had to be excluded from analysis. In short, Hypotheses 1 to 3 were supported.

Studies 2 and 3 tested two individual differences – need for uniqueness and personal sense of uniqueness – as well as decision outcome valence as potential moderators for the main effect that AI decision methods have on uniqueness neglect and indirectly on subjective well-being. I did not find any significant interaction effects from any of the proposed moderators, which were selected because of theoretically they appeared to be the most relevant ones. Hypotheses 4-5 were not supported. One implication of this could be that the AI decision methods as a contextual variable had much greater influence than these proposed variables, and that perceptions of uniqueness neglect were more sensitive to situational rather than individual factors.

This also points to a need to examine other individual differences that could prove more appropriate as moderators. Given that uniqueness neglect arises out of self-concern and a belief that one’s special characteristics are important, individual differences that relate to a concern for the self and a belief in the importance of self may be relevant. Plausible examples could include egoism, which emphasizes self-interest over others’ interests (Barelds & Luteijn, 2002), egotism, which focuses on self-enhancement but not at the expense of others and measures preferences for attention and to be recognized

(Paulhus & Jones, 2015), or other measures that relate to nonconformity or anticonformity (Willis, 1965). Another could be narcissism or narcissistic personality which is a composite construct that describes someone who is "relatively dominant, extraverted, exhibitionistic, aggressive, impulsive, self-centered, subjectively self-satisfied, self-indulgent, and nonconforming" (Raskin & Terry, 1988, p. 899). Study 4 did not provide conclusive findings to clearly support Hypotheses 6 (a)-(c) although there was partial support for Hypothesis 6(a). This was due in part due to design flaws and also a lack of power in the study (after large numbers of low-quality responses were excluded). Nevertheless, findings in Vignette 2 did show that AI decision methods influenced decision *makers* similarly as they influenced decision *recipients* to trigger higher perceptions of uniqueness neglect and lower SWB. There was no evidence however that decision role was an effective moderator.

Study 5 showed that for high-power decision *makers*, AI decision methods perceived to replace leaders (rather than augment them) in decision tasks cause leaders to feel a significant loss in power and in turn lead to greater perceptions of uniqueness neglect. This negative effect ultimately leads to lower SWB in leaders. Results from this study provided full support for Hypotheses 7(a), 7(b), 7(c).

Theoretical Implications

My dissertation makes three contributions to theory development in the study of AI. First, I combine literatures in uniqueness, identity and power to develop a model for an alternative mechanism that explains aversion to AI decision methods. I provide evidence that this alternative mechanism explains incremental variance over and above the dominant mechanism studied in existing literature, namely justice and fairness perceptions. In doing so, I contribute to the diversity of perspectives in an emerging line of research.

Second, I expand the criteria space to study negative effects of AI decision methods beyond general resistance or acceptance of the technology, linking it to subjective well-being. Subjective well-being is an important employee outcome. Unhappy employees are less satisfied at work, less committed to the organization, perform more poorly and are more likely to quit. (Jain et al., 2009), Wright & Bonett, 2007, Wright & Cropanzano, 2000). Importantly, lower SWB is also linked to poor physical health (Keyes, 2004). This theory extension enhances understanding of the broader impact of AI in organizational decision-making.

Finally, I show that similar to their effect on decision *recipients*, AI decision methods can also influence decision *makers* negatively through perceptions of uniqueness neglect. For higher-status decision *makers* with power such as leaders in organizations, the negative effect of AI decision methods on uniqueness neglect is mediated by power perceptions. Overall, Study 5 shows that using AI decision methods results in lower power perceptions in leaders if they believe that such methods replace – rather than augment – them in their leadership role, and such lower power perceptions are associated with greater perceptions of uniqueness neglect, which ultimately damages leaders' subjective well-being. Overall, this contributes to further understanding of how AI decision method impacts people in different decision roles and positions in organizations.

Practical Implications

My dissertation helps organizations to identify important concerns that people may have about the use of such a powerful technology as AI, and how it might trigger negative responses not just in decision *recipients* such as employees but also in other important stakeholders such as decision makers, who are often managers and leaders who hold power in organizations.

Extolling the virtues of AI – even with hard evidence (e.g. reducing bias, improving objectivity and effectiveness in decision-making) – would not be sufficient to allay concerns over such technologies. Organizations need to understand that concerns about AI decision methods also stem from people's deep-seated beliefs that AI decision methods somehow overlook them as distinct individuals, are incapable of individualized considerations, and this violates a fundamental need in human beings to be moderately unique. For decision *makers* in leadership positions, there is an additional layer of concern that AI decision methods could rob them of their power and compromise their identity as leaders. The consequences of such negative perceptions extend beyond an impact on attitudes and have actual significant effects on employees' mental and potentially physical well-being. In short, people are likely to become unhappy, stressed, and less healthy when AI decision methods are used in place of human decision methods. These are important risks for organizations to consider when they contemplate introducing such new technologies, as the costs could far outweigh the benefits if these risks are not properly addressed.

To mitigate such concerns and negative effects, one solution could be to lower the perceived threat from AI by approaching the adoption of AI decision methods as a strategy to *augment* rather than *replace* people in decision tasks, and positioning AI methods as tools that enhance them in their roles. Findings from this dissertation show that such an approach helps reduce perceptions of power loss and uniqueness neglect in decision *makers* (e.g. team supervisors). For decision *recipients* such as general employees, ensuring individualized considerations with AI decision methods – and making such individualized considerations transparent to these stakeholders – could mitigate perceptions of uniqueness neglect. This could be achieved perhaps through retaining ultimate human control and judgement in such decisions – assuring employees that a human eye would always be watching over these decisions – or by building in specific decision inputs for each employee's unique qualities. A caveat here: these suggestions have yet to be tested empirically.

My research on the importance of identity and uniqueness concerns will also help regulators refine solutions in governing AI risks. Existing discourse on risks of AI applications have largely focused on fairness and bias concerns (EIOPA, 2021; IMDA & PDPC, 2019; Jillson, 2021). Understanding that implementing AI decision methods could unintentionally harm people by triggering significant concerns about uniqueness and lowering their psychological well-being would help regulators govern such risks more effectively.

Limitations and Future Directions

My dissertation has several limitations. First, my studies employ what Spencer and colleagues (2005) term a "measurement-of-mediation" design.

Although mediation analyses support my theoretical model, scholars in research methods have noted that in the study of psychological processes, a better test of mediating processes is to use an ‘‘experimental-causal-chain’’ design that manipulates both the predictor and the mediator (Spencer et al., 2005; Stone-Romero and Rosopa, 2008). My studies have already established the causal relationship between the independent variable (AI decision methods) and the mediating psychological process of uniqueness neglect. What is pending is to demonstrate via experimental methods that this mediator also influences the dependent variable SWB. This is a priority issue to be addressed in future research.

Second, as noted earlier, the design of Study 4 was flawed in that assumptions were made about decision stakes while testing for the effects of decision role, resulting in a conflation of these two factors. A better and cleaner design would have been to manipulate and measure decision stakes separately from decision role. In future research I should develop a better operationalization of decision stakes to test this directly as a potential moderator. A clearer understanding of how decision stakes influence responses to AI decision methods could also help to explain inconsistencies in prior findings, such as when AI methods might elicit algorithm aversion rather than algorithm appreciation and vice versa.

Third, all five studies in this dissertation employ the experimental vignette methodology (EVM) which may limit ecological validity, although I attempted to mitigate this in Study 4 by involving field sample participants who are likely to be considerably more familiar with the use of AI in their sector. The prevalence of EVM in the study of AI decision-making has been noted by Mahmud and colleagues (2022) as well as Langer and Landers (2021), who caution against over-reliance on this design. To address this my future studies should employ a different design, in particular one that provides a more experiential interaction with AI technology, rather than relying on imagination or recall tasks. One potential alternative could be to present visual stimuli by having participants watch videos of decision methods (AI vs humans) in actual application.

Fourth, while the studies in this dissertation provided participants with descriptions of what AI decision methods would do, they did not provide participants with specific technical definitions of AI but rather, relied on participants' general or lay perceptions of AI technologies. This could prove problematic if participants vary widely in their understanding of and assumptions about the nature of AI decision methods. Future research designs could include an additional experimental condition that provides specific definitions and demonstration of AI methods to serve as an active control or comparator.

Finally, future studies could examine other relevant criteria besides subjective well-being. For instance, rather than measuring general negative or positive mood or affect, more discrete emotions relevant to the theoretical model could be tested, such as anger or anxiety (e.g. specific factor items from measures such as the UWIST Mood Adjective Checklist, Matthews et al., 1990). Apart from measures of passive mood responses, future research could also explore compensatory behaviours that people may engage in to restore uniqueness perceptions or counterbalance perceptions of uniqueness neglect.

Conclusion

In conclusion, this dissertation shows how AI triggers psychological responses that have been little explored in existing management research. Beyond fairness issues, AI decision methods affect people deeply because they raise fundamental questions and concerns about what it means to be a unique human being and how our individual human identities separate us from mere machines. My dissertation contributes answers to some of these questions and I hope that more work from other researchers will continue to enrich scholarship in this emerging and exciting research stream.

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TABLES

Table 1

Descriptive statistics and correlations for Study 1

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1. Perceived stress	2.29	0.88	1	5	(.905)							
2. Negative Affect	1.65	0.82	1	4.2	.82**	(.929)						
3. Positive Affect	2.81	0.86	1.1	5	− .33**	− .06	(.897)					
4. System satisfaction	4.69	1.48	1.33	7	− .41**	− .27**	.20*	(.917)				
5. Uniqueness neglect	4.25	1.89	1	7	.32**	.26*	− .08	− .64**	(.966)			
6. Procedural justice	4.43	1.14	1.5	7	− .42**	− .23*	.33**	.76**	− .65**	(.810)		
7. Age	34.43	12.05	18	72	− .10	− .11	.16	.00	− .02	−.09	NA	
8. Decision Method	0.52	0.5	0	1	.22*	.18	− .17	− .40**	.60**	− .41**	− .08	NA

Note. Decision Method: 0 = control condition (human method); 1 = experimental condition (AI method). Cronbach's alpha for each scale is presented within parentheses. * .01 ≤ p < .05. ** p < .01

Table 2

Mediation analysis: Effects of AI decision methods on subjective well-being through uniqueness neglect (Study 1)

	Mediator = Uniqueness Neglect		**DV = Stress**		**DV = NA**		**DV = PA**	
Predictors	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Constant	7.314**	.728	3.823**	.728	2.055**	.626	.022	.619
AI decision method	1.482**	.261	.033	.187	.027	.185	− .252	.183
Age	− .005	.010	− .010	.261	− .008	.006	.015*	.006
Procedural Justice	− .825**	.115	− .297**	.006	− .096	.087	.392**	.086
Uniqueness Neglect	—	–	.026	.060	.068	.059	.158**	.058
Direct and indirect effects			*b*	95% CI	*b*	95% CI	*b*	95% CI
Direct effect of AI	—	—	.033 (.187)	[−.338, .404]	.027 (.185)	[− .339, .392]	− .252 (.183)	[− .614, .110]
Direct effect of AI[η]	—	—	.061 (.196)	[−.327, .449]	.036 (.185)	[− .331, .402]	.286 (.198)	[− .681, .104]
Indirect effect of AI	—	—	.039 (.082)	[− .135, .191]	.101 (.078)	[− .071, .244]	.224 (.092)	[.074, .433]
Indirect effect of Ai[η]	—	—	.317 (.115)	[.094, .553]	.237 (.099)	[.047, .435]	.020 (.120)	[− .229, .250]

Note. *N* = 116. CI = confidence interval. Coefficients presented are unstandardized estimates. Bootstrapped *SE*s are in parentheses (“( )”). $*p < 0.05$, $** p < .01$. [η]Regression results controlling for age but not procedural justice, as comparison.

Table 3

Descriptive statistics and correlations for Study 2

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1. Perceived Stress	2.4	0.91	1	5	(.911)											
2. Positive Affect	2.57	0.91	1	5	−0.48**	(.921)										
3. Negative Affect	1.55	0.7	1	4.4	0.77**	−0.23**	(.926)									
4. System Satisfaction	4.36	1.31	1	7	−0.58**	0.5**	−0.39**	(.900)								
5. Job Satisfaction	4.76	1.41	1	7	−0.36**	0.41**	−0.19**	0.57**	.919							
6. Affective Commitment	3.97	1.41	1	7	−0.38**	0.45**	−0.26**	0.6**	0.75**	(.908)						
7. Quit Intentions	3.96	1.51	1	7	0.42**	−0.45**	0.32	−0.61**	−0.75**	−0.77**	(.916)					
8. Need for Uniqueness	2.96	1.13	1	5	−0.15*	0.33**	−0.06	0.21**	0.08	0.18**	−0.11	(.920)				
9. Personal Sense of Uniqueness	3.47	0.9	1	5	−0.17**	0.37**	−0.05	0.22**	0.15*	0.19**	−0.14*	0.65**	(.828)			
10. Uniqueness Neglect	4.25	1.78	1	7	0.51**	−0.3**	0.38**	−0.55**	−0.36**	−0.42**	0.4**	0.01	-0.06	(.945)		
11. Procedural Justice	4.19	1.06	1	7	−0.57**	0.5**	−0.37**	0.79**	0.48**	0.53**	−0.5**	0.25**	0.22**	−0.57**	(.776)	
12. Decision Method	0.5	0.5	0	1	0.25**	−0.22**	0.11	−0.32**	−0.16*	−0.26**	0.26**	−0.01	0.01	0.44**	−0.31**	NA

Note. Decision Method: 0 = control condition (human method); 1 = experimental condition (AI method). Cronbach's alpha for each scale is presented within parentheses. *.01 ≤ p < .05. **p <.01

Table 4

Moderated Mediation Analysis: Effects of AI methods and individual differences (NeedfU) on subjective well-being through uniqueness neglect (Study 2)

	Mediator = Uniqueness Neglect		DV = Stress		DV = NA		DV = PA	
Predictors	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Constant	6.773**	.687	3.756**	.345	2.12**	.283	.288	.395
AI decision method (AI)	1.17*	.497	− . 009	.107	− .134	.090	− .113	.109
Age	− .004	.007	− .011**	.004	− .007*	.003	.016**	.004
Procedural Justice	− .872**	.101	− .373**	.054	− .171**	.048	.432**	.064
Need for uniqueness (NeedfU)	.254*	.131	—	—	—	—	—	—
AI * NeedfU	− .058	.168	—	—	—	—	—	—
Uniqueness Neglect	—	—	.135**	.031	.106**	.025	.004	.037
Direct and indirect effects			*b*	95% CI	*b*	95% CI	*b*	95% CI
Direct effect of AI	—	—	− .009 (.097)	[− .199, .182]	− .134 (.090)	[−.310, .043]	− .113 (.109)	[− .327, .102]
Indirect effect of AI	—	—						
Conditional indirect effects	—	—						
NeedfU (− 1 *SD*)	—	—	.143 (.044	[.067, .239]	.113 (.036)	[.053, .195]	.004 (.0384)	[− .074, .080]
NeedfU (Mean)	—	—	.134 (.043)	[.061, .229]	.106 (.034)	[.051, .181]	.004 (.036)	[− .075, .067]
NeedfU (+ 1 *SD*)	—	—	.125 (.057)	[.034, .257]	.099 (.043)	[.030, .197]	.004 (.035)	[− .080, .060]
Index of moderated mediation	—	—	− .008 (.022)	[− .049, .040]	− .006 (.018)	[− .040, .031]	.000 (.006)	[− .017, .009]

Note. N = 275. Coefficients presented are unstandardized estimates. *SEs* reported are heteroscedasticity-consistent. CI = confidence internal. No. of bootstrapped samples = 5,000. Bootstrapped *SE*s are in parentheses. * p < .05. ** p < .01.

Table 5

Moderated Mediation Analysis: Effects of AI methods and individual differences (PSU) on subjective well-being through uniqueness neglect (Study 2)

	Mediator = Uniqueness Neglect		DV = Stress		DV = NA		DV = PA	
Predictors	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Constant	7.060**	.733	3.756**	.345	2.116**	.283	.288	.395
AI decision method (AI)	.999	.704	− .009	.107	− .134	.090	− .113	.109
Age	− .006	.007	− .011**	.004	− .007*	.003	.016**	.004
Procedural Justice	− .830**	.105	− .373**	.054	− .171**	.048	.432**	.064
Personal sense of uniqueness (PSU)	.103	.151	—	—	—	—	—	—
AI * PSU	.005	.206	—	—	—	—	—	—
Uniqueness Neglect	—	−	.135**	.031	.106**	.025	.004	.037
Direct and indirect effects			*b*	95% CI	*b*	95% CI	*b*	95% CI
Direct effect of AI	—	—	− .009 (.107)	[− .218, .201]	− .134 (.090)	[− .310, .043]	− .113 (.109)	[−.327, .102]
Indirect effect of AI	—	—						
Conditional indirect effects	—	—						
PSU (− 1 *SD*)	—	—	0.136 (.047)	[.055, .238]	.107 (.036)	[.046, .186]	.004 (.036)	[− .070, .076]
PSU (Mean)	—	—	0.137 (.044)	[.063, .235]	.108 (.034)	[.052, .185]	.004 (.036)	[− .075, .071]
PSU (+ 1 *SD*)	—	—	0.137 (.055)	[.048, .262]	.108 (.043)	[.039, .206]	.004 (.037)	[− .083, .071]
Index of moderated mediation	—	—	.001 (.028)	[−.052, .062]	.001 (.022)	[− .041, .047]	.000 (.007)	[− .019, .012]

Note. N = 275. Coefficients presented are unstandardized estimates. *SEs* reported are heteroscedasticity-consistent. CI = confidence internal. No. of bootstrapped samples = 5,000. Bootstrapped *SE*s are in parentheses. * $p < .05$. ** $p < .01$.

Table 6

Descriptive statistics and correlations for Study 3

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9
1. Perceived Stress	2.47	1.08	1	5	(.945)								
2. Negative Affect	1.63	0.82	1	4.7	0.79**	(.944)							
3. Positive Affect	2.47	0.89	1	5	−0.4**	−0.24**	(.921)						
4. System Satisfaction	3.93	1.6	1	7	−0.57**	−0.41**	0.36**	(.927)					
5. Uniqueness Neglect	4.51	1.78	1	7	0.46**	0.33**	−0.19**	−0.54**	(.961)				
6. Decision Valence	0.5	0.5	0	1	−0.48**	−0.37**	0.25**	0.65**	−0.32**	NA			
7. Procedural Justice	3.9	1.17	1	7	−0.52**	−0.32**	0.41**	0.75**	−0.55**	0.42**	(.829)		
8. Age	35	13.23	18	81	−0.08	−0.10*	0.22**	−0.04	0.00	−0.02	−0.08	NA	
9. Decision Method	0.5	0.5	0	1	0.13**	0.09*	−0.05	−0.11*	0.33**	0.03	−0.17**	0.02	NA

Note. AI: 0 = control condition; 1 = experimental condition. Favourability: 0 = Negative performance evaluation; 1 = Positive performance evaluation. Cronbach’s alpha for each scale is presented within parentheses. *.01 ≤ p < .05. **p <.01

Table 7

Moderated Mediation Analysis: Effects of AI decision methods and decision valence on subjective well-being through uniqueness neglect (Study 3)

	Mediator = Uniqueness Neglect		DV = Stress		DV = NA		DV = PA	
Predictors	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Constant	7.001	9.125	3.20	15.24	1.70	14.36	.987	29.767
AI decision method (AI)	.837**	.185	− .043	.260	− .031	.243	.018	.487
Age	.000	.235	.000	.363	.000	.342	.001	.709
Procedural Justice	− .681**	.254	− .352	.475	− .136	.448	.337	.926
Decision valence	− .557**	.212	—	—	—	—	—	—
AI * Decision valence	.119**	.363	—	—	—	—	—	—
Uniqueness Neglect	—	–	.151	.189	.104	.178	.027	.366
Direct and indirect effects			*b*	95% CI	*b*	95% CI	*b*	95% CI
Direct effect of AI	—	—	− .043 (.260)	[− .554, .468]	− .031 (.243)	[− .509, .447]	.018 (.487)	[− .940, .975]
Indirect effect of AI	—	—						
Conditional indirect effects	—	—						
Negative outcome	—	—	.127 (.033)	[.068, .196]	.087 (.026)	[.042, .142]	.023 (.020)	[−.014, .069]
Positive outcome	—	—	.145 (.039)	[.076, .230]	.099 (.031)	[.046, .167]	.026 (.023)	[−.015, .077]
Index of moderated mediation	—	—	0.018 (.037)	[−.051, .093]	.012 (.026)	[−.038, .066]	.003 (.010)	[−.015, .026]

Note. $N = 518$. Coefficients presented are unstandardized estimates. *SEs* reported are heteroscedasticity-consistent. CI = confidence internal. No. of bootstrapped samples = 5,000. Bootstrapped *SE*s are in parentheses. * $p < .05$. ** $p < .01$.

Table 8

Descriptive statistics and correlations for Study 4 – Vignette 1.

		Mean	S.D.	Min	Max	1	2	3	4	5
1	Follow	5.14	1.25	1	7	N.A.				
2	Uniqueness Neglect	3.57	1.82	1	7	− .35**	(.957)			
3	Age	42.75	10.37	21	73	.03	− .17*	N.A.		
4	Decision Role	0.46	0.50	0	1	− .26**	− .09	− .01	N.A.	
5	Decision Method (AI vs. Human)	0.51	0.50	0	1	− .26**	.09	− .02	− .01	N.A.

Note. Decision Method: 0 = control condition (human method); 1 = experimental condition (AI method). Decision Role: 0 = decision *maker*; 1 = decision *recipient*. Cronbach's alpha for each scale is presented within parentheses. * $p < .05$. ** $p < .001$

Table 9

ANOVA descriptive statistics and analyses for Study 4 Vignette 1

Descriptive statistics

Decision Method	Role	*N*
Human	Wealth manager (decision *maker* coded “0”)	52
	Client (decision *recipient* coded “1”)	45
AI	Wealth manager (decision *maker* coded “0”)	54
	Client (decision *recipient* coded “1”)	45

Note. Total *N* = 196

Summary results

	Uniqueness Neglect					Likelihood to Follow/Endorse Decision				
Source	*df*	MS	*F*	*p*	Effect size (η^2)	*df*	MS	*F*	*p*	Effect size (η^2)
Model	3	4.021	1.22	0.303	.0187	3	17.67	13.41	.000	.173
Decision Method (AI)	1	5.098	1.55	0.215	0.008	1	18.953	14.38	.000	.070
Decision Role (Role)	1	4.519	1.37	0.465	0.007	1	21.509	16.32	.000	.078
AI * Role	1	1.763	0.54	0.465	0.003	1	10.682	8.11	.005	.041

Note. *N* = 196. MS = Mean squares, Eta-squared (η^2) values for individual model terms are partial.

Table 10

Descriptive statistics and correlations for Study 4 – Vignette 2

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	8	10
1	Perceived Stress	2.72	0.94	1	5	(.914)									
2	Positive Affect	2.54	0.84	1	4.8	− .23**	(.913)								
3	Negative Affect	1.67	0.77	1	4.2	.72**	− .01	(.932)							
4	Uniqueness Neglect	4.60	1.65	1	7	.48**	.2*	.32**	(.940)						
5	Perceived Power	5.28	1.8	1	11	− .46**	.27**	.24**	.60**	(.889)					
6	Procedural Justice	3.58	1.11	1	6	− .38**	.19*	− .26**	− .62**	.68**	(.825)				
7	Power Distance	2.87	0.90	1	5.63	.03	.08	.12	− .04	.11	.16*	(.740)			
8	Age	43.46	9.79	21	68	.04	− .11	− .01	.02	− .17*	− .19*	− .03	N.A.		
9	Decision Role	0.52	0.50	0	1	.03	− .16*	.04	.08	− .10	− .10	.11	− .09	N.A.	
10	Decision Method	0.63	0.48	0	1	.12	.05	.15*	.30**	− .18*	− .20*	.05	.08	− .07	N.A.

Note. Decision Method: 0 = human method, 1 = AI method. Decision Role: 0 = decision *maker* (team leader), 1 = decision *recipient* (team member). Cronbach's alpha for each scale is presented within parentheses. * *p* < .05. ** *p* < .001

Table 11

ANOVA descriptive statistics and analyses for Study 4 Vignette 2

Descriptive statistics

Decision Method	Stakes	*N*
Human	Leader (decision *maker* coded "0")	29
	Member (decision *recipient* coded "1")	37
AI	Leader (decision *maker* coded "0)	57
	Member (decision *recipient* coded "1")	55

Note. Total *N* = 178.

Summary results for effects of AI and Stakes on Uniqueness Neglect

Source	*df*	MS	*F*	*p*	Effect size (η^2)
Model	3	.16.493	6.600	.000	.102
Decision Method (AI)	1	46.348	18.56	0.00	.096
Decision Role (Role)	1	4.820	1.93	0.167	.011
AI * Role	1	0.063	0.03	0.874	.000

Note. *N* = 178. MS = Mean squares, Eta-squared (η2) values for individual model terms are partial.

Table 12

Moderated Mediation Analysis: Effects of AI methods and decision stakes on subjective well-being through uniqueness neglect (Study 4 – Vignette 2)

	Mediator = Uniqueness Neglect		DV = Stress		DV = NA		DV = PA	
Predictors	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Constant	8.517**	.665	2.041*	.550	1.584**	.543	3.003**	.606
AI decision method (AI)	.679*	.270	− .055	.129	.104	.119	.237	.128
Age	− .018	.011	.001	.006	− .004	.006	− .009	.006
Procedural Justice	− .897**	.092	− .109	.077	− .082	.006	.068	.078
Decision Role (Role)	.099	.290	—	—	—	—	—	—
AI * Role	− .052	.379	—	—	—	—	—	—
Uniqueness Neglect	—	–	.228**	.047	.103*	.040	− .097	.052
Direct and indirect effects			*b*	95% CI	*b*	95% CI	*b*	95% CI
Direct effect of AI	—	—	− .055 (.129)	[− .309, .199]	.104 (.119)	[− .131, .340]	.237 (.128)	[-.015, .488]
Indirect effect of AI	—	—						
Conditional indirect effects	—	—						
Leader (“0”)	—	—	.155 (.070)	[.033, .309]	.070 (.040)	[.006, .162]	− .066 (.047)	[− .175, .004]
Member (“1”)	—	—	.143 (.071)	[.017, .293]	.065 (.040)	[.003, .153]	− .061 (.043)	[− .162, .005]
Index of moderated mediation	—	—	− .012 (.089)	[− .187, .167]	− .005 (.043)	[− .093, .082]	.005 (.042)	[− .077, .103]

Note. N = 178. Coefficients presented are unstandardized estimates. *SEs* reported are heteroscedasticity-consistent. CI = confidence internal. No. of bootstrapped samples = 5,000. Bootstrapped *SE*s are in parentheses. * $p < .05$. ** $p < .01$.

Table 13

Descriptive statistics and correlations for Study 5

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9
1. Perceived Stress	2.6	1.1	1	5	(.923)								
2. Negative Affect	1.49	0.68	1	4.1	.69	(.927)							
3. Positive Affect	2.84	0.92	1	5	− .43	− .33	(.922)						
4. System Satisfaction	3.76	1.37	1	7	− .58	− .37	.37	(.908)					
5. Job satisfaction	4.52	1.5	1	7	− .56	− .44	.41	.59	(.934)				
6. Perceived Power	4.73	2.06	1	11	− .47	− .26	.36	.62	.46	(.923)			
7. Uniqueness Neglect	4.71	1.74	1	7	.52	.34	− .23	− .68	− .48	− .62	(.932)		
8. Procedural Justice	3.81	1.15	1	7	− .48	− .35	.33	.77	.53	.61	− .59	(.852)	
9. Perception of AI (replace vs augment)	0.5	0.50	0	1	.23	.14*	.02**	− .29	− .22	− .25	.25	− .22	N.A.

Note. All correlations are significant at $p < 0.001$ with the exception of the correlations denoted by * ($p < .05$ and ** ($p > .05$). Cronbach's alpha for each scale is presented within parentheses. AI replaces or augments: 0 = "AI augments" condition; 1 = "AI replaces" condition.

Table 14

Mediation analysis: Effects of Perceptions of AI (“replace vs. augment”) on Uniqueness Neglect through Perceived Power (Study 5)

	Mediator = Power		D = Uniqueness Neglect	
Predictors	*b*	*SE*	*b*	*SE*
Constant	6.538**	.506	6.13**	.461
Perception of AI (replace vs. augment)	− .998**	.254	.371*	.177
Age	− .032**	.011	.017*	.008
Power	—	—	− .489**	.047
Direct and indirect effects			*b*	95% CI
Direct effect of Perception of AI	—	—	.371* (.177)	[.440, 1.277]
Indirect effect of Perception of AI (through Power)	—	—	.488 (.132)	[.241, .759]

Note. *N* = 243. Coefficients presented are unstandardized estimates. *SEs* reported are heteroscedasticity-consistent. CI = confidence internal. No. of bootstrapped samples = 5,000. Bootstrapped *SE*s are in parentheses. * *p* < .05. ** *p* < .01.

Table 15 – Supplementary analysis (Study 5)

Serial mediation analysis: Effects of Perceptions of AI ("replace vs. augment") on Subjective Well-being through (1) Perceived Power (stage 1 mediator), and (2) Uniqueness Neglect (stage 2 mediator)

	Mediator 1 = Power		Mediator 2 = Uniqueness Neglect		DV = Stress		DV = NA		DV = PA	
Predictors	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Constant	6.538**	.506	6.13**	.461	2.302**	.384	1.239**	.271	1.518**	.409
Perception of AI (replace vs. augment)	− .998**	.254	.371*	.177	.172	.124	.065	.087	.156	.111
Age	− .032**	.011	.017*	.008	− .008	.006	− .005	.004	.014**	.005
Power	—	—	− .489**	.047	− .124**	.035	− .026	.027	.167**	.039
Uniqueness Neglect	—	—	—	—	.236**	.041	.117**	.031	− .027	.046
Direct and indirect effects					*b*	95% CI	*b*	95% CI	*b*	95% CI
Direct effect of Perception of AI	—	—	—	—	.172 (.124)	[− .072, .415]	.065 (.087)	[− .106, .236]	.156 (.111)	[− .063, .375]
Indirect effect of Perception of AI	—	—	—	—	.115 (.037)	[.051, .197]	.057 (.022)	[.021, .108]	− .013 (.024)	[− .065, .030]
Indirect effect of Perception of AI[η]	—	—	—	—	.030 (.015)	[.004, .062]	.013 (.008)	[.001, .031]	.002 (.008)	[− .014, .019]

Note. *N* = 243. Coefficients presented are unstandardized estimates. *SEs* reported are heteroscedasticity-consistent. CI = confidence internal. No. of bootstrapped samples = 5,000. Bootstrapped *SE*s are in parentheses. * *p* < .05. ** *p* < .01. [η]Regression results controlling procedural justice as well as age, as comparison.

FIGURES

FIGURE 1

Model of indirect relationship between AI decision methods and subjective well-being mediated by uniqueness neglect (Hypotheses 1-3)

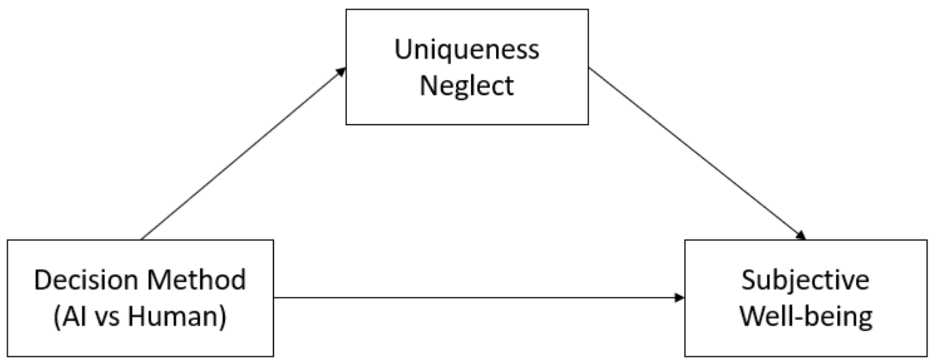
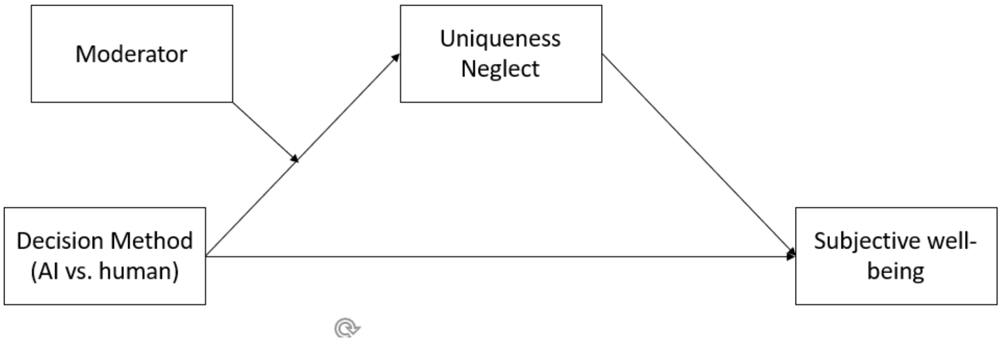


FIGURE 2

Model illustrating proposed moderators for indirect relationship between AI decision methods and subjective well-being (Hypotheses 4-6)



Moderators

1) Individual differences (need for uniqueness, personal sense of uniqueness) – *Hypothesis 4*
2) Decision outcome valence – *Hypotheses 5a, 5b*
3) Decision role – *Hypothesis 6a, 6b, 6c*

FIGURE 3

Model of indirect relationship between leaders' perception of AI decision method ("replace vs. augment") and uniqueness neglect mediated by perceived power (Hypotheses 7a, 7b, 7c).

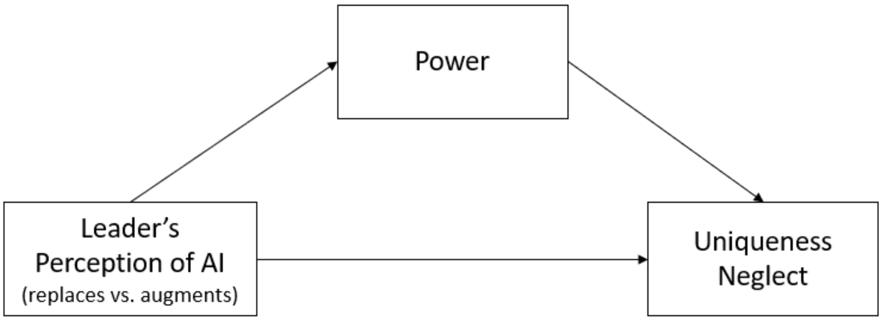
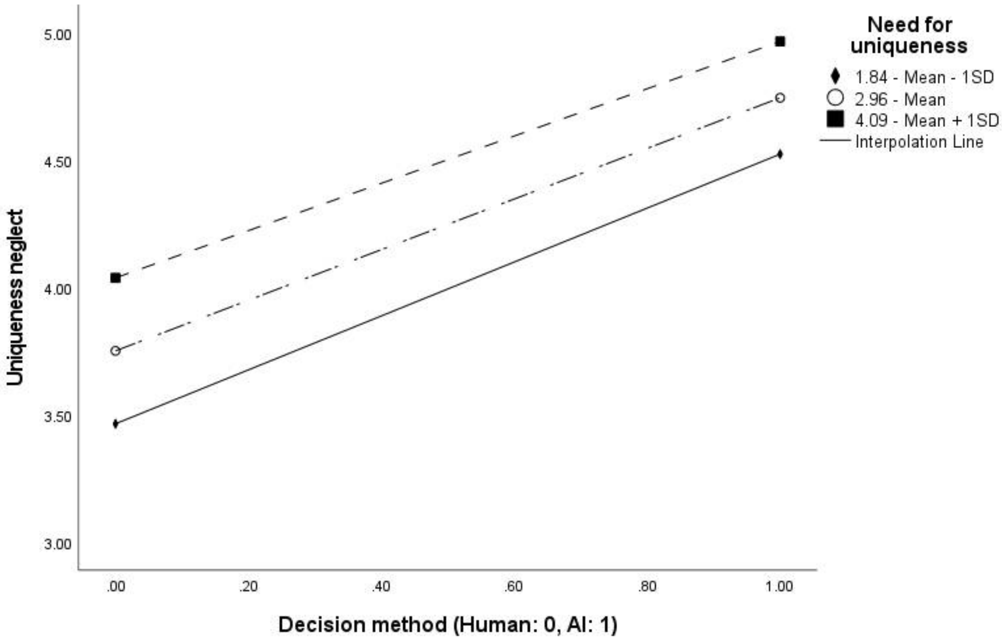
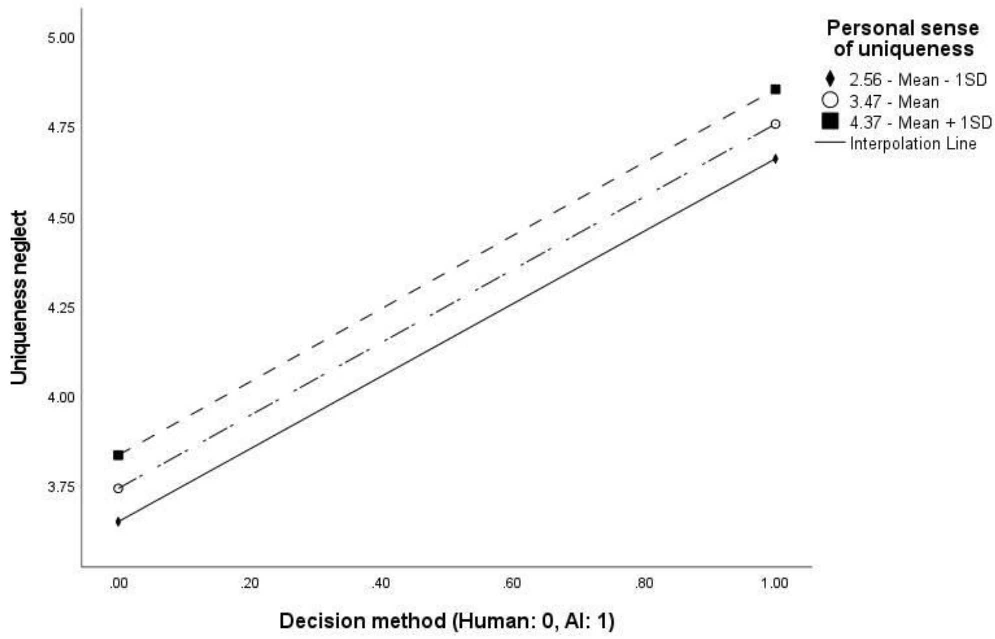


FIGURE 4



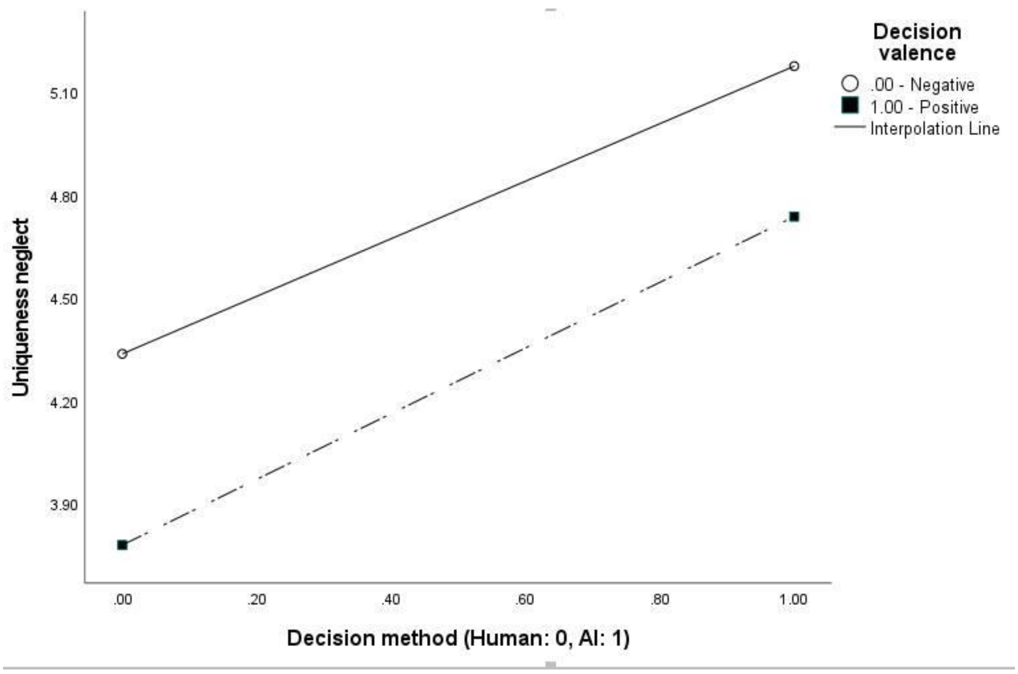
Probing interactive effects of individual differences and AI decision methods on uniqueness neglect, at different levels of participants' self-reported Need for Uniqueness (Mean +/− 1 *SD*) (*Study 2*).

FIGURE 5



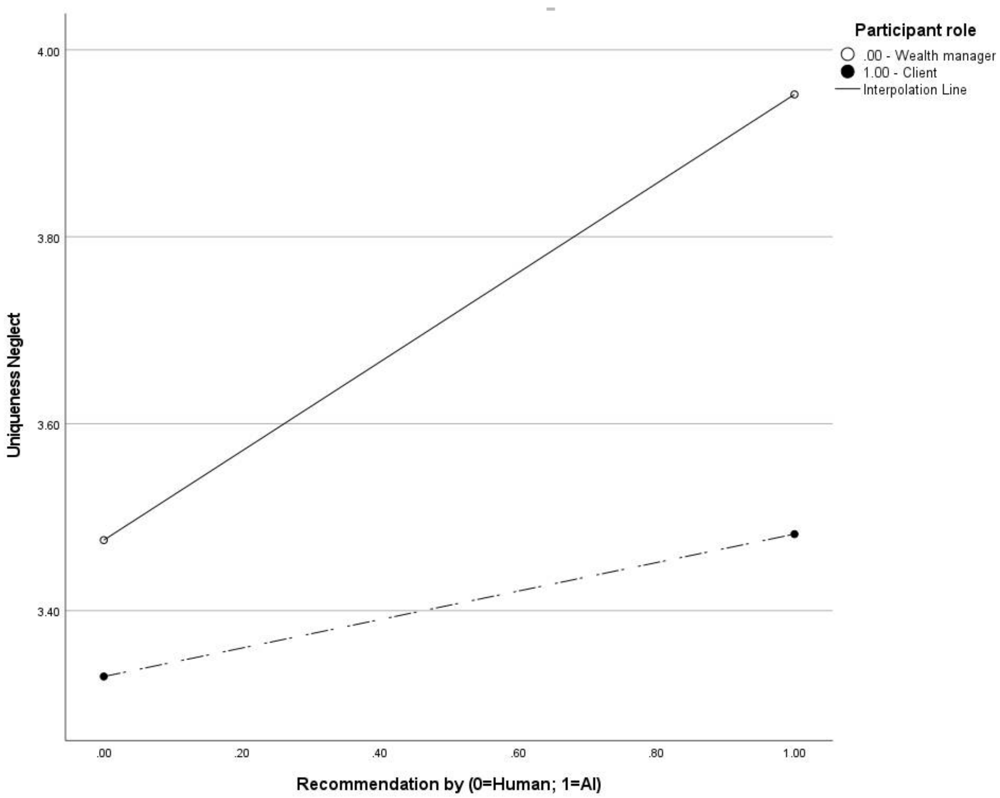
Probing interactive effects of individual differences, and AI decision methods on uniqueness neglect, at different levels of participants' self-reported Personal Sense of Uniqueness (PSU) (Mean +/− 1 *SD*) (*Study 2*).

FIGURE 6



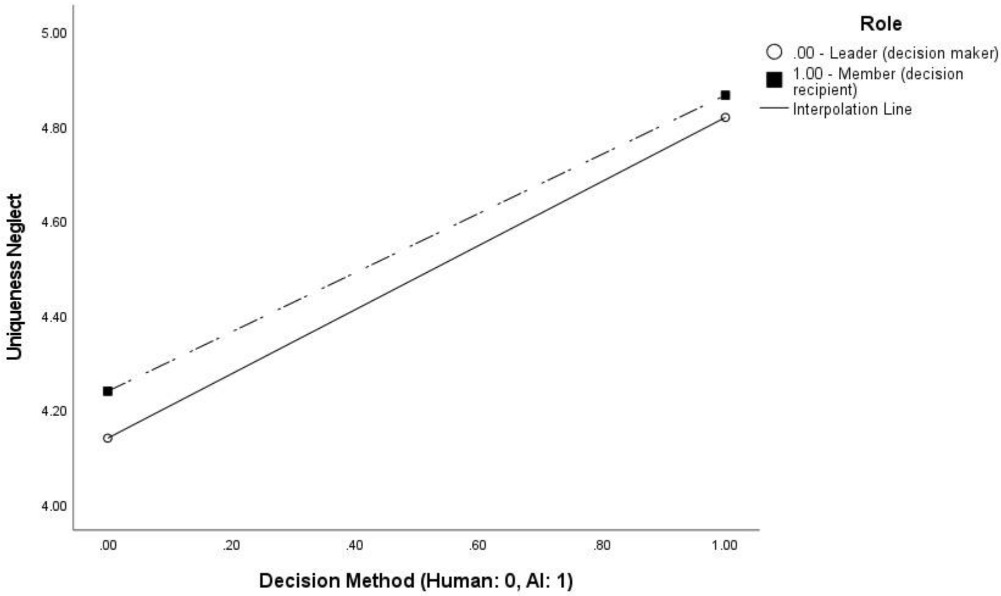
Probing interactive effects of decision valence and AI decision methods on uniqueness neglect (*Study 3*).

FIGURE 7



Probing interactive effects of decision role and AI decision methods on uniqueness neglect (*Study 4 – Vignette 1*).

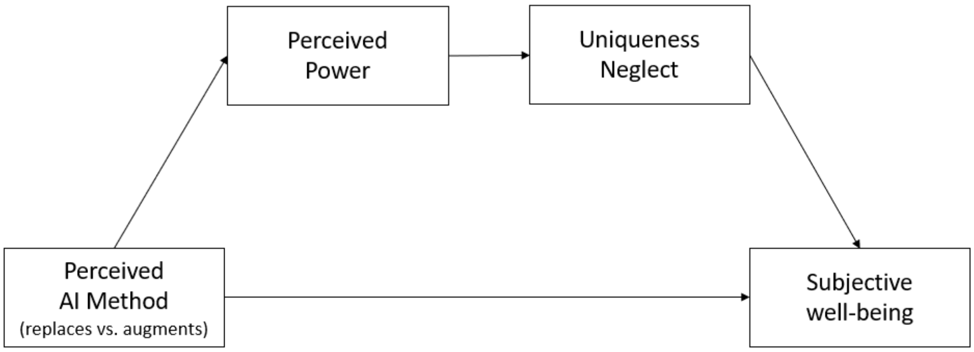
FIGURE 8



Probing interactive effects of decision role and AI decision methods on uniqueness neglect (*Study 4 – Vignette 2*).

FIGURE 9

Model of indirect relationship between perception of AI decision method and subjective well-being with serial mediation (Study 5)



APPENDICES

Appendix A Study 1 Vignette

Imagine that you work at a company called **Smart Data, Inc..**

The following passages describe Smart Data, your role at the company, and how your performance on the job would be evaluated or appraised.

After going through the materials, you will be asked to share your thoughts and feelings about your job and Smart Data's performance appraisal system. So please read through everything carefully before you respond to the survey questions.

Do make sure that you fully understand Smart Data, your role and how performance is appraised at the company.

Smart Data, Inc, is a multinational corporation that provides global business and financial data to companies.

You have been working as a **business development executive** for two years at Smart Data.

Together with your team, you manage several large corporate customers that subscribe to Smart Data's products and services.

Your role as a business development executive requires you to:

- **<u>Identify</u> new business opportunities** among existing and potential customers
- **<u>Promote</u> latest products and services** to existing and potential customers
- Work with your team-mates to **<u>address</u> customer concerns and feedback** and to provide after-sales support where needed
- **<u>Build</u> long-term relationships** with all customers

Using 200 to 1,500 characters (about 50–300 words), please imagine **what you would do and how you would feel** on a typical day at Smart Data, while working as a business development executive.

You could describe what you'd be working on, who you'd be meeting and working with, what you might enjoy or excel at, or what goals or challenges you might have.

Smart Data conducts a **performance appraisal** for all employees every year.

At the end of this year, you receive an email from Smart Data's human resources (HR) team.

Dear Employee,

Thank you for your hard work over the past 12 months!

We'd like to share with you that our company will be introducing a new performance appraisal system this year.

Specifically, you will be appraised on:

1. **Revenue retained** in existing customer accounts
2. **New business** won from existing and new customers
3. **Customer satisfaction levels** with your service as well as your team's overall service (based on surveys, feedback and complaints)
4. How well you **support and collaborate** with your team-mates
5. How well you have performed in **personal targets and goals** set and agreed with your manager at the start of the year

We'll be drawing the above data from a combination of objective measures, observations of your behavior, and feedback from relevant stakeholders.

The data will be assessed by our new **Artificial Intelligence (A.I.) performance appraisal software**.

This A.I. software will evaluate your performance and compare it against the performance of your peers in the company.

Based on the assessment, the A.I. software will then decide how much **bonus and salary adjustment** you'll be receiving, and whether you'd be getting a **promotion**.

Please feel free to contact us if you have questions or concerns about any of the processes in this new system.

We'd love to hear from you as well, and we'll be asking you soon for your feedback and suggestions on how to improve the system.

Best wishes,
Your Smart Data HR team

Appendix B Study 3 Vignette

Same as Study 1 Vignette, with the addition of one more section for the manipulation of decision valence.

Below is the manipulation for AI x Negative Decision

**

A month after this email, you receive another letter from HR informing you that the A.I. software has completed your performance evaluation.

You were given an overall rating of "**Needs improvement"**.

Based on this rating, your performance did not merit a salary increment. The letter from HR confirms that your pay will remain the same until the next appraisal period.

Appendix C More Descriptive Statistics for Study 4

Geographical distribution of participants' nationalities

No.	Nationality	Freq.	Percent	Cum.
1	Australia	5	2.34	2.34
2	Bahrain	1	0.47	2.8
3	Bangladesh	2	0.93	3.74
4	Canada	9	4.21	7.94
5	China	10	4.67	12.62
6	England	1	0.47	13.08
7	France	4	1.87	14.95
8	Germany	2	0.93	15.89
9	Hong Kong	7	3.27	19.16
10	India	15	7.01	26.17
11	Indonesia	4	1.87	28.04
12	Italy	3	1.4	29.44
13	Japan	3	1.4	30.84
14	Lebanon	1	0.47	31.31
15	Malaysia	25	11.68	42.99
16	Mauritius	2	0.93	43.93
17	New Zealand	4	1.87	45.79
18	Pakistan	3	1.4	47.2
19	Philippines	2	0.93	48.13
20	Saudi Arabia	1	0.47	48.6
21	Singapore	83	38.79	87.38
22	South Korea	1	0.47	87.85
23	Switzerland	4	1.87	89.72
24	Taiwan	3	1.4	91.12
25	United Kingdom	8	3.74	94.86
26	United States	9	4.21	99.07
27	Vanuatu	1	0.47	99.53
28	Yemen	1	0.47	100
	Total	214	100	

** Two participants declined to provide nationality details*

Study 4: Geographical distribution of participants' current country/territory of residence

No.	Country or territory of residence	Freq.	Percent	Cum.
1	Australia	7	3.27	3.27
2	Bahrain	1	0.47	3.74
3	Bangladesh	2	0.93	4.67
4	Canada	5	2.34	7.01
5	China	3	1.4	8.41
6	Germany	3	1.4	9.81
7	Hong Kong	20	9.35	19.16
8	India	10	4.67	23.83
9	Indonesia	6	2.8	26.64
10	Italy	2	0.93	27.57
11	Japan	2	0.93	28.5
12	Kuwait	1	0.47	28.97
13	Malaysia	18	8.41	37.38
14	Mauritius	2	0.93	38.32
15	Pakistan	2	0.93	39.25
16	Philippines	1	0.47	39.72
17	Saudi Arabia	2	0.93	40.65
18	Singapore	104	48.6	89.25
19	South Korea	1	0.47	89.72
20	Switzerland	2	0.93	90.65
21	United Arab Emirates	4	1.87	92.52
22	United Kingdom	4	1.87	94.39
23	United States	11	5.14	99.53
24	Vatican City	1	0.47	100
	Total	214	100	

** Two participants declined to provide nationality details*

Study 4: Distribution of Participants' Occupations

No.	Occupation	Freq.	Percent	Cum.
1	Accountant or Auditor	3	1.4	1.4
2	Chief Executive Officer (CEO)	16	7.48	8.88
3	Chief Financial Officer (CFO)	7	3.27	12.15
4	Chief Investment Officer (CIO)	11	5.14	17.29
5	Chief Operating Officer (COO)	3	1.4	18.69
6	Compliance Analyst/Officer	8	3.74	22.43
7	Consultant	19	8.88	31.31
8	Corporate Financial Analyst	10	4.67	35.98
9	Credit Analyst	2	0.93	36.92
10	Economist	7	3.27	40.19
11	Financial Advisor/Planner Wealth Manager	9	4.21	44.39
12	Financial Examiner	1	0.47	44.86
13	Information Technology	2	0.93	45.79
14	Investment Strategist	6	2.8	48.6
15	Manager of Managers	13	6.07	54.67
16	Portfolio Manager	19	8.88	63.55
17	Professor/Academic	4	1.87	65.42
18	Regulator	4	1.87	67.29
19	Relationship Manager/Account Manager	5	2.34	69.63
20	Research/Investment/Quantitative Analyst	15	7.01	76.64
21	Risk Analyst/Manager	9	4.21	80.84
22	Sales Agent (Securities, Commodities, Financial Services)	3	1.4	82.24
23	Trader	2	0.93	83.18
24	Other (please specify)	36	16.82	100
	Total	214	100	

Appendix D Study 4 Vignettes

<u>Vignette 1 (Wealth Manager x AI Decision)</u>

The following is a scenario exercise modelled on developments in the **investment industry**.

Please read through it carefully as we will be asking you questions later based on the scenario.

Take a few moments to immerse yourself as deeply as you can in the scenario before responding to the questions.

FairWell Advisors ("FairWell") is an international firm that manages investments for private clients.

FairWell follows an established system in handling new clients.

The process begins with a FairWell team – led by a wealth manager – gathering and discussing information from the client to understand the client's investment needs, constraints, and objectives.

The FairWell team then works with the client to develop an investment policy statement (IPS).

The IPS is a planning document that sets out the client's investment objectives, constraints and parameters, as well as the client's risk tolerance and risk capacity, over a relevant time horizon. It also identifies the asset classes that comprise the client's investment portfolio.

Traditionally, **wealth managers and their teams** analyse the data from clients to construct recommended investment portfolios. They...

- are guided by their judgement and experience with many other clients;
- determine how much to allocate to each asset class, and
- optimize the expected return for an expected level of risk.

Recently, FairWell's management acquired a ***new Artificial Intelligence (AI) investment tool.*** The AI investment tool...

- is trained on data drawn from a large number and variety of previous and existing client portfolios;
- performs similar analyses as wealth managers to construct recommended investment portolios.

Portfolio allocations developed by the AI investment tool have ***consistently matched*** the success rates of allocations created by human wealth managers and their teams in meeting performance benchmarks.

Imagine that you are now working as a **wealth manager** at FairWell Advisors.

You and your team have just received a new client mandate. The new client prefers investing in Asian and US equities.

According to FairWell's risk tolerance assessment, the new client is comfortable with a portfolio standard deviation of return of about 10%.

FairWell's management asks you and your team to start using the recently acquired **AI investment tool** to perform analyses and portfolio construction.

The **AI investment tool** analyses your new client's data and constructs the following recommendation:

Portfolio Allocation	
	Recommended Allocation (%)
Short-term debt investments	10
Intermediate-term bonds	25
Asian equities	30
US equities	22
Global real estate securities	8
Commodities	5
	100
Expected return	6.75
Standard deviation	10.00

What is the extent to which you think your new client should follow this recommended portfolio allocation?

Study 4 Vignette 2 – Team Member x Human Decision

The following is a scenario exercise modelled on developments in **employee performance management practices**.

Please read through it carefully as we will be asking you questions later based on the scenario.

Take a few moments to immerse yourself as deeply as you can and really imagine what it is like to be in the scenario before responding to the questions.

Zenith Asset Management ("Zenith") is an independent fund manager that invests in a wide range of asset classes.

Imagine that you have now joined Zenith as an employee. You work in a team of five as an analyst.

At Zenith, you and your team members **report directly** to a team leader.

About six months after you joined the firm, you receive an email from Zenith's human resources (HR) team.

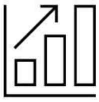
**

Dear Employee,

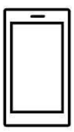
We'd like to share an exciting development with you!

Our company will be introducing a new **performance management and evaluation system**.

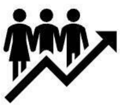
Here's a preview of the new system's key features:



- Quick, regular self-reviews and surveys with team members
- Data collected from other stakeholders, e.g. clients



- Easily accessed via mobile app and online platforms
- User-friendly HR dashboard



- Real-time, 360-deg all-round feedback
- Regular check-ins between team leaders and members
    - ✓ Review performance
    - ✓ Discuss training and skills building as and when needed

Each employee's performance data includes frequent feedback from team members, team leaders, clients, and other relevant stakeholders.

The data will be gathered to the HR dashboard**.**

Your team leader will regularly analyze the data to evaluate your individual performance and make recommendations.

At the end of the year, **your team leader** will make a final appraisal based on evaluations made throughout the year. This involves comparing your performance with the performance of your peers in Zenith.

Your team leader will then recommend how much bonus and salary adjustment you should receive, and whether you should be promoted.

Please feel free to contact us if you have questions, suggestions or concerns about any of the processes in this new system. We'd love to hear from you.

Best wishes,
Your Zenith HR team

Appendix E Study 5 Vignette

Instructions:
The following is a scenario exercise modelled on developments in **employee performance management practices**.

Please read through it carefully as we will be asking you questions later based on the scenario.

Take a few moments to immerse yourself as deeply as you can and really imagine what it is like to be in the scenario before responding to the questions.

Zenith Asset Management ("Zenith") is an investment management firm. Imagine that you have now joined Zenith as an employee.

You work as a **portfolio manager** at Zenith.

You are responsible for creating and implementing investment strategies for Zenith's clients. You help clients decide what and when to buy and sell investments in assets such as stocks, bonds, commodities, etc.

At Zenith, you are a **team leader**.

You oversee four analysts in the team who report directly to you. They support you in doing research, analyzing market data, as well as monitoring and measuring how well your investment strategies for clients are performing.

Your duties as a team leader are as follows:

- Manage day-to-day activities of the team, including coordinating and assigning tasks
- Help set goals for team members and motivate them to achieve their goals
- Provide feedback to team members on their work and how they can improve – be a supportive coach and mentor
- Ensure team members work well together – resolve conflicts as needed
- Evaluate team members' performance and conduct annual performance reviews with them
- Build a strong team spirit and ensure success of team projects

Using 200 to 1,500 characters (about 50-250 words), please **imagine what it would be like to lead your team of four analysts** at Zenith Asset Management.

Think about **what you would do as a team leader** on a typical day at work. What would be your core or usual duties as a team leader? What would you have to take note of? What might you enjoy doing as a team leader? What might be your major concerns or challenges as a team leader?

You could also describe what might happen with team members and what would you do.

Continue to imagine being a team leader employed at Zenith.

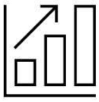
About a year after you joined the firm, you receive an email from Zenith's human resources (HR) team.

Dear Team Leader,

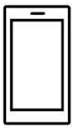
We'd like to share an exciting development with you!

Our company will be introducing a new **performance management system**.

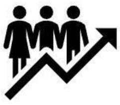
Here's a preview of the new system's key features:



- Quick, regular self-reviews and surveys with team members
- Data collected from other stakeholders, e.g. clients



- Easily accessed via mobile app and online platforms
- User-friendly HR dashboard



- Real-time, 360-deg all-round feedback
- Regular check-ins between team leaders and members
    - ✓ Review performance
    - ✓ Discuss training and skills building as and when needed

[Note: Following section displayed to participants assigned to "Replace" condition]

Each employee's performance data includes *frequent feedback* from team members, team leaders, clients, and other relevant stakeholders.

The data will be gathered to the HR dashboard**.**

An **Artificial Intelligence (AI) evaluation tool** will *continuously* analyze the data. It is an extremely powerful tool that processes vast quantities of data from a variety of sources to provide real-time analysis of performance.

With this tool, we no longer need you to evaluate your team members' performance. The AI tool replaces you in providing a much more data-driven performance evaluation, in a way that's much more efficient and effective.

Similarly, the AI tool will take over your duty of recommending how much bonus and salary adjustment your team members should receive, and whether they should be promoted.

You will continue to be responsible for other tasks in team leadership, such as coordinating and managing the team, helping team members to set goals and motivating them to achieve or exceed these goals, resolving any conflicts, and building a strong team spirit overall.

Please feel free to contact us if you have questions, suggestions or concerns about any of the processes in this new system. We'd love to hear from you.

Best wishes,
Your Zenith HR team

**
[Note: Following section displayed to participants assigned to "Augment" condition]

Each employee's performance data includes *frequent feedback* from team members, team leaders, clients, and other relevant stakeholders.

The data will be gathered to the HR dashboard**.**

An **Artificial Intelligence (AI) evaluation tool** will *continuously* analyze the data. It is an extremely powerful tool that processes vast quantities of data from a variety of sources to provide real-time analysis of performance.

With this tool, you will no longer need to evaluate your team members' performance. The AI tool enhances your role as a team leader by providing a highly data-driven performance evaluation, allowing you to be more efficient and effective.

Similarly, the AI tool will free up your resources by recommending how much bonus and salary adjustment your team members should receive, and whether they should be promoted.

You can now focus your energy on other important tasks of team leadership, such as coordinating and managing the team, helping team members to set goals and motivating them to achieve or exceed these goals, resolving any conflicts, and building a strong team spirit overall.

Please feel free to contact us if you have questions, suggestions or concerns about any of the processes in this new system. We'd love to hear from you.

Best wishes,
Your Zenith HR team