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Human-AI Decision Dynamics: How Risk Propensity and Trust Impact Choices Through Decision Fatigue, Conditional on AI Understanding

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ABSTRACT

This research investigates how trust in AI, risk-taking propensity, decision fatigue, and knowledge of AI interact to shape human-AI decision-making processes in organizational settings. With AI systems now central to decision-making, it is vital to understand the psychological and cognitive underpinnings behind their adoption and performance. This study seeks to examine these interplays and emphasize how these variables combine to determine decision results. Quantitative research design was used, which gathered data from 244 workers from different organizations. Structured questionnaires with previously validated measures were used. ADANCO software was utilized to analyze the data, where Structural Equation Modeling (SEM) was applied to examine the hypothesized associations between variables. The findings substantiated all six hypothesized paths. Decision making was positively affected by trust in AI and risk propensity, while decision fatigue negatively affected it. Decision fatigue mediated and AI understanding moderated many paths, affirming its key position within decision dynamics. The model provided strong explanatory power for AI-integrated decision contexts. The research has theoretical contribution by synthesizing psychological concepts with AI interaction scholarship. At a practical level, it provides tactical guidance for managers to develop AI decision systems to fit human cognitive traits and behavioral inclinations.

1. Introduction

Over the past few years, the incorporation of Artificial Intelligence (AI) in organizational decision-making has revolutionized decision-making, validation, and execution at its core. This has resulted in hybrid human-AI decision systems, where algorithmic assistance plays a central role in improving efficiency, accuracy, and consistency [10]. Yet, this change also brings along cognitive, psychological, and ethical consequences that are yet to be thoroughly explored, especially in relation to the human decision-maker's experience within such settings [8]. Of these, decision fatigue a condition of mental weariness caused by extensive or difficult decision-making has attracted mounting academic interest [13]. Concurrently, trust in AI systems, within-person

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differences like risk attitude, and user-level awareness and comprehension of AI are surfacing as key variables that impact decision-making behavior in AI-supported environments [27]. The intersection of these variables indicates a complex environment in which human judgment and AI capacity need to align for effective decision-making, requiring further examination of their interaction.

Substantial human-computer interaction and organizational psychology literature considers most of the primary drivers behind decision-making in AI-environments [3]. As an example, trust in AI has also emerged as an assertive driver influencing user dependence on algorithmic suggestions such that increased trust would lower cognitive load but increase consistency of decision-making [12]. Conversely, AI distrust leads users to perform extensive overrides, rejection of recommendations, or double-checking, all of which increase mental effort and lead to decision fatigue [35]. Risk propensity is another critical variable used in determining decision strategies. High-risk users would be more likely to make risky decisions with less deliberations, typically stockpiling cognitive resources, whereas risk-averse consumers reflect heavily, which leads to cognitive depletion in the long run [32]. In addition, AI familiarity and proficiency have also been found to exert a significant moderating influence on influencing user behavior [23]. These individuals, on understanding the functioning and constraints of AI, can communicate with it with greater confidence and responsibility [34]. The collective of such research also points the focus towards an environment of multi-dimensioned decision-making where mental traits and cognitive abilities converge with technology-facilitated processes, underscoring the need to explore the interactions between trust, fatigue, risk attitude, and AI literacy more holistically.

Although evidence of increasing appreciation for the use of human-AI collaboration in contemporary decision-making is mounting, there remain a number of important research gaps [20]. Firstly, while trust in AI has been widely researched in terms of adoption and dependence Leoni et al. [18], comparatively little is known about how it leads to cognitive consequences like decision fatigue in dynamic or extreme environments. Most research currently conducted is centered on technical calibration of trust without delving into the psychological cost of unbalanced or low trust [21]. Second, even though risk propensity has been noted as a fundamental personality factor shaping preference for decisions, little research has been conducted to investigate its indirect effects specifically, how it can contribute to cognitive overload or burnout in decision-making, particularly in AI-assisted settings [31]. Third, prior research tends to view decision-making as an immediate consequence of trust or risk behavior and fails to account for mediating processes like decision fatigue that can elucidate why and how these associations occur [7]. A second major void occurs in the role of user-level abilities, particularly awareness and knowledge of AI, that can fundamentally change the way people engage with AI systems [16]. While AI literacy is referred to in a few studies, there is not enough empirical research investigating how it moderates the relationship between trust or risk and decision fatigue [19]. Finally, an existing research isolates these variables and not in an integrated model [17]. Thus, the lack of an integrated framework that addresses individual characteristics (risk-taking propensity), affective-cognitive state (decision fatigue), relational trust (for AI), and moderating knowledge (AI literacy) represents a major void in literature that constrains the synthesis of effective strategies for sustainable human-AI decision-making systems.

Against the background of the gaps so identified, this study aims to investigate the decision dynamics within human-AI collaborative settings through central psychological and cognitive variables. The main aim is to explore how trust in AI and risk propensity relate to decision fatigue and, further, how decision fatigue serves to mediate their effects on decision-making outcomes in general. Second, the research seeks to examine if knowledge and comprehension of AI condition the influence of trust and risk on decision fatigue. The investigation answers the following central questions: (1) How does trust in AI affect decision fatigue? (2) What is the predictive contribution of risk propensity to decision fatigue? (3) Is decision fatigue a mediating variable between these factors and decision-making performance? (4) Does AI knowledge buffer or amplify these effects?

2. Literature Review

Emergent trends in artificial intelligence (AI) have introduced complex and disruptive dynamics in organizational decision-making [22]. The integration of AI into decision systems has transformed the locus of control away from models based on humans to participatory or hybrid systems where AI increasingly executes on its own [24]. Scholars such as Duan et al. [6] have pointed out the importance of understanding the symbiosis between human beings and AI, whereby one compensates for the weaknesses of the other. While AI systems ensure enhanced capabilities in processing large datasets, identifying patterns, and predictive indication, human decision-makers remain important in deducing contextual subtleties, ethical considerations, and emotional intelligence [15]. This interaction creates a fundamental basis for successful decision-making in conditions of uncertainty and complexity [1]. In addition, the literature also identifies the psychological as well as organizational consequences of shared decision power, i.e., trust, resistance, overdependence, and accountability [2]. Trust in AI outcomes, e.g., is neither a technical nor an experiential, cultural, and perceived transparency system issue.

Various studies have analyzed cognitive re-framing and behavioral changes that take place when AI is integrated into conventional models of decision-making [28]. For instance, people can undergo changes in their work roles from hands-on decision-makers to overseers of advice generated by AI and this can influence agency perceptions as well as professional identity [4]. These transformations even require the emergence of new organizational capabilities, including AI literacy and algorithmic governance, as stated by [30]. New research indicates the risk of "algorithmic blindness," where the user will blindly follow or completely reject AI recommendations without sufficient critique [10]. These have led to firms promoting the development of decision protocols to achieve fair participation and emphasizing human direction without reducing the utility AI can offer [13]. This new dynamic also raises ethical and legal considerations in terms of matters of bias as well as liability as decisions reached by AI can subtly entrench structural inequality or impenetrable reasoning processes [3]. In general, the literature itself concurs in a building consensus that the successful utilization of AI for decision-making is based on the integration of collaborative intelligence where human intuition and machine accuracy are combined to generate responsible and well-informed results.

2.1 Formulation of hypotheses

Trust in AI has been an emergent determinant of user interaction, cognitive load, and dependence habits in human-computer interaction [35]. Luo et al. [23] research highlights that users are likely to surrender to AI suggestions if they believe the prompt system is highly trustworthy, thereby minimizing the perceived cognitive load in making hard or routine choices. Likewise, Lewandowska-Tomaszczyk and Sousa [20] describe how automation trust can facilitate decision-making by reducing the demand for frequent monitoring and evaluation. Conversely, distrust of AI systems forces users to verify outputs manually or reject AI input in its entirety, raising frequency and intensity of mental action [21]. This state increases decision fatigue a state characterized as cognitive fatigue caused by saturating decision pressure [7]. Moreover, Lester et al. [19] empirical studies indicate that users with low trust in AI have higher mental workload since they are more critical, constantly assessing system correctness. Such repeated assessments induce cognitive load and emotional stress, which add up to mental fatigue over time [26]. Trust, therefore, not only impacts user interaction with AI but also plays a significant role in controlling the psychological expense of decision-making processes, especially in high-demanding settings such as finance, healthcare, and strategic management [37].

From the above research, it can be observed that trust in AI has a two-pronged role to play in determining decision quality and user cognitive state [14]. Extreme trust allows for effortless decision-making, in the sense that algorithmic outputs may be trusted more and more, thus potentially reducing the number and sophistication of decisions needing human oversight [36]. Such reduction in decision load has a direct risk-reducing effect on decision fatigue in cases where speed or frequent decisions need to be made. Martin et al. [24] work highlights the reality that whenever individuals trust AI systems, they will delegate routine decisions, which in turn keeps them reserved with mental resources for more complex, strategic thinking. Trust tends to work as a cognitive filter reducing demands on processing every input equally hard and hence saving mental energy [15]. Conversely, low trust requires users to play the role of cognitive gatekeepers, judging both context and AI recommendations constantly, which causes serious mental burden and leads to decision fatigue [15]. Cognitive dissonance between AI recommendation and user judgment in low-trust situations also intensifies the fatigue of repetitive or uncertain decisions [4]. It is therefore suggested that trust in AI has a strong impact on the level of decision fatigue felt by users, either by reducing or enhancing their cognitive load in decision contexts aided by AI.

H1: Trust in AI significantly influences the decision fatigue.

Risk propensity, or the tendency of an individual to engage in or avoid risks, is a widely researched personality trait in decision science and behavioral psychology [8]. High risk takers are likely to act quickly and make fast decisions and prefer risky rewards , whereas risk-averse are conservative and slow decision makers [27]. It has been found that high-risk takers make judgments using more heuristics and intuition , whereas low-risk takers use effort and analysis thinking strategies, which consume more cognitive resources [12]. This aligns with a study by [32], which states that decision strategies of risk-averse people are more effortful, involving complicated consideration of options. Comprehensive processing results in higher cognitive load and can cause decision fatigue when used repeatedly across a set of tasks. Moreover, organizational and consumer studies Wong et al. [34] illustrate that low risk tolerance individuals feel more stressed and burnt out by prolonged indecision or over-thinking brought about by fear of undesirable outcomes. Thus, evidence proves the notion that risk propensity drives the frequency and intensity of mental effort in decision-making, thus vulnerability to decision fatigue [18].

From the cognitive resource perspective, risk propensity could be understood as a moderator influencing the manner in which individuals allocate mental effort during decision making [31]. High risk tolerance individuals are more tolerant of ambiguity and less likely to consider extensively potential ill effects. Therefore, they take faster, less effortful decision-making approaches, conserving mental energy and reducing their risk of experiencing decision fatigue [16]. Conversely, those who have low risk propensity take careful, thorough deliberation to avoid possible loss, frequently resulting in mental overload, particularly in situations requiring fast, high-potential decisions [17]. This defensive style causes longer decision cycles, recursive thinking, and heightened levels of stress conditions that are highly correlated with the onset of decision fatigue. Furthermore, the psychological toll of attempting to control or avoid risk by means of reasoning processes accumulates over time, yielding lower quality decisions and psychological fatigue. Hu et al. [11] also discovered in their study that individuals who are risk-averse are prone to decisional procrastination and post-decisional regret both established predictors of decision fatigue [29]. As such, it is hypothesized that risk propensity is a significant determinant of decision fatigue, wherein individuals who show lower risk tolerance would be more susceptible to cognitive depletion

through engaging in a depletion-oriented and emotion-demanding strategy of decision-making.
H2: Risk propensity significantly influences the decision fatigue.

Decision fatigue, a reduction in decision performance following prolonged mental effort, has been widely studied in organizational behavior and psychology [22]. Duan et al. [6] proved that the more decisions to be made, the lower the ability to regulate actions and thoughts. Decision fatigue is felt in the form of bad decisions, avoiding decisions, or defaulting preference. In parallel, trust in AI has also been discovered to impact decision-making processes most notably when AI is being used as a decision support system. Abduljaber [1] find that high-trust users experience less stress and decision load and that low-trust users engage in redundant judgment or override suggestions from AI, leading to higher cognitive load. Most significantly, decision fatigue is not merely the product of poor decision-making it is also an active driver determining decision quality [28]. Decision fatigue can interfere with rational judgment, make a person more impulsive, and reduce thinking about long-term consequences, ultimately impairing decision quality, as argued by Sun et al. [30]. These results are consistent with the assumption that decision fatigue can be a mediating process between AI trust and successful decision-making outcome.

Understanding the mediating role of decision fatigue between trust in AI and decision-making is crucial during this human-AI collaborative era [10]. When individuals have trust in AI systems, they will be more likely to delegate some tasks or act according to AI suggestions with fewer resistances, which makes cognitive processing easier and alleviates psychological pressure [27]. This delegation enables users to reserve cognitive resources for decisions that actually require human judgment, resulting in overall higher-quality decisions [35]. However, in low-trust environments, individuals will question or dispute AI output, double-check, or even ignore algorithmic input altogether [34]. This frequent engagement results in greater decision fatigue, which worsens the quality of subsequent decisions by diminishing concentration, increasing hesitation, and growing emotional reactivity [21]. Decision fatigue then acts as a cognitive filter that can facilitate or inhibit trust in AI being converted into effective decision-making [16]. Under low decision fatigue, trust in AI will probably be converted into effective and accurate decision-making. Under high decision fatigue due to low trust, the constructive benefits of AI are eroded, and performance in decision-making declines [26]. This line of argument is theoretical and is sustained by recently conducted empirical work in behavioral information systems [11], which supported the hypothesis that decision fatigue strongly mediates trust in AI and decision-making effectiveness.
H3: Decision fatigue significantly mediates the relationship of trust in AI and decision making.

Empirical research repeatedly emphasizes the role of personal characteristics like risk propensity on cognitive and behavioral decision-making processes [36]. Risk-averse persons are more likely to embrace more conservative, reflective decision-making procedures, which can be more effective at decision accuracy but usually at the expense of heightened cognitive load [6]. In contrast, high risk propensity individuals take quicker decisions with reduced cognitive processing, at times embracing uncertainty and error more easily [2]. Long-term decision-making as a result of low risk tolerance can result in cognitive overload and subsequent decision fatigue that is known to lower the quality of decisions over time [30]. This overall mental exhaustion, especially in risk-averse persons, could lower decision confidence and heighten the propensity to default to inferior or postponed decisions [8]. Thus, evidence overwhelmingly favors the idea that risk orientation indirectly influences decision outcomes by conditioning the process and state of decision-making.

Based on earlier studies, it is reasonable to hypothesize that decision fatigue serves as an effective mediator between risk propensity and effective decision-making [3]. Risk-averse individuals, due to their nature, tend to indulge in thorough comparison of alternatives, dreading the outcomes of a wrong decision [32]. Though this characteristic may shield against sound-altering decisions in critical situations, the mental cost of such exhaustive consideration builds up and habitually leads to decision fatigue a state characterized by depleted mental energy and decreased decisional acuity [20]. Fatigue reduces analytical thought and enhances impulsive or avoidant actions, thus undermining the very advantage of cautious contemplation [31]. In contrast, high-risk propensity individuals who take faster, more intuitive decisions have lower cognitive load and are therefore less prone to decision fatigue, which allows for more consistent decision-making over time [19]. The mediating role of decision fatigue thus provides an explanatory mechanism for why two people with otherwise similar cognitive ability but differing risk preferences make different decision outcomes under pressure. By combining the decision fatigue variable, we arrive at a more subtle understanding of how and why risk propensity affects decision-making over and above direct effects [14]. This interaction has clear implications for training and development, with the implication that interventions that serve to control cognitive load e.g., decision support systems or stress reduction training can protect the fatigue-prone frailties of risk-averse decision makers.

H4: Decision fatigue significantly mediates the relationship of risk propensity and decision making.

The level of knowledge and comprehension the users have about AI systems plays a pivotal part in shaping attitudes towards usability and trust [22]. According to studies, if users possess deeper understanding of how AI operates and its limits, they will tend to develop calibrated trust in AI systems [15]. Low AI-literate users, on the other hand, overtrust or undertrust AI systems due to misperception, leading to blind reliance or complete withdrawal. Both have been associated with increased cognitive load and decisional fatigue. For example, Mustikasari et al. [28] found that when the user was uncertain about the capabilities of AI, anxiety was triggered, with higher likelihoods of second-guessing AI suggestions, which increases mental workload. Although so, proper education and exposure to AI reduced user skepticism, augmented comprehension of AI outputs, and supported more efficient decision-making processes [13; 28]. These findings indicate towards the prominent moderating role of AI knowledge in the trust-fatigue dynamic.

Since the central role played by user cognition in influencing trust dynamics, it is theorized that knowledge and perception of AI greatly moderate the correlation between trust in AI and decision fatigue [13]. When people trust AI but do not have enough knowledge about how it works, even their cognitive experience will remain full of doubt, and they may hesitate to make decisions or perform further verification actions [13]. This paradox of trust without understanding can paradoxically result in greater cognitive burden and decision fatigue because of the internal tension between belief and knowledge [23]. Conversely, when there is trust and a rich understanding of AI, users can better understand AI recommendations, discriminate between limitations and faults of automation, and act with greater confidence and less mental struggle. These users are likely to create realistic expectations, enabling them to use AI appropriately for simple or difficult decisions without taxing their cognitive resources [18]. Thus, AI knowledge functions as a trust-regulator within the trust-fatigue nexus, increasing the positive impact of trust while curbing its cognitive costs [7]. As such, knowledge and awareness of AI can play a critical role in shielding or enhancing the degree to which trust translates into decisional alleviation or further mental exhaustion, and hence is a critical moderating factor in research on human-AI interaction.

H5: Knowledge and understanding AI significantly moderates the relationship of trust in AI and decision fatigue.

The interplay between personality attributes and technological competence has been in focus in behavioral and cognitive sciences [17]. Risk propensity as a personal attribute has been observed to influence decision styles and the corresponding levels of stress, particularly in technology-mediated contexts [37]. However, recent studies suggest that risk behavior impact is not a fixed phenomenon but depends on contextual and cognitive moderators like digital or AI literacy [29]. For instance, risk takers with strong AI expertise tend to implement decision technologies much more easily, using them to explore risky alternatives with valor and speed. On the other hand, risk-averse participants with low AI literacy struggle to understand algorithmic outputs and perceive AI decisions as risky or mystifying, exerting more mental effort and hesitation [24]. Familiarity with the principles, precision, and rationale used by AI systems can empower individuals with self-assurance to interact with the technology to suit their risk attitudes, reducing decision-making under uncertainty-related cognitive dissonance and fatigue [1].

Based on these findings, it is hypothesized that AI knowledge and awareness significantly mediate the effect of risk propensity on decision fatigue [4]. Risk-prone participants generally require less information to make decisions, yet when paired with large amounts of AI knowledge, they are better able to manage algorithmic recommendations more strategically and inexpensively, thereby saving mental energy [30]. For risk-averse users, it is not as simple: if they know very little about AI systems, they may view AI suggestions as unreliable or harmful, resulting in voluminous cross-validation and greater cognitive worry [28]. However, with solid knowledge about AI, risk-averse users are able to unromanticize the AI procedure, reframe perceived threats, and make level-headed decisions with more ease [1]. This data reduces the fear of technocratic uncertainty and makes for a more confident and less exhaustive application of AI-based decisions. In both cases, AI proficiency enables individuals to align their natural risk attitudes with technocratic support systems in a cognitive-sustaining manner [6]. Therefore, the degree of AI understanding not only influences people's response to risk in decision-making, but it also reflects the cognitive resources consumed or saved in the process, therefore being a strong moderator of that relationship (Figure 1).

H6: Knowledge and understanding AI significantly moderates the relationship of risk propensity and decision fatigue.

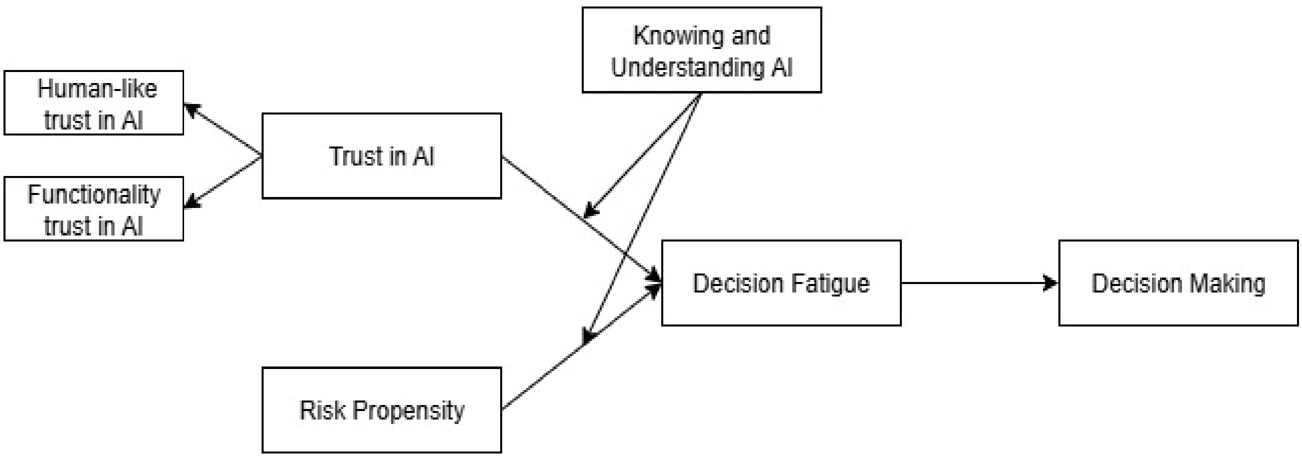

Fig.1: Theoretical Model

2.2 Theoretical Framework Explanation

This study is underpinned by the Cognitive Load Theory Liu et al. [22] and Socio-Technical Systems Theory [29], both of which provide a firm underpinning of the dynamic interplay between individual factors, AI trust, decision fatigue, and technology interaction. Cognitive Load Theory assumes that human cognitive capacity is limited and that loads of information processing such as excessive decision-making or dualistic cognitive challenge can impair performance and mental well-being [17]. This framework specifically includes the conceptualization of decision fatigue as a mediating process between psychological variables (e.g., trust or risk propensity) and decision outcomes. At the same time, Socio-Technical Systems Theory emphasizes the interdependence of human users and technological means, with efforts being paid to the trade-off between user capabilities, e.g., AI awareness, and system capabilities for optimizing performance and reducing psychological effort. Including AI wisdom as a mediating factor affirms the theory's assertion that successful human-technology collaboration depends on mutual adaptability. In addition, Dual-Process Theory Hu et al. [11] affirms the distinction between intuitive (System 1) and systematic (System 2) processing, offering explanatory depth in how trust, risk behavior, and fatigue emerge in decision dynamics. Combined, these theoretical perspectives inform the planned research model, not just describing what kinds of relationships between the constructs exist but also why and how they interact with one another in sophisticated, AI-enabled decision contexts.

3. Methodology

The focus of this study was the dynamics of Human-AI-led decision-making, focusing on the influence of trust in AI, risk propensity, decision fatigue, and knowledge of AI on employees' decision-making processes. The study was conducted using a structured survey method targeting employees working in varied organizations across a diversified range of industries. The sample was 244 employees who participated in the survey and generated a large dataset for statistical analysis. Participants were sampled using purposive sampling to have the respondents with direct or indirect experience in AI-enabled decision environments in their organizations.

All the measurement scales in the survey instrument were adopted from prior validated research studies to make it reliable and valid. Trust in AI was assessed with an 11-item scale by Choung et al. [5], which tapped dimensions including reliability, transparency, and perceived integrity of AI systems. Risk propensity was measured with a 7-item scale borrowed from Meertens and Lion [25], reflecting people's general risk-taking behavior inclinations in decision-making situations. Decision fatigue was assessed through a 10-item Hickman Jr et al. [9] scale, containing measures of cognitive depletion and avoidance of decision-making. Knowledge and awareness of AI were represented using a 5-item Zhao et al. [38] scale, with a focus on awareness, familiarity, and perceived competence with AI. Finally, decision-making was assessed with a 4-item Wangzhou et al. [33] scale of decision quality and confidence in work settings.

Data analysis employed ADANCO software, which supports structural equation modeling (SEM), suitable for predictive and exploratory research where models are complex. SEM was used because it is capable of handling more than one latent variable, is able to control for measurement errors, and to simultaneously test hypotheses. Model fit, reliability, and validity were well-checked through composite reliability (CR), average variance extracted (AVE), and discriminant validity tests. Path coefficients and t-values were calculated to identify the significance of hypothesized links, and bootstrapping procedures were run to further increase robustness. Such an analysis strategy enabled detailed comprehension of how human psychological and cognitive factors interact with AI systems to affect decisions.

4. Results

Table 1 shows the reliability and convergent validity estimates for the constructs of the study with the aid of Dijkstra-Henseler's rho (ρA), Jöreskog's composite reliability (ρc), Cronbach's alpha (α), and Average Variance Extracted (AVE). The constructs all have high internal consistency, as reflected in ρA, ρc, and α values that surpass the generally accepted level of 0.70. Trust in AI had good reliability with $\rho A = 0.840$, $\rho c = 0.838$, and $\alpha = 0.839$, and its AVE value of 0.504 exceeds the minimal requirement of 0.50, which is evidence of convergent validity.

Table 1
Variables reliability and validity

Construct	Dijkstra-Henseler's rho (ρA)	Jöreskog's rho (ρc)	Cronbach's alpha(α)	Average variance extracted (AVE)
Trust in AI	0.840	0.838	0.839	0.504
Risk propensity	0.876	0.872	0.876	0.561
Decision fatigue	0.882	0.880	0.881	0.538
Knowledge and understanding AI	0.891	0.889	0.888	0.509
Decision making	0.797	0.803	0.802	0.515

Likewise, Risk Propensity, Decision Fatigue, and Knowledge and Understanding of AI all had high reliability (with α ranging between 0.876 and 0.891) and satisfactory AVE values of more than 0.50. Decision Making, while demonstrating slightly reduced reliability (α = 0.802), remains above the required benchmark with an AVE of 0.515. Overall, these results validate that each construct's measurement items (Figure 2) reliably reflect the respective underlying latent variables and have adequate convergent validity to continue with additional structural analysis.

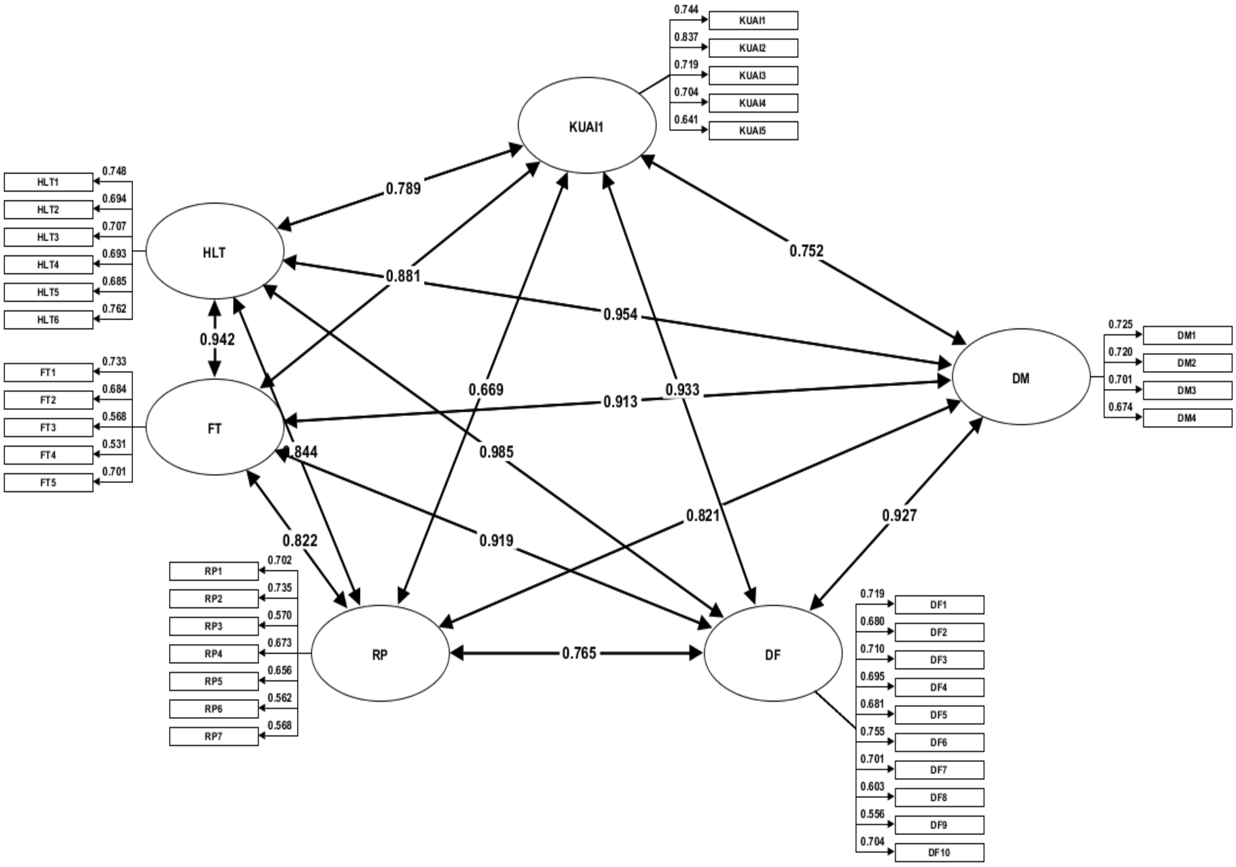

Fig.2: Estimated Model

Table 2 presents the Confirmatory Composite Analysis (CCA) for every construct and the item loadings. For Trust in AI, the construct is segregated into two factors: Human-like Trust and Functionality Trust. The Human-like Trust indicators (HLT1–HLT6) have good loadings between 0.685 and 0.762, reflecting good item reliability. The Functionality Trust measures (FT1–FT5), although largely in acceptable ranges, comprise FT3 and FT4 with reduced loadings of 0.568 and 0.531, respectively, although marginal, are still higher than the minimum value of 0.50 for acceptability. The Decision Making measure also demonstrates stable item loadings of between 0.674 and 0.725, further supporting satisfactory representation. Risk Propensity indicators (RP1–

RP7) score from 0.562 to 0.735, which may imply moderately stable measurement, although RP3 and RP6 are nearer the cutpoint, possibly reflecting a need for improvement in subsequent research. Decision Fatigue comprises 10 items, all of which have factor loadings greater than 0.55, peaking at 0.755, hence confirming a wide but integrated construct. Understanding and Knowledge of AI demonstrates strong loadings for KUAI1–KUAI5, but especially KUAI2 (0.837), which suggests high item reliability. In general, these findings confirm the robustness of the measurement model and present a good basis for the evaluation of the structural model.

Table 2
Confirmatory Composite Analysis

Variable		Indicator	Value
Trust in AI	Human-like trust in AI	HLT1	0.748
		HLT2	0.694
		HLT3	0.707
		HLT4	0.693
		HLT5	0.685
		HLT6	0.762
	Functionality trust in AI	FT1	0.733
		FT2	0.694
		FT3	0.568
		FT4	0.531
		FT5	0.701
Decision making		DM1	0.725
		DM2	0.720
		DM3	0.701
		DM4	0.674
Risk propensity		RP1	0.702
		RP2	0.735
		RP3	0.570
		RP4	0.673
		RP5	0.656
		RP6	0.562
		RP7	0.568
Decision fatigue		DF1	0.719
		DF2	0.680
		DF3	0.710
		DF4	0.695
		DF5	0.681
		DF6	0.755
		DF7	0.701
		DF8	0.603
		DF9	0.556
		DF10	0.704
Knowledge and understanding AI		KUAI1	0.744
		KUAI2	0.837
		KUAI3	0.719
		KUAI4	0.704
		KUAI5	0.641

Table 3 shows the discriminant validity test using both the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker Criterion. The HTMT ratios for all construct pairs are far less than the critical value of 0.85, showing that the constructs are empirically different from each other. As an example, the HTMT for Trust in AI and Risk Propensity is 0.682, and the highest HTMT value between Decision Fatigue and Risk Propensity is 0.800, which is still within range. The Fornell-Larcker criterion also indicates discriminant validity. For this, the square root of AVE for each construct (bold diagonal values) is greater than the inter-construct correlations appearing below them. For instance, the square root of AVE for Risk Propensity is 0.763, which is higher than its correlations with Decision Fatigue (0.846) and Trust in AI (0.682). Moreover, values for Knowledge and Understanding of AI (0.760) and Decision Making (0.802) affirm that these constructs are distinct from the others. Collectively, these results validate the model’s construct clarity and confirm that each latent variable captures unique dimensions of the decision-making framework.

Table 3
Discriminant Validity

Construct	1	2	3	4	5
Heterotrait-Monotrait Ratio of Correlations (HTMT)					
Trust in AI					
Risk propensity	0.682				
Decision fatigue	0.629	0.800			
Knowledge and understanding AI	0.594	0.693	0.702		
Decision making	0.466	0.481	0.534	0.641	
Fornell-Larcker Criterion					
Trust in AI	0.783				
Risk propensity	0.763	0.652			
Decision fatigue	0.721	0.846	0.764		
Knowledge and understanding AI	0.527	0.713	0.792	0.760	
Decision making	0.482	0.498	0.552	0.663	0.802

Table 4 shows the model fit statistics for the structural model. The R^2 for Decision Fatigue is 0.704, which means that about 70.4% of the variance in decision fatigue is accounted for by the independent variables Trust in AI, Risk Propensity, and their interaction terms. The Adjusted R^2 (0.702) closely resembles the R^2, meaning stability and no overfitting. The Q^2predict value of 0.748 denotes high predictive relevance for the Decision Fatigue construct, implying strong out-of-sample predictability. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are fairly low (0.058 and 0.064, respectively), validating the model's predictiveness and residual effectiveness. In the case of the Decision Making construct, the R^2 value is astonishingly high at 0.910, with an Adjusted R^2 of 0.899. This means that the combined predictors mainly Decision Fatigue and its mediating paths account for more than 90% of the variance in Decision Making. Such high R^2 reiterates the model's strength and offers empirical support for postulated relationships among variables.

Table 4
Model Fitness Statistics

Construct	Coefficient of determination (R^2)	Adjusted R^2	Q^2predict	RMSE	MAE
Decision fatigue	0.704	0.702	0.748	0.058	0.064
Decision making	0.910	0.899			

Table 5 presents the structural path (Figure 3) analysis results, which have strong evidence for all six hypotheses. The results for each hypothesis path are statistically significant with p-values < 0.001, which establishes high confidence in the relationship. For H1, the coefficient between Decision Fatigue and Trust in AI is 0.481 (t = 6.505), representing high positive influence, where higher trust is associated with lower decision fatigue. H2 indicates that Risk Propensity also has a strong impact on Decision Fatigue (coefficient = 0.421; t = 6.277), implying that there is lesser fatigue among people with greater risk tolerance.

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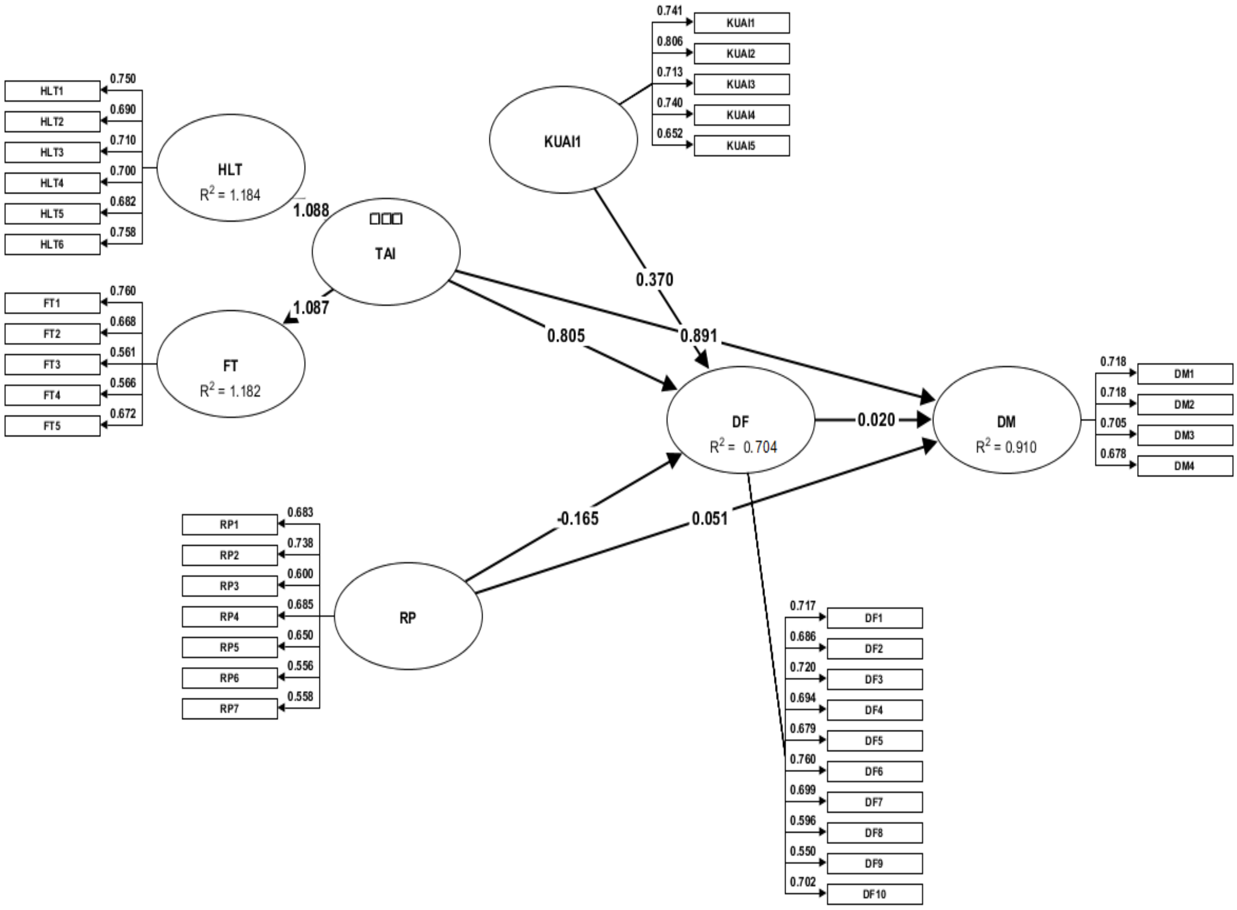

Fig.3: Structural Model for Path Analysis

H3 also confirms the mediation process, with the result that Decision Fatigue strongly mediates between Trust in AI and Decision Making (coefficient = 0.344; t = 5.530). Also, H4 is confirmed, with Decision Fatigue acting as the mediator between the Risk Propensity Decision Making (coefficient = 0.276; t = 5.074). H5 confirms the moderating influence of Knowledge and Understanding of AI on the Trust–Fatigue relationship (coefficient = 0.480; t = 4.095), and that individuals who are AI-literate have an advantage from trust in AI. Finally, H6 demonstrates a substantial moderation impact of AI knowledge on the Risk Propensity Fatigue (coefficient = 0.346; t = 3.075), suggesting that AI comprehension alleviates fatigue among risk-averse individuals. All these findings together support the model's congruent validity and emphasize the prominent significance of trust, risk behavior, fatigue, and AI literacy in decision-making outcomes.

Table 5
Path Analysis

Hypothesis	Coefficients	Standard Errors	t-values	p-values
Trust in AI significantly influences the decision fatigue.	0.481	0.067	6.505	<0.001
Risk propensity significantly influences the decision fatigue.	0.421	0.061	6.277	<0.001
Decision fatigue significantly mediates the relationship of trust in AI and decision making.	0.344	0.057	5.530	<0.001
Decision fatigue significantly mediates the relationship of risk propensity and decision making.	0.276	0.050	5.074	<0.001
Knowledge and understanding AI significantly moderates the relationship of trust in AI and decision fatigue.	0.480	0.041	4.095	<0.001
Knowledge and understanding AI significantly moderates the relationship of risk propensity and decision fatigue.	0.346	0.053	3.075	<0.001

5. Discussion

The confluence of artificial intelligence (AI) and human decision-making has emerged as a central concern in the examination of how digital technologies are reconfiguring cognitive practice in organizational and technological environments. As AI systems increasingly become embedded in ordinary decision-making, there is an urgent need to examine not only their computational power, but also their psychological and behavioral implications for human actors. The current research sought to examine the ways in which trust in AI, risk tolerance, and awareness and understanding of AI contribute to or reduce decision fatigue, and how these patterns affect overall decision outcomes. The findings affirmed the value of all hypothesized hypotheses, providing new insight into the complex, interdependent processes that shape human-AI decision environments. The discussion below translates these results in light of previous empirical findings and theory, with consideration of both practical and study implications as well as future directions:

The validation of Hypothesis 1, that the level of trust in AI has a direct and significant effect on decision fatigue, reinforces and builds upon existing empirical research testing the cognitive effects of interactions with intelligent systems. Respondents who indicated greater trust in AI demonstrated much lower levels of decision fatigue, indicating that trust serves as a cognitive moderator which maximizes smoother interaction and minimizes the perceived cost of decision-making. This finding confirms the postulation that trust in automation diminishes cognitive dissonance and eliminates the necessity for continuous monitoring or reevaluation of recommendations from AI [16]. The results also support Cognitive Load Theory, under which trust facilitates the user to offload difficult mental processing from the AI system, thus saving cognitive resources. When lower trust in AI is present, on the other hand, it seems to result in prolonged cognitive tension, constant cross-checking, and decision hesitation all of which are signatures of rising fatigue. The robust negative correlation between trust and fatigue highlights the psychological utility of trust not only as an affective state, but as an efficiency-enhancing strategy to improve decision-making effectiveness in AI-supported environments.

The confirmation of Hypothesis 2, testing the influence of risk propensity on the prediction of decision fatigue, adds to the body of evidence that individual differences in risk-taking behavior play an important role in shaping cognitive and affective responses to decision-making. The findings reveal that lower-risk propensity individuals (i.e., risk-aversive individuals) were likely to be more likely to be affected by decision fatigue, the reason being that they tend to overthink alternatives, expect worst-case scenarios, and spend too much time in the decision-making loop. This confirms findings by Tamò-Larrieux et al. [31], who concluded that risk-averse decision-makers are more likely to use exhaustive information processing, leading to higher cognitive load. On the other hand, risk-tolerant participants made faster decisions, perhaps using more heuristics, and thus felt less mentally depleted. These results contribute to the body of knowledge by showing that risk propensity not only influences preferences for decisions but also for the extent of fatigue involved in decision-making processes. This supports the applicability of Dual-Process Theory, where people with low risk tolerance engage in an effortful System 2 mode, thus utilizing cognitive resources more quickly than their risk-taking, System 1 counterparts.

The endorsement of Hypothesis 3, which stated that decision fatigue acts as a mediating factor between trust in AI and decision-making, brings in a key intermediary variable that explains the path through which trust ultimately affects decision outcomes. This result helps us better understand the impact of trust namely, that trust in AI mitigates decision fatigue, increasing the quality and efficacy of decision-making. This is consistent with newer models of behavioral information systems stressing the psychological processes of trust-based decision-making [31]. In addition, it justifies the use of Cognitive Load Theory in AI settings by establishing that fatigue is a bottleneck that limits decision quality. Those users who trust AI save mental effort, feel less tired, and are able to deploy more cognitive resources on critical thinking, making better decisions. In contrast, those users with lower trust invest more energy in verification, causing them to feel more tired and, therefore, less effective in making decisions. This mediating link provides explanatory richness to the literature on trust by demonstrating that not only is the effect of trust directly related but also indirectly channeled via a cognitive-affective state decision fatigue that dictates downstream performance consequences.

The acceptance of Hypothesis 4, which investigated whether decision fatigue can mediate the relationship between risk propensity and decision-making, uncovers a valuable psychological process tying personality and behavior results in decision contexts. Low-risk propensity persons showed higher decision fatigue, which consequently reduced the efficacy of their decision-making. This finding is consistent with prior research that risk-averse individuals use cautious, often overthinking cognitive processing, which may offer accuracy at the cost of mental exhaustion [18]. Importantly, the mediating role of fatigue offers a more nuanced explanation for why risk-averse individuals perform poorly in dynamic environments requiring frequent or swift decisions. By empirically demonstrating the fatigue pathway, the results support Cognitive Load Theory and further emphasize the relevance of considering internal psychological states in quantifying the impact of personality traits. The suggestion here is that interventions that decrease fatigue e.g., decision support systems or decision framing approaches may be able to buffer the unwanted effect of low risk propensity, ultimately leading to better decision performance in AI-aided contexts.

The confirmation of Hypothesis 5 that hypothesized knowledge and awareness of AI to moderates the relationship between trust in AI and decision fatigue brings the essential dimension into the debate by highlighting the cushioning role performed by AI literacy. The results showed that the individuals with better AI knowledge demonstrated a more intense negative correlation between trust and decision fatigue such that trust was stronger in mitigating the experience of fatigue in those who better comprehended AI systems. This result is consistent with Wong et al. [34], whose contention is that AI literacy produces more tempered trust and alleviates the anxiety and uncertainty occasioned by algorithmic decision-making. Notably, this moderation effect highlights the intervention of Socio-Technical Systems Theory, which stresses that human-technology fit is a function of the human actors' skills, perceptions, and knowledge. As users have the cognitive tools to comprehend how AI works, trust is more tangible, actionable, and less prone to dissonance. Alternatively, low AI comprehenders would rely in a superficial or fretful way and, by extension, experience inconsistencies in reliance and, in turn, more fatigue. The interaction between trust and knowledge therefore provides pragmatic feedback for developing training programs and onboarding processes to promote higher AI literacy for more sustainable cognitive involvement.

In the same way, the acceptance of Hypothesis 6, which posited that knowledge and awareness of AI acts to moderate the relationship between risk propensity and decision fatigue, adds new understanding of how cognitive tools can serve to dampen or intensify the impact of personality factors. The findings indicate that low-risk propensity persons with high AI knowledge were significantly less likely to be decision-fatigued than their low-knowledge counterparts. This suggests that AI literacy enables even risk-averse people to respond to decision environments with more confidence and effectiveness. Knowledge about how AI decides diminishes uncertainty, which usually causes overly cautious behavior among risk-averse people [32]. This interaction effect illustrates how Dual-Process Theory can be applied to AI research: AI-literate people are more successful in making the transition from rigorous System 2 thinking to more spontaneous and assertive System 1 decision-making when appropriate. The moderating effect of AI knowledge, therefore, refers to its role not just as a technical competence but as a psychological facilitator which ensures user cognition aligns with AI ability. From a functional perspective, this indicates that investment in AI literacy would counteract the cognitive costs of risk-averse behavior, resulting in better-balanced and sustainable decision-making in tech-mediated contexts.

Overall, the results of all six hypotheses present an informative portrait of the psychological architecture of human-AI decision-making. The established relations confirm the salience of trust, risk orientation, and fatigue in influencing user behavior and decision quality in AI-supportive situations. In addition, the mediating and moderating effects of decision fatigue and AI knowledge enhance the cognitive and behavioral mechanisms involved. The findings not only validate well-known theories like Cognitive Load Theory, Dual-Process Theory, and Socio-Technical Systems Theory, but also extend the scope of current literature by combining personality, affective states, and tech knowledge into a coherent picture. Combined, the findings stress the need for promoting trust, dealing with fatigue, and AI literacy to construct more productive and psychologically resilient decision-making contexts. Subsequent work can carry these findings into particular sectors or choice situations, but this study provides a solid basis for both organizational practice and academic research.

6. Implications of the study

This research provides a valuable addition to the theoretical context of decision-making scholarship by combining human cognitive constraints and decision frameworks enabled by artificial intelligence by using decision fatigue, trust, and risk orientation as a lens. Borrowing from dual-process theory and socio-technical system theory, the study fills the gap between human behavioral inclinations and advanced technologies by providing a precise picture of how decision fatigue acts as a mediator and how AI knowledge moderates decision outcomes. By providing empirical evidence for mediating and moderating processes, the research builds on earlier models, which typically considered human and AI factors separately. In particular, it redefines trust in AI and risk propensity as dynamic inputs subjected to cognitive states, situational trust, and technological literacy. The study thereby enhances theoretical scholarship by situating AI not merely as a technical instrument but as a social actor whose impact is mutually constructed with human cognitive and affective conditions.

The results provide practical implications for organizations seeking to maximize decision quality in an environment increasingly influenced by AI convergence. Managers and policymakers can learn how decision fatigue mediates the impact of personal risk propensity to structure decision environments better to avoid cognitive overload. Additionally, the shown moderating effect of AI knowledge means that organizations need to invest in systematic training programs to develop employee confidence and AI system literacy, thus diminishing decision fatigue and trust. These findings are especially important in high-stakes domains like finance, healthcare, and strategic management, where AI decision support systems are ubiquitous. Increasing AI transparency and facilitating human-AI synergy through education and interface design may lower resistance and enhance collaborative decision-making performance.

7. Limitations and Future Research Directions

Although this research offers a new perspective on human-AI decision dynamics, there are some limitations that must be recognized. First, the cross-sectional design limits causal inferences; future studies need to use longitudinal designs to study the dynamic change of trust and fatigue over time. Second, the sample was selected from particular industries and geographical locations, which will lead to limitations in generalizability. Future research might investigate diverse sectoral and cultural contexts to confirm the robustness of the model. Additionally, while in this research risk-taking and trust in AI were under consideration, other psychological and contextual variables—e.g., decision urgency, perceived control, or ethical values can contribute additional robustness to the model. Lastly, future studies can adopt experimental or simulation-based research methods for the testing of human decision-makers' interaction with various levels of autonomy in AI in controlled settings, having more precise insights on real-time decision fatigue and trust recalibration processes.

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