

The Role of AI Literacy and Generative AI Reliance in Decision Making Tasks: Case Studies Using Business Simulation Games

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Abstract

This study examines how AI literacy, trust, and decision-making style shape reliance on Generative AI in high-stakes business decisions. Fifty-two participants completed an inventory management task in the MonsoonSIM business simulation, supported by a Generative AI advisor powered by Google Gemini. We measured AI literacy, trust, decision-making style, and performance expectancy via survey, and reliance, decision quality, and business outcomes from participant responses and game data. AI literacy and performance expectancy significantly predicted reliance and trust, respectively. Avoidant decision-makers showed the strongest tendency to rely on AI, while rational decision-makers remained cautious. Reliance alone did not improve decision quality or business outcomes, but experience in data analysis buffered the negative effect of over-reliance on decision quality. These findings highlight the importance of AI literacy, trust calibration, and analytical competence, rather than reliance itself, in shaping effective human-AI decision-making.

Keywords: Generative AI, AI Literacy, Decision-Making Style, Trust, Reliance, Business Simulation

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1. Introduction

Generative Artificial Intelligence (AI) has emerged as a fundamental component of modern information systems (Deldjoo et al., 2024), facilitating a diverse array of tasks such as data analysis, educational support, travel planning, advisory services, text translation, and email composition. The accessibility and versatility of Generative AI have contributed to its widespread adoption across multiple fields, as it provides users with real-time assistance on a 24/7 basis. Its ease of use has made it a popular tool among individuals from various backgrounds. However, an increasing number of users tend to place unwarranted trust in the accuracy and reliability of AI-generated outputs, often failing to engage in independent verification. This tendency has led to concerns regarding overreliance on AI-generated information at the expense of critical thinking and self-reliance. A particularly concerning phenomenon associated with Generative AI is the occurrence of AI hallucinations, wherein the system produces false or misleading information. One of the most notable instances of this issue was observed in the 2023 U.S. legal case *Mata v. Avianca*. In this case, attorneys submitted a legal brief to a New York court that contained fabricated legal precedents and case citations, all of which were generated by ChatGPT (Jabotinsky & Sarel, 2023; Weiser, 2023). Klingbeil et al. (2024) found that advice from AI can lead to overreliance, causing individuals to follow it despite conflicting context or personal judgment, often resulting in inefficiencies and unintended negative effects. These two cases emphasize the profound risks associated with reliance on AI-generated content and raise significant questions regarding the interplay between human decision-making processes and dependence on AI-driven recommendations.

In the context of decision-making, Generative AI significantly enhances business operations across various sectors. For example, in the medical field, recent research demonstrates that Generative AI models like ChatGPT can support clinical decision-making processes. Rao et al. (2023) found that ChatGPT excels in clinical decision-making, especially in providing accurate final diagnoses with more data. However, limitations such as potential model hallucinations and unclear training data composition remain. In tourism, Rivas and Zhao (2023) argue that using ChatGPT tools accelerates content creation, enriches research, deepens customer insights, automates customer service, and boosts overall marketing efficiency. Nonetheless, companies must carefully consider the potential risks and benefits before integrating ChatGPT into their marketing strategies.

Understanding what AI can and cannot do helps individuals make better-informed judgments about when to use it and how much to trust its output (Long & Magerko, 2020). AI literacy refers to a set of competencies that enable a person to understand AI systems, use them effectively, apply them to specific tasks, critically evaluate their outputs, and create simple AI-based solutions, together with an awareness of the ethical issues that AI raises. Drawing on data science, computational thinking, and multidisciplinary knowledge, AI literacy cultivates an "AI-centric" way of thinking: a habit of reasoning about problems in terms of what data, models, and machine reasoning can contribute (Ng et al., 2021). Yet capability alone does not determine adoption. Even when AI systems demonstrate clear technical competence, some individuals remain reluctant to incorporate them into their decisions. Prior research has consistently identified trust as a central factor explaining this gap between an AI system's objective capability and a user's willingness to rely on it (Glikson & Woolley, 2020; Lee & See, 2004). Without sufficient trust, users either ignore AI recommendations or treat them with excessive caution, regardless of how accurate the underlying system may be.

While trust has been studied extensively in the context of traditional decision support systems and automation (Lee & See, 2004; Parasuraman & Riley, 1997), three gaps remain in the literature on Generative AI specifically. First, most studies of AI adoption examine intention to use rather than actual reliance behavior during a decision task; the two are known to diverge, yet behavioral evidence in Generative AI settings remains limited (Bansal et al., 2021). Second, the role of AI literacy — as distinct from general technology acceptance — has been theorized (Long & Magerko, 2020; Ng et al., 2021) but rarely tested as a predictor of how users actually integrate AI recommendations into consequential decisions. Third, individual differences in decision-making style have been largely overlooked in the human–AI interaction literature, even though decision style is one of the strongest predictors of information-seeking and advice-taking behavior in non-AI contexts (Scott & Bruce, 1995). Whether and how decision style shapes Generative AI reliance — and whether high AI literacy can compensate for unfavorable decision styles — remains an open question.

The present study addresses these gaps by examining how AI literacy, trust, and decision-making style jointly influence reliance on Generative AI during a complex, time-sensitive business decision task. Using a business simulation game (MonsoonSIM) with an embedded Generative AI advisor, this research moves beyond intention-based measures to capture actual reliance behavior, and tests whether this reliance translates into improved decision quality and business outcomes. By integrating AI literacy, trust, and decision-making style within a single behavioral model, the study contributes a more complete account of when — and for whom — Generative AI assistance enhances or undermines high-stakes decision-making.

2. Theoretical Background

Reliance on Generative AI in consequential decision-making sits at the intersection of three established research streams: human–AI collaboration (Dellermann et al., 2019; Vaccaro et al., 2024), automation bias (Parasuraman & Manzey, 2010), and explainable AI (Adadi & Berrada, 2018). Each stream offers partial insight into the conditions under which AI input helps or hinders decision quality, but they are rarely integrated, and behavioral evidence specific to Generative AI in dynamic business settings remains scarce. This section develops the theoretical background for the present study by drawing on these streams alongside the foundational literatures on decision-making styles, AI literacy, performance expectancy, and trust, building the basis for the six hypotheses that follow.

2.1 Decision Making Style and Reliance Generative AI

Decision-making is essential in both personal and professional realms. The emergence of Generative AI has significantly transformed the decision-making landscape (Schemmer et al., 2023). As a subset of artificial intelligence, Generative AI produces new content, including text, recommendations, explanations, and analyses, by drawing on patterns learned from vast underlying data. For decision-makers, this introduces a different kind of input: rather than receiving a discrete prediction or score, they are presented with fluent, plausible-sounding output whose reliability and usefulness must be assessed without the familiar cues of source, confidence, or provenance. This shift places a new evaluative burden on the user, transforming the act of consulting an AI system from a verification task into an interpretive one. How individuals respond to this interpretive burden is not uniform. Decades of decision research show that people differ systematically in how they approach decisions: in the amount of information they seek, the weight they give to analysis versus intuition, and their willingness to defer to external input. These stable patterns of behavior are captured in the literature on decision-making styles.

Decision-making styles, regarded as learned habits of how individuals make decisions, are believed to be characterized by two main aspects: information use and focus (Driver et al., 1998). Initially, three styles were identified: rational, intuitive, and dependent (Harren, 1979). Later, the avoidance style was introduced by Phillips et al. (1984). Finally, Scott and Bruce (1995) introduced the spontaneous decision-making style. These five styles were then integrated to create the widely recognized General Decision-Making Style (GDMS) instrument. Their empirical research contributed to the development of items for measuring decision-making styles. The rational style emphasizes a logical and systematic evaluation of alternatives. Individuals who adopt this approach carefully assess the consequences of previous decisions and rely on accurate information to guide their choices. In contrast, the avoidant style is characterized by a tendency to postpone or evade decision-making, often due to uncertainty or reluctance to take responsibility for the outcome. Similarly, the dependent style involves seeking advice and direction from others, as individuals who exhibit this approach prefer external input over independent decision-making. The intuitive style, on the other hand, is based on instincts, emotions, and hunches rather than structured analysis. Individuals who follow this style engage in minimal information-seeking, as they primarily trust their feelings when making choices. Lastly, the spontaneous style is driven by a sense of urgency and a desire to complete the decision-making process as quickly as possible, often prioritizing speed over thorough evaluation.

This foundational work serves as the primary basis for constructing this study, as it provides a comprehensive and empirically validated framework for understanding decision-making styles. Recent research has investigated how each decision-making style utilizes Business Intelligence (BI) systems. The rational decision-making style, which relies heavily on information for making decisions, is distinct in this regard. The other four decision-making styles show less motivation to seek information (Ritbumroong, 2023). So consequently, decision-making styles can be categorized into two main types: Rational and Non-Rational styles. Recently, generative AI has emerged as another form of Decision Support System (DSS). However, there is still a lack of research on how decision-making styles influence reliance on generative AI. Therefore, the Decision-Making Style Hypothesis (H1) will be divided into two sub-hypotheses.

The hypothesized relationship between decision-making style and AI reliance is grounded in the broader literature on automation bias referred as the systematic tendency of users to over-rely on automated systems, accepting their output even when contradicting evidence is available (Parasuraman & Manzey, 2010; Skitka et al., 1999). Automation bias has been documented across high-stakes domains including aviation, clinical decision-making, and financial forecasting, and is amplified under time pressure, cognitive load, and low domain expertise (Goddard et al., 2012). Recent work on Generative AI specifically has shown that fluent, articulate output increases user acceptance independently of accuracy, a phenomenon some authors describe as the hallucination as authority problem (Bender et al., 2021; Buçinca et al., 2021). Decision-making style is expected to moderate vulnerability to this bias: rational decision-makers, who deliberately evaluate alternatives, are theoretically more

resistant; non-rational decision-makers — particularly those with avoidant or dependent styles — may be especially prone to over-reliance, since AI offers a low-effort path to discharge the decision.

Hypothesis 1a: There will be a significant correlation between a Rational Style of decision-making and Reliance on Generative AI.

Hypothesis 1b: Non-rational decision-making styles will be positively associated with Reliance on Generative AI.

2.2 AI Literacy and Reliance on Generative AI

The capacity to evaluate AI output critically — central to avoiding the automation bias discussed above — depends in part on user expertise with AI systems. This insight connects to the literature on *explainable AI* (XAI), which investigates how the design of AI systems and the capacity of users to interpret AI reasoning jointly shape trust and reliance (Adadi & Berrada, 2018; Barredo Arrieta et al., 2020). A core finding from this stream is that explanations tend to increase trust regardless of whether the underlying AI is correct, which can paradoxically worsen decision quality when explanations make wrong answers more persuasive (Bansal et al., 2021; Zhang et al., 2020). However, users with higher AI literacy are better able to use explanations diagnostically, distinguishing well-reasoned outputs from confident-sounding ones (Long & Magerko, 2020). This positions AI literacy not merely as a predictor of *whether* users rely on AI, but as a determinant of *how well* they interpret what AI tells them.

AI literacy refers to the understanding and knowledge individuals possess about artificial intelligence technologies, their capabilities, and their limitations. Long and Magerko (2020) identified 17 human competencies and 15 design considerations, structuring them around five key questions to define AI literacy comprehensively. Building on this Ng et al. (2021) applied Bloom's taxonomy to categorize AI literacy into three categories. Further advancing this domain, Pinski and Benlian (2023) developed the first AI literacy instrument, which enables empirical measurement of AI literacy as a construct. This study will incorporate this AI literacy instrument as one of the key constructs in our research model, facilitating an analysis of its relationship with user Reliance on Generative AI.

As individuals become more knowledgeable about AI, they are more likely to recognize the benefits and practical applications of these technologies in their decision-making processes. Therefore, it is hypothesized that as AI literacy increases, individuals will be more inclined to rely on generative AI systems to enhance their tasks and decisions.

Hypothesis 2: AI Literacy will be positively correlated with Reliance on Generative AI.

2.3 Performance Expectancy and Trust in Generative AI

Performance Expectancy is a key construct from the Unified Theory of Acceptance and Use of Technology (UTAUT), which evolved from the Technology Acceptance Model (TAM) developed by (Davis, 1985, 1989). It is defined as “the degree to which an individual believes that using the system will help him or her to attain gains in job performance.” The UTAUT model includes four key constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. However, only Performance Expectancy is considered in this context because Effort Expectancy becomes insignificant after prolonged technology use (Chauhan & Jaiswal, 2016), and Social Influence varies widely depending on culture and environment. As noted by Venkatesh and Davis individuals might use technology due to compliance requirements rather than personal preferences (Venkatesh & Davis, 2000). Facilitating Conditions are not relevant to this study.

Performance expectancy, social influence, and effort expectancy are key components of the AI Device Use Acceptance (AIDUA) framework developed by (Gursoy et al., 2019). Chi et al. (2023) examined the role of trust and cultural influences in AI robot acceptance within the hospitality industry using the AIDUA framework. Their study found that performance expectancy has a positive relationship with Trust in Generative AI interactions. When users expect generative AI to enhance their performance, their trust in the technology is likely to increase. This trust is built on the perceived efficiency, accuracy, and reliability of generative AI in producing valuable and accurate outputs.

Hypothesis 3: Performance Expectancy will be positively correlated with Trust in Generative AI.

2.4 Trust in Generative AI and Reliance on Generative AI

Trust is defined as “the user’s judgment or expectations about how the AI system can help when the user is in a situation of uncertainty or vulnerability” (Cheng et al., 2024; Vereschak et al., 2021). In the era of artificial intelligence, trust refers to the extent to which users perceive AI-generated advice and recommendations as reliable, accurate, and credible, influencing their willingness to engage with and depend on AI-driven solutions (Shin, 2021).

Reliance, on the other hand, is described as the final behavioral outcome influenced by attitudes and beliefs that lead to an intention to act (Lee & See, 2004). It represents the user’s decision to use and follow the system’s recommendations. Reliance has been widely studied in the context of decision support systems (Alvarado-Valencia & Barrero, 2014; Bussone et al., 2015; Cao & Huang, 2022; Chen et al., 2023). Alvarado-Valencia and Barrero (2014) identified trust as a key moderator of reliance, emphasizing that trust functions as an attitude that ultimately shapes behavior. Given this perspective, the present study will examine Generative AI as a modern decision support system to explore the relationship between trust and reliance.

Extensive research has investigated trust and reliance in both automation (Hoff & Bashir, 2015; Körber et al., 2018; Lee & See, 2004) and AI (Benda et al., 2022; Cao & Huang, 2022; Klingbeil et al., 2024). These studies consistently highlight that user trust in automated and AI-driven systems directly affects their reliance on such technologies, particularly in decision-making and task execution processes.

The concept of trust in generative AI was introduced by (Knoth et al., 2024), who adapted it from the broader framework of trust in technology—a fundamental topic in human-computer interaction research (Lankton et al., 2015). Trust in generative AI is particularly relevant due to the system’s ability to generate new content, respond to user inputs dynamically, and assist in various tasks, including content creation, problem-solving, and decision support.

Previous studies have established a significant positive relationship between trust and reliance on automation (Körber et al., 2018; Lee & See, 2004) and AI (Klingbeil et al., 2024). Research on clinical decision support systems further indicates that system confidence has only a minor effect on trust and reliance. More importantly, providing a comprehensive explanation of the rationale behind a diagnosis enhances trust but may also lead to over-reliance (Bussone et al., 2015). These findings suggest that as users develop greater trust in AI systems, they are more likely to rely on them for assistance and decision-making. Consequently, as trust in generative AI increases, reliance on generative AI is also expected to rise, underscoring the importance of fostering user confidence in AI-driven systems.

Hypothesis 4: Trust in Generative AI will have a positive correlation with Reliance on Generative AI.

2.5 Reliance on Generative AI in Decision Quality and Business Outcomes

Spetzler (2016) defines Decision Quality (DQ) as a framework for evaluating decisions before action. A high-quality decision meets six key criteria: appropriate frame, creative alternatives, reliable information, clear values, sound reasoning, and commitment to action. Since the weakest element determines overall quality, deliberate effort is required to improve decision outcomes. In decision-making processes, tools such as Decision Support Systems (DSS) can enhance understanding and reduce logical errors, particularly in high-information environments (Williams et al., 2007). However, DSS may also introduce unintended mechanical errors, which in some cases, outweigh their benefits and result in lower decision quality. This highlights the importance of not only leveraging technology but also ensuring its proper use to enhance rather than hinder decision-making.

Generative AI, a central focus of this research, offers the potential to improve decision quality by providing data-driven insights, reducing cognitive biases, and fostering creative solutions. When individuals rely on AI with knowledge and understanding, their decisions are more likely to be informed, accurate, and innovative. As Eigner and Händler (2024) emphasize, trust in AI, user mental models, and information processing characteristics significantly influence AI-assisted decision-making.

The relationship between reliance and decision outcomes is the central concern of the human–AI collaboration literature, which studies how humans and AI systems jointly perform tasks that neither could perform as well alone. Early work framed this relationship as one of complementarity — humans contribute contextual judgment and ethical reasoning, while AI contributes scale and pattern recognition (Dellermann et al., 2019). More recent empirical work has shown that complementarity is not automatic: it depends on appropriate reliance — relying on AI when it is correct and overriding it when it is wrong (Bansal et al., 2021; Schemmer et al., 2023). A meta-analysis of human–AI team performance found that such teams often underperform either the human or the AI alone, primarily because users either over-rely on incorrect AI output or under-rely on correct AI output (Vaccaro et al., 2024). This literature thus predicts a non-trivial relationship between reliance and

outcome quality: reliance may be positively, negatively, or non-significantly associated with decision quality and business outcomes, depending on whether users calibrate their reliance to AI accuracy.

Hypothesis 5: Reliance on Generative AI will be correlated with Decision Quality.

The impact of reliance on generative AI extends beyond individual decision quality to broader business outcomes. Effective use of generative AI can lead to improved efficiency, cost savings, and competitive advantages. Therefore, it is hypothesized that reliance on generative AI will positively correlate with favorable business outcomes as Brynjolfsson and McAfee (2014) argued that digital technologies are driving the reinvention of both our lives and the economy. They suggested that as digital technologies continue to evolve, they will accomplish many tasks once considered uniquely human, transforming industries and forcing companies to either adapt or risk obsolescence. In this study, the focus will be on cash on hand due to game mechanics.

Hypothesis 6: Reliance on Generative AI will be correlated with Business Outcomes.

The theoretical discussion has led to hypothetical relationships as illustrated in the proposed research model in Figure 1. The section will discuss research methods employed to empirically test the model.

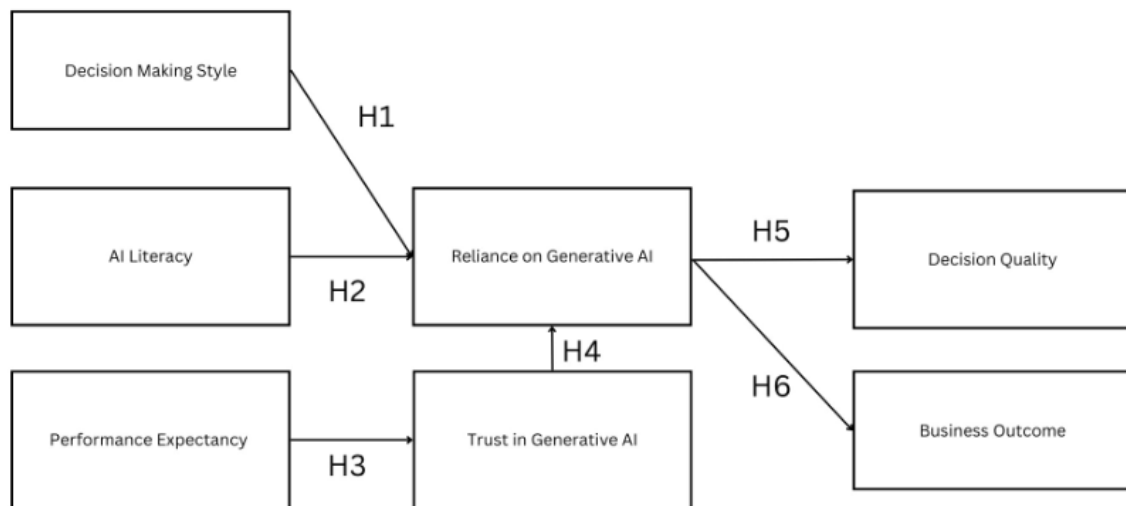


Figure 1 Proposed research model

3. Research Methodology

This study utilizes the MonsoonSIM business gamified simulation platform, which offers diverse business simulations across Finance and Accounting, Marketing Management, Supply Chain Management, Human Resources, and Entrepreneurship. In an educational research context, Tumphasuwan (2023) used MonsoonSIM to modernize teaching, reporting improved student engagement and strategic decision-making, with post-test scores increasing from 56% to 75% relative to traditional lecture delivery. Shafudin et al. (2018) investigated factors influencing MonsoonSIM adoption among undergraduate students and found that perceived usefulness, ease of use, and enjoyment were all positively correlated with adoption, with perceived enjoyment being the strongest determinant. More recent research on MonsoonSIM continues to support these findings: Mohd Khalil et al. (2024) studied its effectiveness in Malaysian higher education institutions; Shafiai and Omar (2019) confirmed that MonsoonSIM contributes to the development of core 21st-century skills — particularly teamwork, decision-making, and problem-solving; and Septiawan et al. (2023) revealed that most students exhibit medium to high levels of technological readiness for ERP gamification, especially among explorer and pioneer learner profiles. MonsoonSIM was selected for the present study because it combines time-pressured, multi-round business decisions with quantifiable performance metrics (cash on hand, stockouts, expired inventory), making it well-suited for behavioral observation of AI-assisted decision-making in a realistic yet controlled environment.

This research focuses on inventory management strategies within the Supply Chain Management domain, using Generative AI as an advisor. Data were collected across five game sessions involving two participant cohorts distinguished by prior MonsoonSIM experience. Sessions 1 and 2 involved novice participants new to the MonsoonSIM platform, with 14 and 13 participants respectively. Sessions 3, 4, and 5 involved experienced participants with prior MonsoonSIM exposure, with 10, 10, and 5 participants respectively. For clarity, sessions are numbered by cohort rather than by date of collection. Because MonsoonSIM supports a maximum of 10 teams per round, some novice participants in Sessions 1 and 2 were assigned to play in pairs, while all experienced participants in Sessions 3, 4, and 5 played as single-person teams. A total of 52 participants took part. Experience level is incorporated as a participant-level covariate in subsequent analyses rather than as a between-group experimental factor.

Table 1 Details of sessions

Session	Experience	Team structure	Participants
1	Novice	Mixed (some pairs)	14
2	Novice	Mixed (some pairs)	13
3	Experienced	One-per-team	10
4	Experienced	One-per-team	10
5	Experienced	One-per-team	5
		Total	52

All participants were equipped with an AI advisor powered by Gemini 1.5 Flash, deployed via Streamlit with a single system prompt. Participants were required to consult the AI advisor seven times during the game and were not allowed to place orders without first consulting the AI. Mandatory consultation was a deliberate exposure manipulation rather than a measure of trust: without it, low-trust or low-literacy participants might never have consulted the advisor, eliminating the variance needed to study reliance. The seven consultations span the full range of fluctuating AI accuracy described in Section 3.1, ensuring each participant encountered the AI advisor under varying levels of reliability rather than only when it happened to be performing well or poorly. Reliance was therefore operationalized not as whether participants consulted the AI — which was required — but as the degree to which their final orders aligned with AI recommendations versus their independent pre-consultation interpretation of the same forecast data. At the end of the simulation, participants completed a survey and a short self-report interview to provide qualitative insights into their experience.

3.1 AI Advisor

The AI advisor was powered by Gemini 1.5 Flash and deployed via Streamlit. It generated strategic recommendations for inventory management decisions based on forecast data produced by a custom Prophet model.

The Prophet model was trained on the simulated demand data underlying the MonsoonSIM scenario and achieved a baseline forecast accuracy of approximately 60%. A moderate baseline was chosen deliberately, since the study examines how participants respond to AI advice under realistic conditions of imperfect reliability rather than near-perfect accuracy. To simulate fluctuation in AI performance across the seven consultation rounds, a random multiplier drawn from the uniform range [0.7, 1.0] was applied to each forecast value, producing round-by-round variation in the AI's predicted quantities.

AI consultation became active from Day 13 of the simulation onward. Each of the seven consultation rounds followed a two-phase structure. In Phase 1, participants received the Prophet forecast without AI commentary and entered an initial planned order quantity based on their own interpretation of the data. In Phase 2, the same forecast was passed to the Generative AI advisor, which produced a recommended order quantity accompanied by a natural-language rationale. Participants then made their final order, either committing to their Phase 1 quantity or revising it in light of the AI's recommendation.

The simulation platform recorded the AI's recommended order quantity, the participant's Phase 1 and Phase 2 orders, and the resulting inventory and financial outcomes for every consultation round. Immediately after each consultation, participants completed a brief in-task survey containing three round-level perception items reported in Section 3.2.

3.2 Data Collection

Data were collected from two sources: a survey administered once per participant after the simulation, and the simulation platform's automatic recording of in-game actions and outcomes throughout the game.

3.2.1 Survey Items

Five constructs were measured at the participant level. Four constructs were measured using validated multi-item Likert scales, each rated from 1 (strongly disagree) to 7 (strongly agree). Cronbach's alpha values for the constructs are reported in Table 2 and exceeded the 0.70 threshold for acceptable reliability (Hair et al., 2010).

AI Literacy was measured with 28 items adapted from Pinski and Benlian (2023).

Decision-Making Style was measured with the 25-item General Decision-Making Style (GDMS) inventory developed by Scott and Bruce (1995), capturing rational, intuitive, dependent, avoidant, and spontaneous styles.

Performance Expectancy was measured with four items adapted from Lu et al. (2019), originally derived from Venkatesh et al. (2003).

Trust in Generative AI was measured with six items adapted from Knoth et al. (2024), originally derived from Lankton et al. (2015).

Reliance was measure with an item adapted from Cao and Huang (2022), I relied on the AI suggestion in the game tasks. Participants rated this item on the same 7-point Likert scale, providing one Reliance value per participant. Because Reliance is a single-item measure, Cronbach's alpha is not applicable.

The survey also collected demographic information and self-reported experience in working, data analysis, Generative AI tool usage, MonsoonSIM gaming, and inventory or supply chain management.

3.2.2 Measuring Decision Quality and Business Outcomes from Business Simulation Game

Data

Decision Quality (DQ) was computed from each participant's accumulated in-game performance using two indicators: the number of shortage days (ST), representing the total duration during which inventory levels fell below required demand, and expired inventory expenses (WEI), representing the financial loss from inventory that expired before it could be sold. These two indicators were selected because they capture the two principal failure modes of inventory decisions: under-ordering, which produces stockouts, and over-ordering, which produces waste. They are also the two cost components that the MonsoonSIM platform uses to compute the player's financial position, making them direct measures of inventory decision performance within the simulation environment.

A Multi-Criteria Decision Analysis (MCDA) framework is applied to derive the DQ metric, utilizing a Weighted Scoring Model (WSM). The formula for Decision Quality is structured as follows:

$$DQ_{\{1-7\}} = 1 + 6 \times [1 - (\alpha \cdot ST_{\{norm\}} + \beta \cdot WEI_{\{norm\}})] \quad (1)$$

where ST_norm and WEI_norm are the min-max normalized values of ST and WEI (Union & Centre, 2008). The parameters α and β are the weighting factors assigned to ST and WEI, respectively. In this study, equal weights ($\alpha = \beta = 0.5$) are used to balance both indicators because the MonsoonSIM platform penalizes both failure modes equally in its underlying cost structure, making equal weighting consistent with the simulation's own financial logic rather than imposing an external preference. The final DQ score is scaled between 1 and 7 for interpretability and to align with the response scales used elsewhere in the analysis.

The Weighted Scoring Model was selected over alternative aggregation frameworks such as the Performance Index (PI), Multi-Attribute Utility Theory (MAUT; Keeney & Raiffa, 1993), and the Composite Indicator (CI; Union & Centre, 2008). All three frameworks offer related approaches to combining normalized metrics into a single score, but the WSM was preferred for its transparency: it allows the contribution of each indicator to be inspected directly, and its equal-weighting assumption is defensible given the underlying simulation mechanics. The DQ metric should therefore be interpreted as a task-specific measure of inventory decision performance in this simulation, not as a generalized decision-quality construct.

Business Outcomes were operationalized as the cash in bank accumulated by each participant at the end of the simulation. Cash in bank integrates the financial consequences of all decisions made during the game,

including inventory ordering, stockouts, spoilage, sales, and operating costs, into a single end-of-game measure of business performance.

4. Data Analysis

All hypothesis tests in this study are conducted at the participant level ($N = 52$). Each participant contributed one observation per variable: trait-level survey responses (AI Literacy, Decision-Making Style, Performance Expectancy, Trust in Generative AI, and Reliance on Generative AI), and end-of-game outcomes (Decision Quality and Business Outcomes). The profile of the 52 participants is summarized in Table 2. The sample is nearly evenly split by gender (51.92% male, 48.08% female), with the majority aged 26-30 years (51.92%). Participants come from a range of occupational backgrounds: Data Science and Analytics (28.85%), Business and Strategy Analysts (25.00%), General Employment (19.23%), Freelance and Independent Work (9.62%), Engineering and Technical Roles (7.69%), Entrepreneurs (1.92%), and miscellaneous occupations including nursing, research, production supervision, and quality assurance (7.69%). Working experience is distributed across short and mid-career stages, with 34.62% having 3-5 years of experience, 26.92% having 6-8 years, and 17.31% having 0-2 years. The remainder have 9-14 years (17.31%) or more than 14 years (3.85%) of working experience.

Participants vary in domain-relevant experience. Most have substantial experience in data analysis, with 65.38% reporting one year or longer. Generative AI tool usage is also relatively common, with 48.08% reporting one year or longer of experience and another 30.77% reporting six months to one year. MonsoonSIM gaming experience is more limited, concentrated in the three-to-six month range (38.46%) and under three months (32.69%). Experience in inventory or supply chain management is the most limited dimension, with 75.00% reporting no prior experience in this domain.

Table 2 Sociodemographic characteristics of respondents

Baseline Characteristic	n	%
Gender		
Male	27	51.92
Female	25	48.08
Age		
21-25	7	13.46
26-30	27	51.92
31-35	12	23.08
36-40	4	7.69
41-50	2	3.85
Occupation		
Data Science and Analytics	15	28.85
Business & Strategy Analysts	13	25.0
General Employment	10	19.23
Freelance and Independent Work	5	9.62
Engineering and Technical Roles	4	7.69
Entrepreneur	1	1.92
Miscellaneous	4	7.69
Working Experience (Years)		

Table 2 Sociodemographic characteristics of respondents (cont.)

Baseline Characteristic	n	%
0-2	9	17.31
3-5	18	34.62
6-8	14	26.92
9-11	6	11.54
12-14	3	5.77
more than 14	2	3.85
Experience in data analysis		
Less than 3 months	6	11.54
At least 3 months but less than 6 months	6	11.54
At least 6 months but less than 1 year	6	11.54
1 year or longer	34	65.38
Experience in using Generative AI such as ChatGPT, Gemini, MidJourney, etc.		
Less than 3 months	5	9.62
At least 3 months but less than 6 months	6	11.54
At least 6 months but less than 1 year	16	30.77
1 year or longer	25	48.08
MonsoonSIM gaming experience		
Less than 3 months	17	32.69
At least 3 months but less than 6 months	20	38.46
At least 6 months but less than 1 year	9	17.31
1 year or longer	6	11.54
Experience in inventory or supply management		
No experience	39	75.0
Less than 3 months	1	1.92
At least 3 months but less than 6 months	2	3.85
At least 6 months but less than 1 year	4	7.69
1 year or longer	6	11.54

For Generative AI experience, the majority have used it for at least 6 months but less than 1 year, while others have over 1 year of experience. Regarding MonsoonSIM gaming experience, most respondents reported at least 3 months but less than 6 months, followed by those with less than 3 months of experience. Finally, with respect to inventory or supply management experience, the majority of respondents reported having no experience in this area.

Table 3 Descriptive statistics

Construct	Cronbach's Alpha	Mean	Standard Deviation
Rational Style	0.89	6.02	0.73
Intuitive Style	0.88	4.11	1.29
Dependent Style	0.81	4.80	1.19
Avoidant Style	0.87	3.17	1.35
Spontaneous Style	0.86	3.82	1.18
Trust in Generative AI	0.89	4.88	1.00
Performance Expectancy	0.87	4.82	0.98
AI Literacy	0.89	4.42	1.12
Reliance on Generative AI	-	4.63	2.03
Decision Quality	-	6.37	0.94
Business Outcomes	-	2,146,260.65	1,422,979.54

4.1 Descriptive Statistics

Table 3 reports the Cronbach's alpha, mean, and standard deviation for each construct measured in this study. All multi-item scales met the conventional threshold for acceptable internal consistency ($\alpha \geq 0.70$; Hair et al., 2010). Among the decision-making styles, the rational style has the highest mean ($M = 6.02$, $SD = 0.73$), indicating that participants generally identify as analytical decision-makers, while the avoidant style has the lowest mean and highest variability ($M = 3.17$, $SD = 1.35$). AI Literacy ($M = 4.42$, $SD = 1.12$), Performance Expectancy ($M = 4.82$, $SD = 0.98$), and Trust in Generative AI ($M = 4.88$, $SD = 1.00$) cluster around the midpoint of the 7-point scale.

Reliance on Generative AI, Decision Quality, and Business Outcomes are also reported in Table 3. Cronbach's alpha is not applicable to these three variables because each was derived from a different source: Reliance is a single-item self-report measure adapted from (Cao & Huang, 2022), Decision Quality is a composite score computed from in-game performance, and Business Outcomes is the cash in bank accumulated at the end of the simulation.

Table 4 Correlation

Variables	1	2	3	4	5	6	7	8	9	10
1. Rational	-									
2. Intuitive	-0.01	-								
3. Dependent	0.17	0.16	-							
4. Avoidant	-0.08	0.24	0.28	-						
5. Spontaneous	-0.06	0.68	0.31	0.14	-					
6. AI Literacy	0.37	0.09	0.09	0.02	0.16	-				
7. Trust in Generative AI	0.03	0.20	-0.05	0.12	0.36	0.20	-			
8. Performance Expectancy	0.14	0.16	-0.05	0.08	0.31	0.08	0.63	-		
9. Reliance on Generative AI	0.01	0.12	0.01	0.39	0.21	0.36	0.19	0.23	-	
10. Decision Quality	0.05	-0.14	-0.17	-0.27	-0.23	-0.23	-0.06	-0.11	-0.15	-
11. Business Outcomes	0.12	0.17	0.07	0.02	0.12	0.35	0.06	0.12	0.16	-0.05

The correlation table illustrates the relationships between decision-making styles and other theoretical constructs. The rational style exhibits a weak positive correlation with the dependent style ($r = 0.17$) and a strong positive correlation with AI literacy ($r = 0.37$). These results suggest that individuals who adopt a rational decision-making approach tend to possess greater AI knowledge. The avoidant style shows positive correlations with both the dependent style ($r = 0.28$) and the intuitive style ($r = 0.24$). These findings imply that individuals who avoid making decisions may also depend on others and display intuitive tendencies. Moreover, the intuitive style is strongly correlated with the spontaneous style ($r = 0.68$), highlighting a significant overlap between these decision-making tendencies. AI literacy is positively correlated with trust in generative AI ($r = 0.20$) and reliance on generative AI ($r = 0.36$), providing evidence that individuals with higher AI knowledge are more likely to trust and depend on AI systems. Trust in generative AI is also strongly correlated with performance expectancy ($r = 0.63$), underscoring its crucial role in shaping perceptions of AI effectiveness. This is in the line with the proposed research hypothesis 3

Reliance on generative AI is positively correlated with the avoidant style ($r = 0.39$) and the spontaneous style ($r = 0.21$), suggesting that individuals with less structured decision-making tendencies may rely more on AI systems. Additionally, reliance on generative AI shows a moderate positive correlation with AI literacy ($r = 0.36$). This indicates that individuals with greater knowledge of AI are more likely to incorporate generative AI into their decision-making processes, as their understanding of the technology enhances their confidence in its capabilities. This is also in the line with the proposed research hypothesis 2. However, it is important to note that a weak negative correlation exists between Reliance on Generative AI and decision quality (DQ) ($r = -0.15$), implying that excessive Reliance on Generative AI, even among those with higher AI literacy, might slightly diminish decision quality. This highlights the need for a balanced approach where AI is used as a supportive tool rather than as a sole decision-making mechanism.

4.2 Hypothesis Testing

To evaluate the proposed research hypotheses, Ordinary Least Squares (OLS) regressions were conducted. Results are summarized in Table 4 and reported below using Cohen (1988) conventions for interpreting effect sizes in behavioral research: R^2 values of approximately .02, .13, and .26 are considered small, medium, and large, respectively, and standardized coefficients of $|\beta| \geq .10$, .30, and .50 are similarly small, medium, and large. Given the sample size of $N = 52$, post-hoc power to detect small effects is limited; non-significant results are therefore interpreted as inconclusive rather than as evidence of no effect.

For Hypothesis 1a, reliance on generative AI was regressed on rational decision-making style, $F(1, 50) = 1.999$, $R^2 = 0.075$. Rational decision-making style was not a significant predictor ($\beta = 0.031$, $t = 0.081$, $p > .05$). For Hypothesis 1b, reliance on generative AI was regressed on non-rational decision-making style, $F(1, 50) = 4.072$, $R^2 = 0.075$. A significant positive relationship was observed between non-rational decision-making style and reliance on generative AI ($\beta = 0.646$, $t = 2.018$, $p < .05$), representing a medium effect.

To further explore the combined effects of decision-making styles, a multiple regression analysis was conducted with reliance on generative AI as the dependent variable and the five individual decision-making styles (rational, intuitive, dependent, avoidant, spontaneous) as independent variables, $F(5, 46) = 2.720$, $R^2 = 0.228$. The model explains 22.8% of the variance in reliance, a medium effect by Cohen's conventions. The avoidant style emerged as the only significant predictor ($\beta = 0.680$, $t = 3.234$, $p < .01$), a large effect. The spontaneous style approached significance ($\beta = 0.622$, $t = 1.917$, $p = .061$). The rational ($t = 0.766$), intuitive ($t = -1.087$), and dependent ($t = -1.461$) styles were not significant predictors.

For Hypothesis 2, reliance on generative AI was regressed on AI literacy, $F(1, 50) = 7.579$, $R^2 = 0.132$. AI literacy was a significant predictor of reliance ($\beta = 0.660$, $t = 2.753$, $p < .01$), a medium effect.

For Hypothesis 3, trust in generative AI was regressed on performance expectancy, $F(1, 50) = 33.42$, $R^2 = 0.401$. Performance expectancy was a strong predictor of trust in generative AI ($\beta = 0.647$, $t = 5.781$, $p < .001$), with $R^2 = 0.401$ indicating that performance expectancy alone accounts for 40.1% of the variance in trust, a large effect.

For Hypothesis 4, reliance on generative AI was regressed on trust in generative AI, $F(1, 50) = 1.954$, $R^2 = 0.038$. Trust in generative AI was not a significant predictor of reliance ($\beta = 0.393$, $t = 1.398$, $p > .05$). The non-significant result, combined with a small R^2 of 0.038, suggests that trust does not directly translate into reliance in this study.

For Hypothesis 5, decision quality was regressed on reliance on generative AI, $F(1, 50) = 1.088$, $R^2 = 0.021$. Reliance on generative AI was not a significant predictor of decision quality ($\beta = -0.068$, $t = -1.043$, $p > .05$). For Hypothesis 6, business outcomes was regressed on reliance on generative AI, $F(1, 50) = 1.271$, $R^2 =$

0.025. Reliance on generative AI was not a significant predictor of business outcomes ($t = 1.128$, $p > .05$). The small R^2 values for both H5 and H6 indicate that variation in reliance alone does not meaningfully explain variation in decision quality or business performance in this study.

The findings indicate partial support for the proposed hypotheses. Hypotheses 2 and 3 were supported, with AI literacy predicting reliance on generative AI (medium effect) and performance expectancy predicting trust in generative AI (large effect). Hypothesis 1a was not supported, while Hypothesis 1b was supported in aggregate (non-rational style positively predicted reliance), and within the non-rational styles the avoidant style emerged as the dominant driver. Hypotheses 4, 5, and 6 were not supported.

Table 5 Regression analysis

Model	Beta	t	Sig.	R^2
1. Decision-Making Style				0.075
H1a Rational → Reliance	0.0311	0.081	0.936	
H1b Non-Rational → Reliance	0.6456	2.018	0.049	
Decision-Making Style (ALL)				0.228
H1a Rational → Reliance	0.2863	0.766	0.447	
H1b1 Intuitive → Reliance	-0.3129	-1.087	0.283	
H1b2 Dependent → Reliance	-0.3657	-1.461	0.151	
H1b3 Avoidant → Reliance	0.6802	3.234	0.002	
H1b4 Spontaneous → Reliance	0.6218	1.917	0.061	
2. AI Literacy				0.132
H2 AI Literacy → Reliance	0.6601	2.753	0.008	
3. Performance Expectancy				0.401
H3 Performance Expectancy → Trust	0.6473	5.781	0.000	
4. Trust In Generative AI				0.038
H4 Trust → Reliance	0.3925	1.398	0.168	
5. Decision Quality				0.021
H5 Reliance → Decision Quality	-0.068	-1.043	0.302	
6. Business Outcomes				0.025
H6 Reliance → Business Outcomes	110,400	1.128	0.265	

Table 6 Summary of findings

Hypothesis	Results
H1a: There will be a significant correlation between a Rational Style of decision-making and Reliance on Generative AI.	Not Supported
H1b: There will be no significant correlation between a Non-Rational Style of decision-making and Reliance on Generative AI.	Not Supported
H1b1: There will be no significant correlation between Intuitive Style of decision-making and Reliance on Generative AI.	Supported
H1b2: There will be no significant correlation between Dependent Style of decision-making and Reliance on Generative AI.	Supported
H1b3: There will be no significant correlation between Avoidant Style of decision-making and Reliance on Generative AI.	Not Supported
H1b4: There will be no significant correlation between Spontaneous Style of decision-making and Reliance on Generative AI.	Supported
H2: AI Literacy will be positively correlated with Reliance on Generative AI.	Supported
H3: Performance Expectancy will positively correlate with Trust in Generative AI.	Supported
H4: Trust in Generative AI will correlate with Reliance on Generative AI.	Not Supported
H5: Reliance on Generative AI will be correlated with Decision Quality.	Not Supported
H6: Reliance on Generative AI will be correlated with Business Outcomes.	Not Supported

4.3 Model Refinement

The hypothesis tests in Section 4.2 reveal two patterns that motivate further analysis. First, trust in generative AI did not significantly predict reliance (H4), and rational decision-making style did not directly predict reliance (H1a), even though the avoidant style did. This suggests that the relationship between user characteristics and reliance may not be uniformly direct; decision-making style may instead moderate how AI literacy and trust translate into reliance behavior. Second, reliance on generative AI did not significantly predict either decision quality (H5) or business outcomes (H6), even though both relationships were theoretically expected. This suggests that the link between reliance and downstream outcomes may depend on the user's capacity to interpret and integrate AI input, which is not captured by reliance alone.

To examine these possibilities, the following moderated regressions were conducted. For the relationships involving reliance as the dependent variable, decision-making style was tested as a moderator of the effects of AI literacy and trust on reliance. For the relationships involving decision quality and business outcomes as dependent variables, the participants' background experience was tested as a moderator. Four experience dimensions were measured in the participant survey (Section 3.2.1): experience in data analysis, familiarity with generative AI tools, MonsoonSIM gaming experience, and experience in inventory or supply chain management. These dimensions were not part of the original conceptual model and the analyses below should therefore be treated as exploratory, aimed at identifying boundary conditions for the hypothesized relationships rather than confirming new theoretical claims. The results of the model refinement are presented in Table 6.

4.3.1 Decision-Making Style × AI Literacy

The regression analyses examined whether AI literacy moderated the relationship between different decision-making styles and reliance on generative AI. The results indicated that rational decision-making style was not a significant predictor of reliance on generative AI, $t(50) = -1.655, p > .05$, and the interaction term was also not significant, $t(50) = 1.448, p > .05, R^2 = .184$. Similarly, intuitive decision-making style did not significantly predict reliance, $t(50) = 0.322, p > .05$, nor was the interaction with AI literacy significant, $t(50) = -0.136, p > .05, R^2 = .140$.

For dependent decision-making style, no significant effect was found on reliance, $t(50) = -0.490, p > .05$, nor was the interaction with AI literacy significant, $t(50) = 0.466, p > .05, R^2 = .136$. However, avoidant decision-making style had a significant positive effect on reliance on generative AI, $t(50) = 2.152, p < .05$, as did AI literacy, $t(50) = 2.360, p < .05$. The interaction term was not significant, $t(50) = -1.400, p > .05, R^2 = .305$. Spontaneous decision-making style did not significantly predict reliance, $t(50) = 1.344, p > .05$, nor did its interaction with AI literacy, $t(50) = -1.097, p > .05, R^2 = .177$.

4.3.2 Decision-Making Style × Trust in Generative AI

The regression analyses tested whether trust in generative AI moderated the relationship between decision-making styles and reliance on generative AI. Rational decision-making style was not a significant predictor, $t(50) = 1.492, p > .05$, and its interaction with trust was also not significant, $t(50) = -1.508, p > .05, R^2 = .081$.

For intuitive decision-making style, a significant negative effect was found on reliance, $t(50) = -2.038, p < .05$. Additionally, the interaction term was significant, $t(50) = 2.195, p < .05, R^2 = .102$, suggesting that trust in generative AI moderated the relationship. In the case of dependent decision-making style, trust significantly predicted reliance on generative AI, $t(50) = 2.145, p < .05$, while the interaction term approached significance, $t(50) = -1.844, p = .071, R^2 = .102$.

No significant effects were found for avoidant decision-making style, $R^2 = .173$. Similarly, spontaneous decision-making style and its interaction with trust were not significant, $R^2 = .063$.

4.3.3 Reliance × Experience in Data Analysis

A regression analysis examined whether experience in data analysis moderated the relationship between reliance on generative AI and decision quality. The results showed that reliance on generative AI significantly negatively predicted decision quality, $t(50) = -2.715, p < .01$. Experience in data analysis approached significance, $t(50) = -1.824, p = .074$. The interaction term was significant, $t(50) = 2.471, p < .05, R^2 = .157$, suggesting that experience in data analysis mitigates the negative effect of reliance on generative AI on decision quality.

In Figure 2, experience in data analysis was coded as follows: “Less than 3 months” = 1, “At least 3 months but less than 6 months” = 2, “At least 6 months but less than 1 year” = 3, and “1 year or longer” = 4.

Table 7 Multicollinearity regression analysis

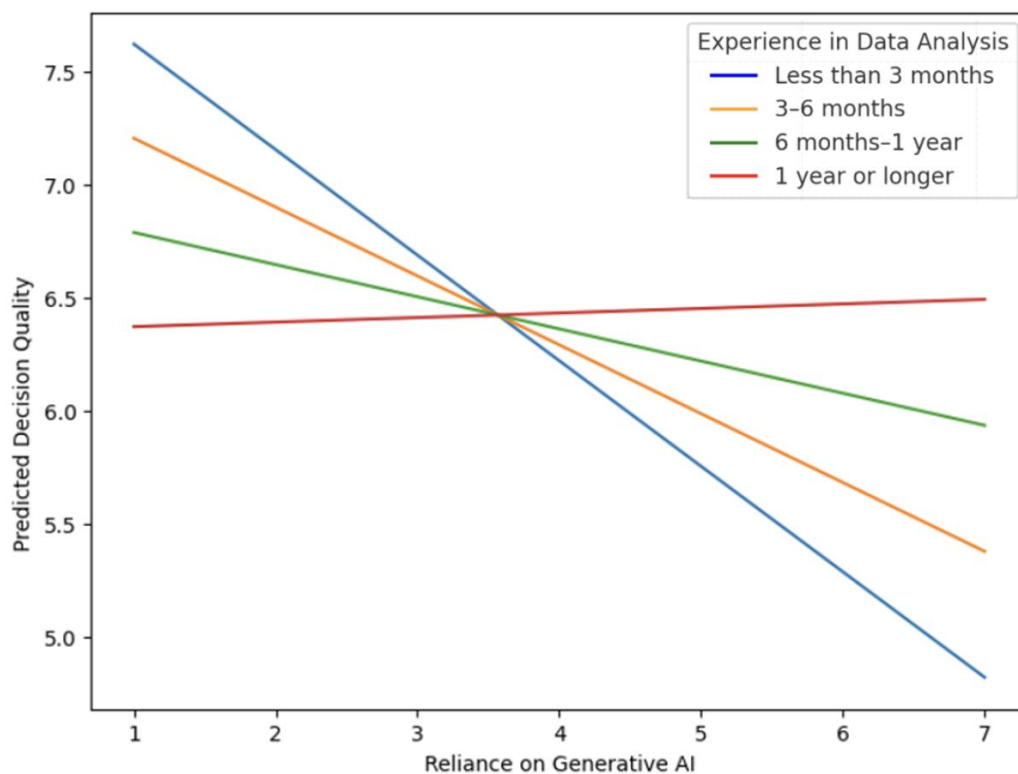
Model Refinement	Beta	t	Sig.	R^2
Model 1.1 Decision-Making Style x AI Literacy				0.184
1. Rational				
1.1 Rational → Reliance	-2.5535	-1.655	0.104	
1.2 AI Literacy → Reliance	-2.3351	-1.087	0.283	
1.3 Rational x AI Literacy → Reliance	0.4947	1.448	0.154	
2. Intuitive				0.140
2.1 Intuitive → Reliance	0.2293	0.322	0.749	
2.2 AI Literacy → Reliance	0.7320	1.071	0.289	
2.3 Intuitive x AI Literacy → Reliance	-0.0208	-0.136	0.893	

Table 7 Multicollinearity regression analysis (cont.)

Model Refinement	Beta	t	Sig.	R²
3. Dependent				0.136
3.1 Dependent → Reliance	-0.4492	-0.490	0.627	
3.2 AI Literacy → Reliance	0.2053	0.203	0.840	
3.3 Dependent x AI Literacy → Reliance	0.0901	0.466	0.643	
4. Avoidant				0.305
4.1 Avoidant → Reliance	1.5398	2.152	0.036	
4.2 AI Literacy → Reliance	1.4460	2.360	0.022	
4.3 Avoidant x AI Literacy → Reliance	-0.2305	-1.400	0.168	
5. Spontaneous				0.177
5.1 Spontaneous → Reliance	1.3457	1.344	0.185	
5.2 AI Literacy → Reliance	1.4258	1.831	0.073	
5.3 Spontaneous x AI Literacy → Reliance	-0.2209	-1.097	0.278	
Model 1.2 Decision-Making Style x Trust				0.081
1. Rational				
1.1 Rational → Reliance	3.1669	1.492	0.142	
1.2 Trust → Reliance	4.4927	1.644	0.107	
1.3 Rational x Trust → Reliance	-0.6548	-1.508	0.138	
2. Intuitive				0.132
2.1 Intuitive → Reliance	-2.2972	-2.038	0.047	
2.2 Trust → Reliance	-1.6756	-1.733	0.090	
2.3 Intuitive x Trust → Reliance	0.5001	2.195	0.033	
3. Dependent				0.102
3.1 Dependent → Reliance	1.8913	1.833	0.073	
3.2 Trust → Reliance	2.3457	2.145	0.037	
3.3 Dependent x Trust → Reliance	-0.3928	-1.844	0.071	
4. Avoidant				0.173
4.1 Avoidant → Reliance	0.7358	0.698	0.489	
4.2 Trust → Reliance	0.4164	0.588	0.559	
4.3 Avoidant x Trust → Reliance	-0.0357	-0.174	0.862	
5. Spontaneous				0.063
5.1 Spontaneous → Reliance	-0.1241	-0.087	0.931	
5.2 Trust → Reliance	0.0023	0.002	0.998	
5.3 Spontaneous x Trust → Reliance	0.0791	0.294	0.770	
Model 2.1 Reliance x Experience in data analysis				0.157
Reliance → Decision Quality	-0.6286	-2.715	0.009	

Table 7 Multicollinearity regression analysis (cont.)

Model Refinement	Beta	t	Sig.	R ²
Experience in data analysis → Decision Quality	-0.5785	-1.824	0.074	
Reliance x Experience in data analysis → Decision Quality	0.1622	2.471	0.017	
Model 2.2 Reliance x Familiarity with generative AI tools				0.061
Reliance → Decision Quality	-0.2580	-1.141	0.259	
Familiarity with generative AI tools → Decision Quality	-0.4058	-1.363	0.179	
Reliance x Familiarity with generative AI tools → Decision Quality	0.0675	0.992	0.326	
Model 3.1 Reliance x MonsoonSIM gaming experience				0.041
Reliance → Business Outcome	-78,910	-0.314	0.755	
MonsoonSIM gaming experience → Business Outcome	-385,300	-0.655	0.516	
Reliance x MonsoonSIM gaming experience → Business Outcome	99,860	0.829	0.411	
Model 3.2 Reliance x Experience in inventory or supply chain management				0.025
Reliance → Business Outcome	102,000	0.916	0.364	
Experience in inventory or supply chain management → Business Outcome	-63,320	-0.181	0.857	
Reliance x Experience in inventory or supply chain management → Business Outcome	11,770	0.162	0.872	

**Figure 2** Interaction Between Data Analysis Experience and Reliance on Generative AI in Decision Quality

4.3.4 Reliance × Familiarity with Generative AI Tools

The regression analysis tested whether familiarity with generative AI tools moderated the relationship between reliance on generative AI and decision quality. The results indicated that reliance on generative AI was not a significant predictor of decision quality, $t(50) = -1.141, p > .05$. Familiarity with generative AI tools did not significantly predict decision quality, $t(50) = -1.363, p > .05$. The interaction term was also not significant, $t(50) = 0.992, p > .05, R^2 = .061$.

4.3.5 Reliance × MonsoonSIM Gaming Experience

A regression analysis assessed whether MonsoonSIM gaming experience moderated the effect of reliance on generative AI on business outcomes. The results indicated that reliance on generative AI did not significantly predict business outcomes, $t(50) = -0.314, p > .05$. MonsoonSIM gaming experience was also not a significant predictor, $t(50) = -0.655, p > .05$. Additionally, the interaction term was not significant, $t(50) = 0.829, p > .05, R^2 = .041$.

4.3.6 Reliance × Experience in Inventory or Supply Chain Management

The final regression analysis tested whether experience in inventory or supply chain management moderated the relationship between reliance on generative AI and business outcomes. The findings revealed that reliance on generative AI was not a significant predictor, $t(50) = 0.916, p > .05$, nor was experience in inventory or supply chain management, $t(50) = -0.181, p > .05$. The interaction term was also not significant, $t(50) = 0.162, p > .05, R^2 = .025$.

4.3.7 Summary of Model Refinement

The model refinement analyses provided further insights into the conditions under which reliance on generative AI affects decision quality and business outcomes. The findings indicate that AI literacy did not significantly moderate the relationship between decision-making styles and reliance on generative AI. However, trust in generative AI moderated the effect of the intuitive decision-making style on reliance. Moreover, experience in data analysis significantly moderated the negative impact of reliance on generative AI on decision quality. In contrast, neither MonsoonSIM gaming experience nor experience in inventory or supply chain management significantly moderated the relationship between reliance on generative AI and business outcomes.

5. Conclusion

This research aimed to explore how generative AI influences people's trust and reliance in decision-making, particularly in high-stakes scenarios. Additionally, it investigated the relationship between AI literacy and reliance on generative AI. The key findings provide insights into the role of decision-making styles, AI literacy, trust, and performance expectancy in shaping Reliance on Generative AI-assisted decision-making, as well as their broader implications for decision quality and business outcomes.

5.1 Theoretical Contributions

The findings of this study contribute to three intersecting literatures. First, to the appropriate-reliance literature in human-AI decision-making (Lee & See, 2004; Schemmer et al., 2023), the results show that reliance on generative AI is neither uniformly beneficial nor uniformly harmful. Its effect on decision quality depends on the user's analytical competence, consistent with the calibration-of-trust thesis. Second, to decision-style theory (Scott & Bruce, 1995; Ritbumroong, 2023), the results extend the rational versus non-rational distinction by showing that avoidant decision-makers use AI as a delegation channel, supporting Meissner and Keding (2021) typology of skeptics, interactors, and delegators in an experimental setting. Third, to the UTAUT and AIDUA frameworks (Lu et al., 2019; Venkatesh et al., 2003), the results provide evidence that performance expectancy drives trust but not reliance directly. Reliance is instead shaped by individual differences in decision-making style, suggesting that technology-acceptance models need to incorporate cognitive-style moderators when applied to generative AI.

Decision-making styles played a central role in shaping how participants interacted with the AI advisor. Rational decision-makers, despite their analytical orientation, did not exhibit significant reliance on generative AI, suggesting that they engaged with AI-generated insights with caution rather than dependence. Intuitive, dependent, and spontaneous decision-makers also showed no significant direct reliance, although the spontaneous style approached significance. The avoidant decision-making style was the only category that significantly relied on generative AI. This pattern aligns with Meissner and Keding (2021), who classified decision-makers as skeptics (rational), interactors (intuitive, dependent, and spontaneous), and delegators (avoidant). Avoidant decision-

makers, characterized by their tendency to delay decisions or shift responsibility, found AI a useful channel for deflecting decision-making burdens, treating it as a delegation tool rather than an analytical aid.

Decision-making style also moderated the relationship between trust in generative AI and reliance on generative AI. The interaction between intuitive decision-making and trust was significant, indicating that individuals who rely on intuition are more likely to translate trust in AI into actual reliance on its recommendations. This finding aligns with Jarrahi (2018), who argued that AI functions as an augmentative tool rather than a replacement for human cognition. Intuitive decision-makers, who depend on tacit knowledge and experience, appear to integrate AI-generated insights into their reasoning when trust in the system is established. By contrast, the interaction effects between avoidant decision-making and AI literacy or trust were not significant, confirming that avoidant decision-makers' reliance on AI is driven by their own disposition rather than by AI-related beliefs.

AI literacy was a significant positive predictor of reliance on generative AI. AI-literate individuals possess a deeper understanding of both the capabilities and the limitations of AI, allowing them to make informed decisions about when and how to use AI tools effectively (Long & Magerko, 2020). This result highlights the importance of AI education in fostering appropriate reliance, ensuring that users neither over-rely on AI nor dismiss its potential contributions.

Performance expectancy was a strong predictor of trust in generative AI. Users who expect AI to enhance their productivity are more likely to trust the technology, consistent with the findings of Chi et al. (2023). Trust in generative AI is built upon perceptions of the system's efficiency, accuracy, and reliability. However, the present findings also show that trust does not translate directly into reliance: trust in generative AI was not a significant direct predictor of reliance, and instead operated through decision-making style as a moderator. This suggests that trust in generative AI is not universally established or unconditionally translated into reliance; rather, the link between trust and reliance is shaped by user disposition, task context, and perceived domain reliability.

Contrary to expectations, reliance on generative AI did not directly improve decision quality or business outcomes. The relationship between reliance and decision quality was moderated by experience in data analysis: participants with data analysis experience were better equipped to integrate AI recommendations into their decision-making, mitigating the negative effects of over-reliance. Familiarity with generative AI tools such as ChatGPT, Gemini, and MidJourney did not significantly moderate this relationship, suggesting that general exposure to generative AI is not equivalent to the analytical competence required to use AI input effectively. The relationship between reliance and business outcomes was not significantly moderated by MonsoonSIM gaming experience or by experience in inventory or supply chain management, indicating that reliance alone is insufficient to translate AI input into improved business performance.

5.2 Practical Implications

The findings of this study translate into three concrete sets of recommendations for organizations integrating generative AI into decision-making workflows.

For HR and learning and development functions, AI literacy training is necessary but not sufficient. Organizations should pair AI literacy curricula with explicit instruction on ground truth verification: the practice of validating AI-generated outputs against domain-specific facts, established procedures, or independent evidence. This instruction should include hands-on exercises in which employees actively identify and correct hallucinations or inaccuracies in AI output drawn from their own work domain. The present findings show that experience in data analysis significantly moderates the effect of AI reliance on decision quality, while familiarity with generative AI tools alone does not. This indicates that the relevant competency is not general exposure to AI but the analytical ability to evaluate AI output critically. Training programs should therefore prioritize analytical reasoning and verification skills alongside familiarity with AI tools.

For risk and governance functions, decision-making style is a meaningful individual difference that shapes how employees engage with AI advisors. Avoidant decision-makers in particular show significantly higher reliance on generative AI, treating AI as a delegation channel rather than as an analytical aid. For roles involving high-stakes AI-assisted decisions, organizations should consider screening employees on decision-making style using validated instruments such as the General Decision-Making Style inventory (Scott & Bruce, 1995). Where avoidant decision-makers are deployed in high-stakes roles, governance procedures should provide structural safeguards: pairing avoidant decision-makers with rational counterparts in deliberation workflows, requiring documented justification for decisions adopted from AI recommendations, or instituting a human sign-off step before AI recommendations are enacted on consequential actions. These structural measures address a tendency that training alone cannot fully correct.

For AI product and platform teams, different decision-making styles require different forms of AI system support. Intuitive decision-makers translate trust in AI into reliance only when trust is established, indicating that they are sensitive to system credibility cues. Users with higher AI literacy use AI input more effectively when they have access to information about AI reasoning and limitations. AI product teams should therefore build explainability features that surface AI confidence levels, known failure modes, and the reasoning behind recommendations. For users with high AI literacy, these features support diagnostic interpretation of AI output. For users with lower AI literacy, default interface behaviors such as prominently flagging low-confidence outputs, displaying ranges rather than point estimates, and offering "verify this output" prompts can provide protection without requiring the user to assess the AI's reliability unaided.

Across these three recommendations, a common principle emerges from the findings: reliance on generative AI does not in itself improve decision quality or business outcomes. What matters is whether reliance is calibrated to the situation, whether the user has the analytical capacity to evaluate AI output, and whether the organizational context provides appropriate guardrails for users whose decision-making style predisposes them to over-rely. Organizations integrating generative AI should therefore treat AI literacy, analytical competence, decision-style awareness, and system-level safeguards as complementary rather than substitutable.

5.3 Research Limitations and Future Work

This research has several limitations that should be acknowledged when interpreting the findings.

First, several alternative explanations for the observed patterns warrant consideration. Novelty effects may have influenced the results: for many participants, the AI advisor was the first task-specific generative AI tool they had encountered, which may have inflated initial trust and reliance estimates relative to what would be observed among routine AI users. Learning effects may also be present, as reliance may evolve across the seven consultation rounds as participants observe AI accuracy in real time; the aggregate reliance measure used in the participant-level analyses does not separate early naive reliance from later calibrated reliance. Self-selection is a further consideration, as participation was voluntary within the Management of Analytics and Data Technologies (MADT) program, which may have produced a sample biased toward higher AI literacy and openness to AI than the general workforce. Finally, the mandatory consultation design produces a conservative test of reliance variance; in unconstrained settings where AI consultation is optional, the effects of low trust or low literacy on reliance may be substantially larger. These factors should temper any practical generalization of the findings.

Second, the study is limited by a relatively small sample size of 52 participants, all drawn from a single academic program. This sample size is below the threshold conventionally required for moderated regression analyses to detect medium effects with adequate power. A power analysis for moderated regression with two predictors and one interaction at $\alpha = .05$ and $1 - \beta = .80$ requires approximately $N = 89$ to detect a medium effect ($f^2 = .15$) and $N = 395$ to detect a small effect ($f^2 = .02$). Future research should therefore extend this work to a larger and more diverse sample, ideally drawn from multiple organizational and academic contexts, to test whether the avoidant-reliance pattern and the moderating role of analytical experience replicate outside an academic sample. A larger sample would also enable Structural Equation Modeling of the full conceptual model with adequate statistical power, allowing latent and indirect effects that are not detectable through the regression analyses conducted in this study to be examined.

Third, the MonsoonSIM platform offers limited configuration options and a complex underlying mechanism for product demand, the calculation of which is not fully documented by the platform's developers. This limits the ability to standardize the simulation environment across game sessions and introduces minor inconsistencies in product demand between sessions that may affect the comparability of results. Future research could consider developing a customized business simulation environment that provides greater transparency and control over key variables, enabling more precise examination of phenomena such as supply shortages, demand elasticity, and inventory management strategies under AI-assisted decision-making.

Finally, this study does not directly investigate the consequences of under-reliance or over-reliance on generative AI for downstream decision-support outcomes. Although the moderating role of analytical experience suggests that calibration matters, the study does not explicitly identify the threshold at which reliance shifts from helpful to harmful. As generative AI becomes more integrated into business and educational decision-making, future research should examine how patterns of under-reliance and over-reliance affect learning outcomes, decision quality, and organizational performance, providing more direct guidance on appropriate AI use.

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