

**THE PSYCHOLOGICAL IMPACT OF AI ON MANAGERIAL
DECISION CONFIDENCE: A BEHAVIORAL STUDY**

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Dedication

This study is wholeheartedly dedicated to my family and mentor whose unwavering support, patience, and encouragement made this journey possible. Their belief in me sustained me through the challenges of this work.

I am deeply grateful for family's sacrifices, mentor's continuous advice and support to finish this study.

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ABSTRACT

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Abstract

The increasing integration of artificial intelligence (AI) into organizational decision-making has significantly transformed managerial processes, particularly in enhancing decision confidence. This study examines the psychological impact of AI-supported decision systems on managerial decision confidence by analysing the roles of technological usage, psychological perceptions, behavioural responses, and individual differences. Drawing on the Technology Acceptance Model (TAM), Attribution Theory, and Signaling Theory, a comprehensive framework is developed to explain how AI influences managerial cognition and confidence.

A quantitative research design was adopted using a structured questionnaire administered to 280 managerial professionals across multiple industries. Data were analysed using SPSS, employing descriptive statistics, reliability and validity testing, correlation, regression, and moderation analysis through PROCESS Macro Model 1. The findings reveal that AI-supported decision systems usage has a significant positive effect on managerial decision confidence ($\beta = 0.415$, $p < 0.001$), explaining 17.3% of the variance. Among psychological factors, trust in AI ($\beta = 0.484$, $R^2 = 0.235$) and perceived reliability ($\beta = 0.471$, $R^2 = 0.222$) exert strong positive effects, while risk perception has a significant negative impact ($\beta = -0.364$, $R^2 = 0.133$). Behavioural responses also play a critical role, with AI reliance positively influencing decision confidence ($\beta = 0.377$, $R^2 = 0.142$) and AI resistance negatively affecting it ($\beta = -0.363$, $R^2 = 0.131$). However, moderation analysis indicates that managerial experience ($\beta = 0.073$, $p = 0.190$) and familiarity with AI ($\beta = 0.033$, $p = 0.567$) do not significantly moderate the relationship between AI usage and decision confidence.

The study contributes to the literature by extending TAM to post-adoption cognitive outcomes and integrating psychological and behavioural dimensions into AI-supported decision-making research. Practically, the findings highlight the importance of fostering trust,

minimizing perceived risks, and encouraging constructive engagement with AI systems to enhance managerial effectiveness.

Keywords: *Artificial Intelligence, Managerial Decision Confidence, Trust in AI, Perceived Reliability, Risk Perception, AI Reliance, AI Resistance, Technology Acceptance Model (TAM).*

TABLE OF CONTENTS

Abstract.....	vi
List of Tables.....	xii
List of Figures	xiii
Chapter 1: Introduction	1
1.1. Research Background	1
1.1.1. <i>Artificial Intelligence and Its Growing Role in Organizations</i>	1
1.1.2. <i>Managerial Decision-Making in the Age of AI</i>	4
1.1.3. <i>Psychological Dimensions of AI Adoption</i>	7
1.1.4. <i>Decision Confidence and Its Organizational Importance</i>	10
1.1.5. <i>Behavioural Responses to AI-Supported Decision-Making</i>	11
1.1.6. <i>Need for Investigating Psychological Impact on Decision Confidence</i>	13
1.2. Problem Statement	15
1.3. Research Aim	19
1.4. Research Objectives.....	20
1.5. Research Questions	20
1.6. Research Scope	20
1.7. Research Significance	22
Chapter 2: Literature Review	24
2.1. Introduction.....	24
2.2. Artificial Intelligence in Organizational Decision-Making	26
2.3. Managerial Decision-Making and Decision Confidence	31
2.3.1. <i>Managerial Decision-Making</i>	31
2.3.2. <i>Decision Confidence in Management Context</i>	35
2.4. AI Usage and Its Influence on Managerial Decision Confidence.....	40
2.5. Psychological Factors Affecting Decision Confidence.....	43
2.5.1. <i>Trust in Artificial Intelligence</i>	43
2.5.2. <i>Perceived Reliability of AI Systems</i>	47
2.5.3. <i>Risk Perception in AI-Assisted Decision-Making</i>	50
2.6. Behavioral Responses to AI-Assisted Decision-Making	53
2.6.1. <i>Automation Bias and Over-Reliance on AI</i>	53
2.6.2. <i>Algorithm Aversion and Resistance to AI</i>	55
2.6.3. <i>Human-AI Interaction and Behavioral Adaptation</i>	58
2.7. Individual Differences in AI Adoption	60

2.7.1.	<i>Role of Managerial Experience</i>	60
2.7.2.	<i>Familiarity and Technological Competence with AI</i>	63
2.8.	Theoretical Framework	66
2.8.1.	<i>Technology Acceptance Model (TAM)</i>	66
2.8.2.	<i>Attribution Theory</i>	67
2.8.3.	<i>Signaling Theory</i>	68
2.8.4.	<i>Integrated Theoretical Framework</i>	69
2.9.	Research Gap Identification.....	69
2.10.	Conceptual Framework and Hypotheses Development	74
2.10.1.	<i>AI-Supported Decision Systems Usage and Managerial Decision Confidence</i> 75	
2.10.2.	<i>Trust in AI and Managerial Decision Confidence</i>	76
2.10.3.	<i>Perceived Reliability of AI and Managerial Decision Confidence</i>	77
2.10.4.	<i>Risk Perception and Managerial Decision Confidence</i>	77
2.10.5.	<i>AI Reliance and Managerial Decision Confidence</i>	78
2.10.6.	<i>AI Resistance and Managerial Decision Confidence</i>	78
2.10.7.	<i>Moderating Role of Managerial Experience</i>	79
2.10.8.	<i>Moderating Role of Familiarity with AI</i>	80
2.11.	Summary	80
Chapter 3:	Methodology	82
3.1.	Introduction.....	82
3.2.	Research Philosophy	83
3.3.	Research Approach	84
3.4.	Research Design.....	85
3.5.	Population and Sampling	86
3.5.1.	<i>Target Population</i>	86
3.5.2.	<i>Sampling Technique</i>	87
3.5.3.	<i>Sample Size</i>	87
3.6.	Data Collection Method.....	88
3.7.	Instrument Design.....	92
3.8.	Data Analysis Techniques	96
3.8.1.	<i>Preliminary Analysis</i>	96
3.8.2.	<i>Descriptive Statistics</i>	97
3.8.3.	<i>Normality Analysis</i>	97
3.8.4.	<i>Common Method Bias (CMB)</i>	98
3.8.5.	<i>Reliability Analysis</i>	98
3.8.6.	<i>Validity Analysis</i>	98
3.8.7.	<i>Correlation Analysis</i>	99
3.8.8.	<i>Regression Analysis</i>	100

3.8.9. <i>Moderation Analysis</i>	100
3.9. Ethical Considerations	101
3.10. Limitations of Methodology	102
3.11. Summary	103
Chapter 4: Results	105
4.1. Introduction.....	105
4.2. Demographic Characteristics	106
4.2.1. <i>Age</i>	106
4.2.2. <i>Gender</i>	107
4.2.3. <i>Industry Type</i>	108
4.2.4. <i>Managerial Experience</i>	110
4.3. Preliminary Data Analyses	111
4.3.1. <i>Descriptive Statistics</i>	111
4.3.2. <i>Normality Analysis</i>	113
4.3.3. <i>Common Method Bias (CMB)</i>	115
4.3.3. <i>Reliability Analysis</i>	116
4.3.5. <i>Exploratory Factor Analysis</i>	117
4.4. Correlation Analysis.....	121
4.5. Data Analysis for RO1	123
4.6. Data Analysis for RO2	125
4.7. Data Analysis for RO3	129
4.8. Data Analysis for RO4	132
4.9. Hypotheses Testing	135
4.10. Summary	136
Chapter 5: Discussion	138
5.1. Introduction	138
5.2. Discussion of Research Objective 1: AI-Supported Decision Systems Usage and Managerial Decision Confidence	139
5.3. Discussion of Research Objective 2: Psychological Factors Influencing Managerial Decision Confidence	143
5.4. Discussion of Research Objective 3: Behavioural Responses to AI and Managerial Decision Confidence	146
5.5. Discussion of Research Objective 4: Moderating Role of Managerial Experience and Familiarity with AI	148

5.6. Theoretical Implications.....	150
5.7. Practical Implications.....	153
5.8. Summary	156
Chapter 6: Conclusion.....	158
6.1. Introduction	158
6.2. Summary of Data Findings	159
6.3. Limitations of the Study	161
6.4. Future Research Directions	163
6.5. Conclusion.....	165
REFERENCES	167
Appendix 1: Survey Questionnaire.....	207

List of Tables

Table 1: Research Variables	75
Table 2: Age of Respondents	106
Table 3: Gender of Respondents	107
Table 4: Industry Type of Respondents.....	108
Table 5: Managerial Experience of Respondents.....	110
Table 6: Descriptive Statistics of all Variables (N=280).....	111
Table 7: Normality Test for all Variables	114
Table 10: KMO and Bartlett's Test for a Sample Adequacy	117
Table 11: Factor Loadings.....	118
Table 12: Construct Reliability using Composite Reliability (CR) and Validity using Average Variance Extracted (AVE).....	120
Table 13: Correlation Test.....	121
Table 14: Regression Analysis for H1 (AI-SDSU $\rightarrow$ MDC).....	124
Table 15: Regression Analysis for H2 (T-AI $\rightarrow$ MDC).....	126
Table 16: Regression Analysis for H3 (PR $\rightarrow$ MDC).....	127
Table 17: Regression Analysis for H4 (RP $\rightarrow$ MDC).....	128
Table 18: Regression Analysis for H5 (AI-REL $\rightarrow$ MDC).....	130
Table 19: Regression Analysis for H6 (AI-RES $\rightarrow$ MDC).....	131
Table 20: Moderation Analysis for H7 (AI-SDSU $\times$ ME $\rightarrow$ MDC).....	133
Table 21: Moderation Analysis for H8 (AI-SDSU $\times$ F-AI $\rightarrow$ MDC).....	134
Table 22: Summary of Hypotheses Testing	135

List of Figures

Figure 1: Conceptual Framework	74
Figure 2: Age of Respondents (Pie-Chart).....	107
Figure 3: Gender of Respondents (Pie-Chart)	108
Figure 4: Industry Type of Respondents (Bar Chart).....	109
Figure 5: Managerial Experience of Respondents (Bar Chart).....	110

Chapter 1:

Introduction

1.1. Research Background

1.1.1. Artificial Intelligence and Its Growing Role in Organizations

Artificial intelligence (AI) has often shifted into contemporary organizational cultures by allowing automation of critical tasks and data-based decision-making. In the current decade, developments in predictive analytics, natural language processing, and machine learning have permitted AI systems to practice operational assistance and enter the segment of strategic decision-making. Firms increasingly depend on AI tools to examine broad datasets, determine patterns, and produce overviews that inform managerial decisions. Such enhancing reliance has made the managers discuss data, assess the substitutes, and finally make the decisions (Davenport & Ronanki, 2018). At the same time, AI systems seem more cultured and rooted in organizational processes; their role extends beyond technical efficiency to psychological and cognitive aspects of managerial behaviour.

The modern business culture is characterized by enhancing VUCA (“volatility, uncertainty, complexity, and ambiguity”), which has substantially accelerated the incorporation of AI technologies throughout sectors. Firms are not only implementing AI for cost reduction or automation. In the current scenario, AI is being used to assist with higher-order cognitive roles, including scenario analysis, strategic planning, and forecasting. The alignment of AI into business processes like BI (“Business Intelligence”), CRM (“Customer Relationship Management”), and ERP (“Enterprise Resource Planning”) platforms has allowed predictive perspectives and real-time data processing, primarily changing the way organizations stress the decision-making (Jarrahi, 2018).

AI-based tools such as intelligent dashboards, predictive analytics engines, and recommendation systems are increasingly being implemented in managerial practices. Therefore, such processes are capable of producing a wide quantity of unstructured and structured information, thus facilitating managers' valuable perspectives that were impossible via conventional analytical approaches. As an outcome, decision-making seems more data-based, decreasing dependency on completely experience-driven or intuitive judgments. Additionally, such transformation raises complex questions about the extent to which managers assess and discuss AI results, particularly when such results come from critical and dense algorithms usually interpreted as black boxes (Logg et al., 2019).

AI's democratization seems to be another important factor via low-code/no-code platforms and user-friendly interfaces, which enable non-technical managers to be involved with AI processes. Additionally, AI presents barriers regarding misinterpretation, inadequate complex analysis, and overconfidence in system outputs, while such availability promotes the application of AI (Regona et al., 2026). Simultaneously, the AI's influence in an organization is technical and highly associated with human behaviour and cognition, requiring an examination of its psychological applications.

The fast growth of AI tools has shifted operational competence and also interpreted organizational knowledge environments. New firms highly perform as data-based entities where data moves consistently throughout departments, allowing adaptive decision-making and practical overviews. Thus, AI possesses a crucial role in such progress by performing as a skill augmentation technique that promotes human cognitive competencies (Shrestha et al., 2019). Hence, AI systems lead to determining unseen correlations, sense anomalies, and produce predictive frameworks that report managerial policies through improved analytics.

Furthermore, the spread of big data infrastructures and cloud computing has substantially improved the availability and scalability of AI solutions. Firms of different sizes, such as SMEs (“small and medium enterprises”), are competent to organize AI-based tools without significant top investments. Such widespread availability has accelerated the adoption of AI in key business roles, such as human resource management, supply chain improvements, financial planning, and marketing analytics (Siau & Wang, 2020). Managers are highly needed to communicate with the intellectual process as part of their routine decision-making because AI seems ubiquitous.

The enhancing influence of AI is another essential factor, with its ability to leverage data-driven management activities. AI provides a more data-focused and objective method, distinct from conventional decision-making methods that largely depend on subjective judgment and previous experiences. Although such transformation focuses on ethical applications, algorithmic bias, and data quality. Therefore, managers need to discuss the AI-produced perspectives and also examine the following information and traditions (Zhang & Dafoe, 2019). Such combined accountability underscores the difficulty of associating AI with organizational decision-making and emphasizes the significance of measuring its psychological effect on managers.

At the same time, the growing dependency on AI has resulted to the development of new organizational structures and roles (like cross-functional analytics groups, AI specialists, and data scientists). Whereas such developments have framed the decision-making authority and organizational hierarchies, usually enhancing collaborative methods and distributing decision processes. As an outcome, managers need to be directed to a more critical decision culture where AI presents as both a collaborator and a tool, fostering what decisions are taken and how they are prosecuted.

1.1.2. Managerial Decision-Making in the Age of AI

From the conventional perspective, managerial decision-making is considered a cognitive system encompassing rational, intuition, experience, and judgment analysis. Although the association of AI presents an emerging dynamic where human decision-makers communication with algorithmic suggestions. Such communication conducts a hybrid decision-making culture where managers need to maintain their personal skills with AI-produced perspectives. On the contrary, AI raises certain issues regarding decreased autonomy, decreased complex thinking, and over-reliance, while it reduces ambiguity and improves decision accuracy (McAfee & Brynjolfsson, 2017). Simultaneously, assessing how managers obtain and apply AI recommendations seems an essential research context, especially in fields where decisions involve organizational and strategic applications.

Managerial decision-making in the changing field of AI-powered organizations is experiencing a philosophical transformation from individual-focus judgment to particular human-AI communication. Conventionally, decision-making theories underscore intuitive judgment, bounded rationality, and rational choice frameworks. Although, AI's inclusion presents an emerging factor where decisions are co-developed via communications between machine intelligence and human cognition (Davenport & Kirby, 2016). Such hybrid decision-making framework necessitates managers to discuss AI-produced suggestions while continuously implementing their own contextual measurement and expertise.

A core barrier in this field is the adjustment of reliance on AI. Therefore, managers need to ascertain when to trust AI results and when to question them, a procedure that necessitates both critical thinking and technical assessment. Decision confidence might strengthen in the circumstances where AI suggestions integrate with managerial intuition (Jarrahi, 2018). On the contrary, there is an inconsistency between AI results and human judgment while managers

encounter cognitive dissonance, results in hesitation or ambiguity in the process of decision-making.

Alongside, the speed where AI systems produce perspectives lead to conduct stress for fast decision-making, possibly decreasing the time accessible for critical evaluation and reflection. Such growth of decision systems may promote efficacy and results in enhanced reliance on AI suggestions and superficial analysis (Junior Ladeira et al., 2026). Apart from that, in high-stakes cultures, like strategic management, healthcare, or finance, the circumstances of such dependency seem substantial, emphasizing the significance of measuring the way AI fosters managerial confidence and cognition.

At the same time, the association of AI with the processes of decision-making possesses applications for responsibility and obligations. The time decisions are fostered by AI, making it challenging to outline duties between technological systems and human managers.

This ambiguity can affect managerial confidence, particularly in situations where decisions lead to negative outcomes (Wilson & Daugherty, 2018). Managers may either over-rely on AI to justify decisions or underutilize it due to fear of accountability, both of which have important psychological implications.

The integration of AI into managerial decision-making processes has introduced a fundamental shift in how decisions are conceptualized and executed. In traditional settings, decision-making was often a linear process involving problem identification, information gathering, evaluation of alternatives, and selection of the optimal solution (Lehto et al., 2021). However, in AI-enabled environments, this process becomes iterative and dynamic, with continuous feedback loops between human judgment and machine-generated insights.

One notable change is the increased reliance on probabilistic reasoning facilitated by AI systems. Managers are now presented with predictive probabilities, confidence intervals, and risk assessments, which require a different cognitive approach compared to deterministic decision-making (Khodabakhshian et al., 2023). This shift necessitates a higher level of statistical literacy and analytical thinking, as managers must interpret complex outputs and integrate them into their decision frameworks. The ability to understand and contextualize AI-generated probabilities becomes crucial for making informed and confident decisions.

Moreover, AI introduces a layer of abstraction that can complicate the decision-making process. Many AI systems operate using complex algorithms that are not easily interpretable, leading to what is commonly referred to as the “black box” problem. This lack of transparency can create uncertainty and reduce managers’ confidence in the system’s recommendations. In response, there is a growing emphasis on explainable AI (XAI), which aims to provide clear and understandable explanations of how AI systems arrive at their conclusions. The adoption of explainable AI is particularly important in high-stakes decision contexts where accountability and transparency are critical.

Another important consideration is the impact of AI on decision-making speed and efficiency (Mohammed et al., 2025). While AI can significantly accelerate the decision process by providing rapid insights, it can also lead to decision fatigue if managers are required to process large volumes of information continuously. This paradox highlights the need for effective information filtering and prioritization mechanisms to ensure that managers can focus on the most relevant insights without being overwhelmed.

Additionally, the collaborative nature of human-AI interaction introduces new challenges related to communication and coordination. Managers must effectively communicate their objectives, constraints, and preferences to AI systems, while also

interpreting and integrating AI outputs into organizational strategies. This bidirectional interaction requires a high level of cognitive flexibility and adaptability, further emphasizing the psychological dimensions of AI-enabled decision-making.

1.1.3. Psychological Dimensions of AI Adoption

The adoption of AI in decision-making is not purely a technological issue but also a psychological one. Managers' responses to AI systems are influenced by cognitive and emotional factors such as trust, perceived reliability, transparency, and risk perception. Trust in AI plays a central role in determining whether managers accept or reject algorithmic recommendations. When AI systems are perceived as accurate and reliable, managers are more likely to rely on them, potentially increasing their decision confidence (Frenkenberg & Hochman, 2025). Conversely, lack of transparency or understanding of AI processes may lead to skepticism or algorithm aversion. These psychological responses shape how managers interpret AI outputs and integrate them into their decision-making processes.

The psychological acceptance and utilization of AI systems are influenced by a range of cognitive, emotional, and social factors. One of the most critical factors is trust, which determines the extent to which managers are willing to rely on AI-generated recommendations (Riva et al., 2025). Trust in AI is multifaceted, encompassing perceptions of competence, reliability, transparency, and ethical considerations. Managers are more likely to trust AI systems that provide explainable outputs, consistent performance, and alignment with organizational goals.

Another important psychological feature is perceived control. When AI is introduced in the decision-making process, it can cause managers to lose control of the results. Although AI may promote perceived control with the help of detailed information and forecasts, it may also decrease it by delegating the decision-making to algorithms (Li & Huang, 2020). This two-way

impact forms a complicated psychological game in which managers can be empowered and inhibited by AI technologies at the same time.

Another factor that is important in the adoption of AI is cognitive load. Although AI is supposed to decrease the cognitive load of data analysis, it may accidentally lead to cognitive load by requesting managers to interpret non-understandable outputs and be aware of underlying assumptions. This cognitive load may have an impact on confidence in decision-making, especially in managers who are not technical (De Freitas et al., 2023). The necessity to learn and keep up with the changing AI systems regularly may result in cognitive exhaustion, which further affects the decision-making process.

Anxiety, skepticism, or enthusiasm are also emotional reactions to AI, which are important in influencing managerial behaviour. Managers who believe that AI is a threat to their independence or employment can become resistant, whereas managers who see AI as a helpful resource can become more accepting and dependent. The organizational culture, the support of leaders, and the previous experiences with technology tend to affect these emotional responses; the contextual factors play a crucial role in adopting AI.

The psychological effects of AI are not limited to the single cognitive processes but also to more extended areas of identity, self-efficacy, and professional competence (Kim & Lee, 2024). With the growing number of roles that AI systems assume that used to be held by humans, the managers can find themselves in a situation where their perceived value and relevance in the organization change. This may cause some uncertainty, anxiety, or even resistance, especially in persons who see AI as a challenge to their skills and authority.

The capacity of a person to believe is a key factor influencing AI response (Fryer et al., 2020). Highly self-efficacious managers tend to believe that AI is a supplementary resource that increases their abilities, and low self-efficacy managers might experience fear or nuisance

of AI systems. Such a difference in self-concept can considerably affect confidence in decisions since the more managers believe they are capable of using AI, the more they will believe in its results and apply them to make their decisions.

The other key psychological component is the notion of cognitive trust against affective trust. Cognitive trust is founded on the rational assessment of the performance and reliability of AI, whereas affective trust is determined by the emotional reaction and the personal experience (Park et al., 2021). The two types of trust are critical to the successful adoption of AI since they dictate the degree to which managers will be ready to trust AI suggestions. As an example, cognitive trust can be developed through the consistent and reliable performance of AI systems, and affective trust can be boosted by positive user experiences.

Mental models also play an important part in comprehending the interaction between managers and AI (Gerlich, 2023). Mental models are the internal representations that individuals apply in the process of comprehending and interpreting complex systems. Managers who have the correct mental model of AI are in a better position to interpret its outputs and predict its limitations to make informed and confident decisions. Incorrect or unfinished mental models may lead to misinterpretations, misuse, and a lack of trust.

The psychological reactions may depend on the social situation where AI is introduced. The perceptions and behaviour of managers can be influenced by peer influence, norms, and leadership attitudes towards AI. Managers tend to gain a positive attitude and increase the degree of trust in the organization in which the adoption of AI is promoted and reinforced. AI is perceived with suspicion or opposition; managers might not be willing to adopt it.

1.1.4. Decision Confidence and Its Organizational Importance

Decision confidence can be described as the level of confidence that a manager possesses regarding the accuracy or effectiveness of the decisions (Kim & Lee, 2024). It is a decisive aspect that determines the quality of decisions, the success of implementation, and the results of an organization. When the confidence in the decision is high, it may cause decisive actions and successful performance, and when the confidence is low, it may cause indecisiveness, procrastination, or poor decision-making. The implementation of AI in decision-making can either boost or decrease confidence in the decisions made. AI may give evidence-based information that can support managerial decisions. Conversely, non-congruent recommendations between the human intuition and AI results could lead to uncertainty and decrease confidence. The impact of AI on decision confidence is important to explore the expanded influence of AI on organizational performance.

Decision confidence is not only an individual-level phenomenon but a collective one that contributes to the organizational culture and performance (Zhang et al., 2023). The trust of individual managers in a team decision-making situation may influence the dynamics of the group, communication styles, and quality of decisions. The discussion and the decisions made by the group of people, whereas less confident ones can be reluctant to express their views, which can narrow the range of opinions.

The aspect of introducing AI in the decision-making process introduces an additional dimension to this dynamic. AI systems have the potential to be a source of validation or challenge to the managerial decision, and both individual and collective levels of confidence may be affected (Rezaei et al., 2025). AI results cause a conflict between group views; they may cause tension and uncertainty that need to be negotiated and discussed very carefully.

The role of feedback in the formation of decision confidence. Managers can also learn and adapt faster as AI systems can give instant feedback on decision outcomes (Giaccone et al., 2024). This is a continuous feedback loop that can help to improve learning and decision-making skills in the long term. It is also prone to overconfidence when managers may be over-dependent on the positive feedback without the critical assessment of underlying assumptions.

The association between confidence in making a decision and risk-taking behaviour is also specifically applicable in the case of AI. Highly confident managers tend to get involved in risk-taking behaviours, which may fuel innovation and growth (Giaccone & Magnusson, 2022). Lack of confidence could lead to risk aversion, which constrains organizational agility and competitiveness.

The accountability and ethical issues are closely connected with decision confidence. The shared responsibility between humans and machines can be unclear in AI-enabled environments, and this influences how managers view and make their own decisions. This uncertainty may affect the level of confidence, especially in cases where the decision is ethical or social in nature.

1.1.5. Behavioural Responses to AI-Supported Decision-Making

The behavioural responses of managers working with AI systems are different (Queiroz et al., 2024). Moreover, managerial behaviour can be influenced by the perceived role of AI, which can be in the form of a supportive tool or a decision-maker. The relevance of learning these behavioural patterns is to determine the influence of AI integration on the outcomes of decisions.

The communication between AI systems and managers leads to various behavioural reactions, which may have a great effect on the decision-making processes. Automation bias is

one of the most popular phenomena: people are more likely to overuse automated systems and accept their advice without more thorough examination. Such action can cause mistakes, especially when there are mistakes or biased results of the AI systems. The perceived authority and accuracy of AI systems and the perceived cognitive ease of accepting automated recommendations are often the drivers of automation bias (Araujo et al., 2020).

Conversely, algorithm aversion is a propensity to mistrust AI recommendations, even in instances where they are right. This tendency is frequently conditioned by the negative experience with AI, ignorance, or human preferences. Managers with algorithm aversion can underperform AI systems, thus failing to gain their possible advantages. The major issue in AI-assisted decision-making is balancing between these conflicting behaviours.

The other significant behavioural response is selective reliance, whereby managers prefer to depend on AI in some situations but not others. The use of a selective approach depends on the complexity of the task, the perceived risk, and the belief in personal expertise. As an example, managers can use AI in processes that are more heavily focused on data.

The social and organizational factors contribute quite substantially to the development of behavioural reactions to AI as well (Bankins et al., 2024). The organizational culture, leadership support, and peer influence may influence the way managers see and use AI systems. Within the company where innovation and the adoption of technologies are encouraged, the managers have a higher likelihood of adopting AI and incorporating it into decision-making.

The way people behave in response to decisions made with the aid of AI is determined by the intricate interaction of cognitive biases, emotional reactions, and situational factors. Confirmation bias is one of these behaviours, which the managers only choose to interpret AI outputs in a manner that supports their existing belief that already exists.

Adaptive learning is another applicable behaviour in which managers change their dependency on AI according to previous experiences and results. In such a way, a good experience with AI can result in trust and dependence, whereas a bad experience can result in skepticism and decreased use (Park & Yoon, 2025). This dynamic process shows the significance of experience and feedback in the development of behavioural responses.

Another notion that can be used in the interpretation of behavioural responses is that of human-AI supplementary. AI as a substitute for human decision-making, it is also becoming more widely accepted as a supplementary tool that improves human capabilities. Managers who take this view will find it easier to make decisions in a collaborative way, combining the power of the human instinct with machine intelligence.

1.1.6. Need for Investigating Psychological Impact on Decision Confidence

Although there is increased use of AI in organizations, there is a high gap in knowledge about its psychological effects on the confidence of managerial decisions. A large portion of the available studies has addressed technical performance and efficiency benefits, and little has been done regarding behavioural and cognitive outcomes. Since organizations are increasingly incorporating AI into their decision-making, there is a need to examine the role of these technologies on managerial confidence, trust, and behaviour (Brink et al., 2024). The gap by offering a detailed discussion of the psychological processes by which AI influences decision confidence.

AI is becoming common in organizational decision-making, and there is a significant gap in the psychological effects of AI on managerial decision confidence. The technical performance, efficiency increases, and economic performance and that is consideration the human aspects that govern the adoption and use of AI. This is an especially important gap

considering that decision-making is a human process in nature, which is influenced by cognitive, emotional, and behavioural factors.

Human-AI interaction is a complicated process that requires a multidisciplinary methodology that incorporates the knowledge of psychology, management, and information systems. When considering the effects of AI on the level of confidence in decision-making among managers, it is necessary to consider the individual-level (cognitive bias, emotional response) and the organizational-level (culture, governance structures) factors (Zhang & Zhu, 2025). This approach is critical in the creation of effective strategies to incorporate AI in the decision-making processes without compromising on the optimal levels of confidence and performance. AI technologies keep developing; they are bound to have a stronger effect on managerial roles and responsibilities. The changing role highlights the necessity of providing managers with the skills and knowledge required to communicate with AI systems successfully.

The results have significant practical consequences for organizations that intend to make the most of AI. The decision confidence levels, organizations may develop AI systems and learning activities that increase the level of trust, decrease cognitive load, and ensure effective decision-making (Rezaeian et al., 2026). This is a better performance and competitiveness within the organization.

The psychological effects of AI on confidence in managerial decisions are not a simple and one-sided problem. With the further development of AI and its more active penetration into the organizational process, the perception of how AI affects the cognition and behaviour of people will be prerequisite to the effective and responsible use of AI.

1.2. Problem Statement

The fast adoption of AI in organizational decision-making has brought a paradigm shift in the way managers make decisions. The shift has also come with a set of concerning issues that are not thoroughly comprehended, especially psychologically (Davenport & Ronanki, 2018). Given the efficiency, speed, and analytical benefits of AI systems, it is possible to identify a significant gap in terms of the effect that these systems have on confidence in managerial decisions. The majority focuses on performance metrics and technological features and usually overlooks the cognitive and behavioural aspects that define how managers perceive, trust, and respond to AI-driven insights (Jarrahi, 2018). Decision-making is a human-centric process that depends on perception, judgment, and psychological states and not just on technical inputs.

The impact of AI on managerial confidence in the situation of decision-making is one of the significant gaps. The fact that AI systems are created to improve the quality of decision-making via data-driven information means that they can also create uncertainty (Logg et al., 2019). Managers are usually asked to make meaning of complex algorithmic outputs that might not be transparent, which creates confusion over the process of concluding. The fundamental problem with the black box nature of most AI systems is that managers might be unable to comprehend or defend AI-based recommendations in full (Regona et al., 2026). AI may at times destroy it, especially when a decision-maker does not feel linked to the logic behind the results. The use of AI tools is increasingly becoming a dependency, and the influence of this lack of interpretability on the level of managerial confidence is a shortage.

The great importance is that there is a lack of psychological aspects of trust, perceived dependability, and risk perception in decision-making. Trust is generally known as a major factor in the adoption of technology, but trust in AI is multifaceted. The managers need to

consider both the accuracy of AI outputs and their consistency, fairness, and alignment with company objectives (Shrestha et al., 2019). Lack of transparency and explainability of most AI systems also creates a lack of trust, especially in high-stakes decision-making settings. The dynamic and changing character of AI technologies does not allow managers to establish stable trust perceptions over the course of time (Siau & Wang, 2020). This discrepancy can lead to unstable levels of confidence, as managers might be overconfident with AI or completely dismiss it. These psychological processes signify a great gap in the knowledge of the effects of trust and other aspects on confidence in decisions.

The aspect of trust is another significant gap that managers face when communicating with AI-assisted decision-making. The behavioural changes in managerial decision-making related to the AI inputs, especially when it comes to dependence, opposition, and mental (Zhang & Dafoe, 2019). As an example, the lack of automation bias, whereby people are more likely to trust automated systems, may translate into following AI advice and thus make erroneous judgments. Algorithm aversion can make managers stop AI insights even when they are accurate and useful. These conflicting behavioural patterns form a multifaceted decision-making situation where managers have to alter between human judgment and machine intelligence at all times (McAfee & Brynjolfsson, 2017). The specific direct relationship between these behaviours and the confidence in their decision-making is scarce, especially in the organizational context.

The other major issue is that the correlation between the use of AI and managerial confidence in making decisions is not clear, particularly when individual differences like experience and familiarity with AI are consideration. The technological competence, cognitive styles, and openness to innovation of managers differ significantly and may affect their views on AI systems and the ways they use them. Seasoned managers might be more intuitive by

previous experience, and thus less amenable to AI-based recommendations, whereas inexperienced managers might be more susceptible to AI-based suggestions (Junior Ladeira et al., 2026). AI technologies may increase knowledge and trust, which boosts confidence, and the opposite may happen with the absence of such knowledge. The information on how individual differences mediate the association between AI application and confidence in decision making (Wilson & Daugherty, 2018). The capacity of organizations includes specific interventions and training programs that can be used to meet various managerial requirements.

The AI in the decision-making process also creates the issue of cognitive overload and information complexity. AI systems are expected to make the process of decision-making simpler by offering managers relevant insights; they may also help managers with loads of data and analytical results. These outputs are difficult to interpret and demand a high amount of cognitive effort, especially in cases where the managers do not possess technical expertise (Riva et al., 2025). Although the role of cognitive load is increasingly recognized as one of the most crucial determinants of effective decision-making, the impact of cognitive demands caused by AI on managerial performance and confidence is lacking.

The issue of accountability and responsibility also complicates the problem. In AI-assisted decision-making conditions, it is not always clear who should be responsible for the human decision-maker or the system. This uncertainty may cause mental uneasiness and decrease confidence, especially where the decisions made are of great organizational or ethical consequences. Managers might be disinclined to trust AI since they are afraid of being responsible for making decisions that are dependent on an algorithm that are fully comprehend. There is a possibility that certain managers will misuse AI as a way of hiding accountability (Li & Huang, 2020). This problem is further heightened by the absence of clear governance

structures and principles of AI application, which reveals the urgent gap in research and practice.

The ethical and social aspects of AI in decision-making are becoming a point of concern. Algorithms' bias, data privacy, and fairness are some of the issues that may affect the way managers perceive AI systems and their readiness to use them. When managers feel that AI outputs are biased or unethical, they can lose a lot of trust and confidence in the system (Frenkenberg & Hochman, 2025). The effects of these ethical considerations on the confidence of managerial decision-making, especially in different organizational setups.

The other weakness is that there are no context-specific analyse the psychological impact of AI in the context of various industries and organizational environments. The controlled conditions or particular industries, and hence, the generalizability of the results is restricted. The organizational culture and the support of the leadership. The industry-specific considerations could play a crucial role in the way managers engage with AI systems and the level of their confidence in their choice (Mohammed et al., 2025). The design includes effective measures to integrate AI that would provide an added value to, and not a burden to, decision confidence.

The confidence of managerial decisions changes over time as a result of the continued exposure to AI systems, which is lacking. The majority is cross-sectional in nature, which means that it only provides a view of the correlation between AI use and decision confidence. The dynamic quality of human-AI interaction, such as trust, familiarity, and confidence, can vary as managers become more accustomed to AI technologies (Khodabakhshian et al., 2023). These temporal dynamics are crucial to the development of sustainable strategies of AI adoption that can lead to the success of an organization over time.

Considering such restrictions, we state that an urgent necessity is the development that explores the psychological effect of AI on the confidence of managers in their decisions. This gap is crucial to comprehend the impact of AI not only on a final decision but also on cognition and decision-making behaviour, which determines the effectiveness of decision-making (Lehto et al., 2021). The consideration of such aspects as trust, perceived reliability, behavioural reactions, and individual differences can bring a more insightful perspective to the challenges and opportunities that are linked to the adoption of AI in the organizational setting.

Finally, the absence of this field is very risky to organizations. A lack of knowledge about the influence of AI on managerial confidence can lead companies to such problems as poor quality of the decisions, a lack of employee engagement, and the unwillingness to change technology. Fill these gaps by offering empirical evidence on the psychological processes involved in influencing the confidence of decisions made in an AI-assisted setting. Expected to not only inform the field of study but also to have practical uses in contemporary organizations.

The scope is clarified to offer a clear demarcation when exploring the psychological effects of AI on decision confidence in managers, and depth, relevance, and methodological feasibility. The main aim is to comprehend the role of AI on the cognitive, psychological, and behavioural aspects of decision-making processes among managers in the organizational setting. The research is set to include both direct and indirect impacts of AI use on decision confidence, and specifically the interaction between technological inputs and human judgment.

1.3. Research Aim

This research aims to evaluate the AI's psychological impact on managerial decision confidence, with a stress on measuring the way AI fosters behavioural responses, trust, and cognitive perceptions in decision-making.

1.4. Research Objectives

- To examine the influence of AI-supported decision systems usage on managerial decision confidence in organizational decision-making.
- To analyze the effects of key psychological factors, namely trust in AI, perceived reliability, and risk perception on managerial decision confidence.
- To investigate how behavioral responses to AI-assisted decision-making, particularly AI reliance and AI resistance, affect managerial decision confidence.
- To assess whether individual differences, specifically managerial experience and familiarity with AI, moderate the relationship between AI-supported decision systems usage and managerial decision confidence.

1.5. Research Questions

- How does AI-supported decision systems usage influence managerial decision confidence in organizational decision-making?
- How do key psychological factors, namely trust in AI, perceived reliability, and risk perception affect managerial decision confidence?
- How do behavioral responses to AI-assisted decision-making, specifically AI reliance and AI resistance, influence managerial decision confidence?
- Do individual differences, particularly managerial experience and familiarity with AI, moderate the relationship between AI-supported decision systems usage and managerial decision confidence?

1.6. Research Scope

The formulated to establish a clear focus of exploration of the psychological effect of AI on managerial confidence in decisions made, as well as provide depth, relevance, and methodological feasibility. The main areas the cognitive, psychological, and behavioural aspects of decision-making by managers in organizational settings in the context of AI. The

constructed in a way that it will be able to address both direct and indirect impacts of AI use on decision confidence, and specifically on how the technological inputs interact with human judgment.

The aspect of integrating AI-driven decision-making systems and their effects on the level of managerial confidence. The following psychological constructs: trust in AI, perceived reliability, risk perception, and behavioural reactions, such as relying on AI and opposition to algorithmic recommendations. These variables are examined concerning their effect on the confidence in decisions, which is deemed to be the main dependent variable. Incorporating these constructs offers a full view of the AI impact not only on the results of a decision but also on the psychological mechanisms that drive managerial behaviour.

The organizational environments in which managers are actively involved in using AI-driven tools and systems to make decisions. It also covers the settings in which AI is employed in the analysis of data, predicting, strategic planning, or operational decision support. The technical analysis of AI systems, rather, focuses on how humans experience these technologies. The behavioural and cognitive consequences of AI, instead of its computational or algorithmic properties.

The personal differences between the managers, especially their experience and familiarity with the AI technologies. These variables are viewed as moderating factors that could affect the way managers view and use AI systems. There is no universal managerial decision confidence, and it can be different based on individual factors, technological skills, and previous experiences with AI. The influence of these personal traits on the correlation between the use of AI and confidence in decisions.

1.7. Research Significance

The importance is that it fills a vital and open gap at the crossroads of AI, psychology, and managerial decision-making. As organizations continue to incorporate AI in their decision-making processes, its effects are not only limited to the technological efficiency but also to the human cognition, behaviour, and confidence. The significance of making the transition towards the performance-based assessment of AI psychological aspects that eventually lead to the effective use of these technologies in the managerial setting.

The knowledge in behavioural science, decision theory, and information systems. The AI, in terms of technology or operations are highlight the psychological processes by which AI impacts confidence in managerial decisions. The human-AI interaction by investigating such constructs as trust in AI, perceived reliability, risk perception, and behavioural responses. It provides a theoretical basis for subsequent research that may contribute to investigating the cognitive and emotional factors of technology adoption, thus adding value to the developing area.

The significant empirical value as it offers data-driven findings regarding the perception and reaction of managers towards AI-assisted decision-making systems. The help of a quantitative method analyses the connections between AI use and decision confidence systematically. The moderating impact of individual differences, which include experience and familiarity with AI. The assumptions in the literature provide a more subtle insight into the circumstances under which AI can foster or impair managerial confidence. Consequently, that is helps in filling the gap between theory and reality.

The great use of AI technologies for any organization that wants to use AI technologies efficiently. Most organizations have spent a lot of money on AI systems, but fail to consider the human aspect that affects successful adoption. The value of psychological preparedness,

trust-building, and behavioural adjustment in the process of ensuring that AI tools are utilized effectively. Designing AI systems that are not only technically complete but also easy to use and psychologically acceptable by determining which factors should be used to determine the confidence of the decisions made by the managers. These insights can be used to create training programs, improve the transparency of the system, and create conducive environments that may instil confidence in the use of AI to make decisions in organizations.

The psychological effects of AI on the confidence of managerial decisions. It helps to fill a severe gap in the literature and offers valuable insights to organizations and managers, which makes it valuable to the academic and practical scope of application. It emphasizes that human factors can be crucial to the successful integration of AI, which eventually can help to make better, more confident, and responsible decisions in contemporary organizations.

Chapter 2:

Literature Review

2.1.Introduction

The process of decision-making within the organization became more effective with the rapid advancement of AI. Before the implementation of AI, decisions in an organization were made based on experience, human intuition, and gut feeling. Nowadays, AI makes decisions by analyzing large amounts of related data. The efficiency of management in an organization was enhanced with the use of AI. The behavioral and psychological dimensions of the manager's decision-making in an organization were influenced by AI technologies embedded in managerial functions. The research focused on the impact of AI in decision-making contexts based on human cognition and confidence, helping to understand the functional benefits of AI.

The confidence of managers in the decision-making process depends on the actions they take after making a particular decision in an organization, based on their confidence in the decision. The confident managers were able to accept responsibility for the decision's outcome. Various significant factors, such as experience, available information, cognitive judgment, and perceived risk, play a major role in enhancing the manager's confidence in the decision-making process in an organization. The traditional factors considered by managers in the decision-making process were reshaped by the algorithmic inputs provided through AI integration. The decisions made by managers were either supported by AI or challenged their judgment. The causes of uncertainty in the decision-making process were reduced with the use of AI, increasing decision-making confidence. On the other hand, the challenges of ensuring transparency in AI decision-making create ambiguity and skepticism.

Various factors, such as trust in AI systems, individual risk perceptions, and the reliability of algorithmic output, impact the psychological impact of AI on managerial decision-making. The manager's acceptance of AI-generated recommendations depends on establishing trust. The output of decision-making using AI depends on perceived reliability. Trust, reliability, and risk are the three major factors considered by managers when evaluating AI decision-making. The assurance of trust and reliability in the information provided by AI helps enhance decision-making confidence and lowers the risk in the decision-making process. On the other hand, the lack of reliability in AI decisions decreases managers' confidence. The managerial confidence and willingness to accept AI in the decision-making process were significantly dependent on trust, reliability, and risk perception.

The confidence of managers in AI-assisted decision-making depends on psychological factors and managers' behaviour. Managers exhibit varying behaviour, such as combining their own judgment with AI insights, which was preferred by some managers. On the other hand, some managers completely ignore AI decisions. Prior experience in technology, organizational culture, and the perceived role of managers in an organization influences AI within the decision-making framework. The outcomes of AI influence were made clear by the existence of behavioral tendencies.

The interaction between the AI system and managers depends on familiarity with AI technologies and experience level. Established practices and intuition play a major role for experienced managers in making decisions. On the other hand, a manager familiar with technology relies on AI-based insights. The difference between experienced managers and managers who are familiar with technology influences the confidence in using AI in decision-making and forces the need for a nuanced understanding of the various factors that shape the manager's behaviour and confidence in working with AI.

The literature review of the study focuses on analyzing various factors, such as AI in decision-making, psychological factors, manager confidence, and behavioral responses to AI, due to differences in managers' behaviour. The interaction of AI with the human system was explored through various theories related to the study, which helped identify a gap in the current literature. The chapter establishes the conceptual basics for analyzing the development of a robust research framework for the study of the psychological impact of AI on managerial decision-making confidence by synthesizing insights from prior research.

The existence of a complex, multifaceted relationship between AI and manager confidence in decision-making was explored through a review of the literature. The impact of AI on decision-making processes in modern organizations was comprehensively assessed through the integration of psychological, technological, and behavioral perspectives.

2.2.Artificial Intelligence in Organizational Decision-Making

The concept of implementing a decision-making process based on a transformative shift driven by technological advantages such as accuracy, speed, and data processing was explored through an analysis of existing literature on AI. The literature strongly emphasized the technological advances of AI. Gaps and limitations were identified through an analysis of previous literature, particularly regarding managerial behaviour and human cognition.

Page and Kallapur (2025) state that decision-making in an organization by Large Language Models (LLMs) and generative AI is impacted in three major ways: supporting human decisions, replacing human work, and completely disrupting existing processes. On the other hand, the implementation of AI in decision-making sometimes produces hallucinations or is not aligned with the actual goal, and it focuses on exploring the idea of the "inferential dilemma," creating uncertainty in decisions. The complex AI decision-making process was made understandable through the idea of the "inferential dilemma". The study lacks real-world

data and instead focuses more on theoretical concepts. The study acknowledged the opacity of AI reasoning, but the impacts of opacity on managerial confidence were considered central to the present research.

Shrestha et al. (2019) present a clear framework for comparing AI and human decision-making based on major dimensions such as speed, replicability, and interpretability. The aggregated, hybrid, and full delegation are the three major types of decision-making processes used to describe the decision-making process. The existence of collaboration between humans and AI was made clear through the use of a clear framework. On the other hand, the framework ignores major factors such as human behaviour and psychology, and focuses on technical and functional aspects. The decision-making quality was enhanced by the integration of human and AI, predicated on human–AI collaboration in decision-making, but the reality was impacted by the uncertainty caused by the manager's behaviour, which affects confidence in decisions. The human experience of AI integration was lacking in the model, which focused more on structural analysis.

Alshahrani et al. (2024) demonstrate the use of AI in public sector organizations based on a systematic literature review. The scattered research on AI in decision-making was organized efficiently, which was considered a major goal of the study. The comprehensive overview of the field provided the classification of AI used in different government functions. A detailed analysis of decision-making behavior was lacking in the study due to the wide range of topics covered. The impact of human thinking on AI was not deeply explored; the study focuses on challenges such as a fragmented system and difficulties in implementation. The generalizability of the findings was affected by the lack of focus on the public sector, where decision-making processes differed. The study, which focused on AI's decision-making behavior, helps highlight the gap in the research.

Prasanth et al. (2023) explore the benefits of AI in decision-making, focusing on the enablement of data-driven decisions and the enhancement of various factors such as innovation, efficiency, and accuracy. The study lacks a critical analysis of decision-making using AI and adopts an optimistic, descriptive approach. Moreover, the study did not explore various major factors associated with decision-making using AI, such as overreliance, reduced human agency, and decision bias. The study did not explore the manager's interpretation of AI output or the impact of confidence. The gap in the research widened due to the study's one-sided approach. The study did not explore the behavioral and psychological impacts related to AI.

Booyse and Scheepers (2024) revealed that adopting AI in qualitative research helps provide a balanced view of the research. The manager's decisions were affected by a loss of control, poor transparency, and a lack of trust. The human and organizational factors focused on by the study provide greater strength by helping to understand people's reactions to AI. The small sample and qualitative methods used in the study limit its wider application. The quantitative evaluation of decision-making using AI creates a gap in understanding the impact of factors on managers.

Joshi (2025) focused on the integration of theory and technical aspects related to the use of AI in strategic decision-making, which helps provide a detailed review. The analysis was strengthened and made more informative by the inclusion of advanced methods and performance measures. The study lacks a focus on major factors related to humans, instead focusing more on system performance and technical efficiency. Moreover, the study lacks real-world context-specific insights and instead focuses more on existing data and literature. The implementation of technology was given greater priority in AI research on decision-making than on interactions with human beings.

Górka et al. (2025) depicted the impact of AI on decision-making across different industries using real-world evidence. Decisions in an organization were faster and more efficient with the integration of AI into decision-making. Additionally, challenges faced by organizations in implementing AI in decision-making, such as unclear regulations and employee resistance, help provide a balanced view of the problems and benefits. The study explores challenges in adopting AI and focuses on overall organizational enhancement. The study did not explore the impact of manager decision confidence on related behavioral issues. The study lacks analysis of various factors, such as confidence, perception, and trust, related to AI in decision-making.

Baines et al. (2024) demonstrated that a fit-based model helps address the gap by focusing on AI features such as decision environments, human decision makers, and AI as an advisor in decision making. The study explored the real situations managers face in using AI. The manager's behavior in accepting or rejecting the use of AI decision-making was clearly explored in the study. The major challenge in the study is the lack of inclusion of real-world data, which focuses mainly on theoretical considerations, making it difficult to explore decision-making using AI.

Dahlke and Ebersberger (2025) highlight AI research in management by adopting a broader analytical perspective. The study lacked consideration of human factors related to decision-making with AI, focusing instead on the exploration of technological concepts. In comparison with management research, the use of the "double pacing problem" helps predict the rapid growth of advancing technology. The solutions provided by the study for the identified problem focus more on analysis than proving real world insights.

Mekimah et al. (2024) focus mainly on human resource management, business intelligence, and the process of decision making. However, when these areas are fragmented

rather than remaining connected, it creates a gap in the research, especially in combining various fields to study decision-making. The study made the current research trends understandable. The study did not deeply explore the impact of AI on manager behavior. The influence of AI on an organization's decision-making was made clearer through further research that brings together various fields and considers human factors in decision-making.

Agarwal (2025) highlights the impact of AI adoption on the workforce and organization. The successful use of AI depends on the implementation of proper governance and a flexible structure, which was insisted on for future research by the study. The organization's preparation for the adoption of AI was clearly explored in the study. In contrast, the psychological impact of managers on the adoption of decision-making using AI was not clearly illustrated in the study, which focuses more on organizational setup and technology.

In summary, the decision-making process in organizations was made faster, data-driven, and more efficient through the integration of AI. Conversely, the implementation of AI in organizational decision-making was affected by three major limitations. Instead of focusing on human aspects of AI, most studies focus on system performance and technology. The impact of AI on managers' decision-making confidence was explored by only a few studies, which identified the second major challenge in implementation. The major factors impacting the manager's decision confidence, such as trust, transparency, and resistance, were not clearly focuses by the study.

The goal of the current study was matched with the research gap. The main outcome of the study focuses on managerial decision confidence. The earlier study does not focus on risk perception, trust, and perceived reliability, which are considered major psychological factors on in the study. The study examined the real-time behavior of the manager in using AI for

decision-making. The interaction of humans with AI in decision making was provided with a clearer and deeper understanding by the study.

The transformative role of AI in organizational decision-making was briefly explored in the study. Additionally, study focuses more on an integrated human-centered approach, considered a significant part of the study. Both academic knowledge and practical applications of the study were provided, with a comprehensive analysis of the psychological impact of AI on managerial decision-making confidence as the focus of the present research.

2.3. Managerial Decision-Making and Decision Confidence

2.3.1. Managerial Decision-Making

As argued by Zhu et al. (2018), the OIPT views organizations as open systems that manage uncertainties within the decision-making processes to deal with the contextual situations. The open system concept further implies that an organization will not only adapt to the environment, but it also means that inability to adapt or the lack of compatibility undermines the viability of the organization. Zelt et al. (2018) discussed that OIPT sees the difference between management practices and contextual factors as a non-congruence between information-processing capacity and its demands. Vertical information systems can be employed to manage data collected in carrying out any operations without overloading the communication channels and enhance capacity to process information. Conversely, these systems establish the relationship of latitude connections across organizational hierarchies and diminishes decision-making processes. Organizations can process effectively this data with the help of vertical information systems, like an enterprise resource planning (ERP) system. The increased information processing capacity allows organizations to react quickly towards the growing needs of information processing (Srinivasan & Swink, 2018). Lateral connections are supported by information systems that increase information visibility or availability. Srinivasan

and Swink (2018) demonstrated that BI platforms, corporate intranets, or systems that gather valuable and highly updated information sources out of suppliers or clients, enhance information processing abilities, and in turn, leads to improved decision making, and ultimately overall responsiveness of the organization.

Business intelligence (BI) is a group of decision support technologies that attempt to systematically retrieve and transform internal and external systems (sources) into valuable insights to facilitate the making of strategic decisions (Srinivasan and Swink 2018). However, over time, BA has evolved into a data analytics business application and evidence-based identification and resolution of problems by use of the prescriptive, predictive or descriptive analytical methods (Appelbaum et al., 2017). It can also be known as business intelligence and analytics (BI&A), which is either a considerable expansion of BI or sub category of BI that transcends simple reporting systems. With the support of OIPT, certain empirical studies have identified the role of BI&A (Dubey et al., 2021; Yu et al., 2021a, b) and its capacity to handle a greater amount of information with overall organizational impacts on supply chain stability, operation, and decision-making effectiveness.

Depending on the nature and amount of information asymmetry to be addressed, organizations typically use information processing methods (Aben et al., 2021). Based on this, information asymmetry may be defined with regards to equivocality, uncertainty, where equivocality represents the ambiguity, and uncertainty is the lack of knowledge. Moreover, information asymmetry is a concept that is used to describe the differences in the information available to different decision-makers within an organization. Similar to this, there is a popular theory called Agency theory, which emphasizes the asymmetry of knowledge and assumes that managers of a lower tier have an information advantage (Bergh et al., 2019). The management

should grant the decision-making mandate to these managers, and at the same time, should reduce the incidence of information asymmetric (Jensen & Meckling, 2019).

The generation of more data and its interpretation, with the help of the opportunities provided by BA, could help to reduce the problem caused by ambiguity and equivocality in decision-making scenarios (Aben et al., 2021). Besides, by establishing more central control over data, BA transfers information advantage between local and top management (Labro et al., 2023). The argument was also that BA is able to manage information asymmetries, through reducing equivocality and uncertainty. This prospect of BA develops the case in which BA determines the use of data under a decision-making scenario.

Making decisions is one of the primary goals of organizational information processing. Studies in the past recommended several decision-making methods due to the diversities in the gathering and evaluation of managerial information (cited in Szukits & Móricz, 2024). Nonintuitive type of analytical processing involves the collection of information, compiling, assessing and extracting meaning of the available information before making a conscious, rational decision. Intensive information search, inventory, and evaluation of the possibilities prove that rationality present throughout the decision-making process and not only in the final conclusion. The most famous process approach to decision-making has three stages namely identification, development, and selection; four stages of problem identification, problem definition, prioritization, and test of cause-and-effect relationship are also synonymous. Data-driven decision making is also defined by the collection, analysis, and utilization of verifiable data at all decision-making process stages based on these process approaches. With individual-levels, there are data-driven culture, rational decision-making praxis analytical decision-making orientation, and analytical decision-making culture are some of the organizational-levels where the presence of decision rationality and utilization of available data are defined

and analyzed. Such social practices at the organizational level not only promote rationale, but also data-driven decisions (Karaboga et al., 2023; Kulkarni et al., 2017).

Even when the literature about data quality approached the classification of specifics of the requirements to the data to be utilized and appropriate measuring of data in vastly different ways (Knauer et al., 2020), earlier studies on data-driven decision making have proven that the data characteristics have a powerful impact on the usage of data in a decision-making process (Puklavec et al., 2018). In accordance with well-known research on data and information quality, Szukits and Móricz (2024) utilized data and information interchangeably instead of distinguishing like earlier scholars do. To identify evidence of the influence of data quality on the analytic orientation of decision-making of the company, how data quality affects its use moderated by the decision-making culture, and how data quality and data use support higher perceived decision quality (Kulkarni et al., 2017; Visinescu et al., 2017), the diffuse set of quality attributes was discussed within BI context.

Even distribution of information is decreased by the availability of the same pool of high-quality data and this reduction of information asymmetry directly impacts the decision-making, supported by evidences on inter-organizational environment (Ahearne et al., 2022; Mandal & Jain, 2021). Additionally, the information asymmetry could also be caused by the inability to process information and communicate it to the organizational members that necessitates the improvement of the information processing capacity on the firm level (Bergh et al., 2019). As a result, the mechanisms proposed towards the resolution of information asymmetry and to support managerial decision-making usually incorporate the execution of different information systems.

The range of BA software solutions and the continual updates of the product line up give the impression that the characteristics of new BA technologies are not predetermined, but

rather depend on the preferences of the actors involved in deciding whether to adopt them such as the information processing requirements of the organization as well as decision made by managers regarding the factors behind delivering these requirements. The proliferation of it not only possesses behavioral aspects like modifying managerial decision-making skills, processes, but also the organizational consequences are considerable (Lismont et al., 2017). Since the information can be more easily turned into practical insights by lower-level managers than top management is, analytics use may recreate the information asymmetry, which is a decentralization force. Simultaneously, BA provides access to more comprehensive data for higher levels of management; this reduces the information asymmetry. Accordingly, predictive analytics would be associated with increased top management control of data collection and less delegation of decision-making power to local managers (Labro et al., 2022; Szukits & Móricz, 2024).

2.3.2. Decision Confidence in Management Context

Various studies have been done on the suitability of human dependence on AI systems such as improving on broadly automated systems and robotics (Buçinca et al., 2021; Ma et al., 2022; Wischnewski et al., 2023). Some studies shifted their focus to not just enhancing trust in AI but instead enabling proper trust and reliance (Buçinca et al., 2020; Cabrera et al., 2023; Ma et al., 2023; Schemmer et al., 2023; Vasconcelos et al., 2023; Vereschak et al., 2021; Wischnewski et al., 2023; Yang et al., 2023; Zhang et al., 2020). Algorithm aversion and automation bias are two commonly known phenomena that bring out the difficulty of people and their capacity to match their dependence and trust with the capabilities of AI systems. In the field of AI-assisted decision-making studies, the emphasis is now shifted to the management of reliance and trust, the two-fundamental approach which occur case-by-case (Lai et al., 2021; Vereschak et al., 2021; Wischnewski et al., 2023). Trust represents opinions

with regard to AI, which are commonly measured with the aid of self-reporting items, whereas reliance deals with real-life behavior relative to the AI systems (Bansal et al., 2021; Ma et al., 2023; Wang & Yin, 2021; Zhang et al., 2020; Zhao et al., 2023). Interestingly, research has found that reliance and trust are not consistent. More self-reported trust does not always relate to better reliance behaviors (Rechkemmer & Yin, 2022). In this regard, it is appropriate to rely on AI suggestions but not ignoring it when it is wrong. The current available literatures use various definitions and measures of proper reliance and is classified into two categories:

Behavior-Based Measurement: The system evaluates the right dependency in terms of human behaviors, where AI confidence is calculated as a measure of reliability. When an individual follows more suggestions made by the AI where the AI has high confidence (or vice-versa) it is considered to be calibrated and correct. However, the AI confidence may not directly represent the correctness of AI. Thus, it has been found in many studies, which depend on this measure of the suitability of human reliance that even though the trust and reliance of an individual is calibrated the outcome of the final task performance does not decrease (Zhang et al., 2020; Zhao et al., 2023).

Outcome-Based Measurement: This model explicitly evaluates proper reliance concerning the accuracy of AI suggestions and human choices (Bansal et al., 2021; He et al., 2023; Ma et al., 2023; Schemmer et al., 2023; Wang & Yin, 2021). It defines inappropriate reliance as under-reliance and over-reliance, which quantifies the appropriateness of human reliance on AI suggestions. The phenomena of over-reliance and under-reliance happen when individuals conform to the predictions of AI is incorrect and correct, respectively. Certain scholars have agreed to stricter standards and only considered whether individuals can make the right final choices when their original predictions and AI recommendations are different (He et al., 2023; Schemmer et al., 2023).

The field of decision-making with the help of AI is attaining more focus within HCI communities (Buçinca et al., 2020; Ma et al., 2019; Ma et al., 2023; Schemmer et al., 2023; Shi et al., 2023; Vasconcelos et al., 2023; Vereschak et al., 2021; Wischniewski et al., 2023; Yang et al., 2023; Zhang et al., 2020; Zhu et al., 2022). In this human-AI collaborative environment, AI is a consultant, making suggestions that are usually accompanied by ambiguities. The major issue in such a situation is that humans need to use AI advice appropriately (Lai et al., 2021; Zhang et al., 2020). In order to address this problem, the extant literature has explored the following three major approaches or solutions.

One of them is focused on improving the understanding of AI prediction unpredictability in people (Wischniewski et al., 2023; Zhang et al., 2020). The uncertainty of AI prediction is generally determined using a calibrated confidence level of the AI model that can represent the probability of prediction correctness (Guo et al., 2017a; Rechkemmer & Yin, 2022). For instance, a confident score of 0.6 would imply a probability of a 60 percent of a good prediction. The results of research related to the consequences of presenting AI confidence scores to users directly present the calibrated scores to participants (Bansal et al., 2021; Zhang et al., 2020), which investigated the effects of indicating AI confidence on task performance and trust calibration. Some studies used AI-confidence in interface design. For example, Rastogi et al. (2022) set decision-making time frames by AI confidence in order to assist humans in more intellectual thinking in case of low AI confidence. In addition, other methods of confidence representation have also been investigated such as question marks or violin plots (Zhao et al., 2023). Nevertheless, their strategies have not always led to a better reliance appropriateness or task performance (Ma et al., 2023; Zhang et al., 2020; Zhao et al., 2023), which was not proven enough to exhibit AI confidence.

The second solution is aimed at raising the awareness of AI error patterns in people to help them form proper mental AI capability models. For example, Bansal et al. (2019) developed the idea of mental models of AI error boundaries and emphasize the influence of factors on the development of these models. This can allow people to know when AI advice should be taken or ignored. Another study by Cabrera et al. (2023) suggested to present end-users with behavior descriptions of AI models, which would give them an idea of how AI would perform on particular cases. This method allows improving human-AI cooperation since users should be aware of AI failures and more dependent on AI in case it is more accurate.

The third solution sought to clarify the explanations of AI predictions with the help of AI explanations (Bansal et al., 2021; He et al., 2023; Lai & Tan, 2019; Lai et al., 2020; Poursabzi-Sangdeh et al., 2021; Vasconcelos et al., 2023; Wang et al., 2019). These descriptions can be of different types, including the natural language-based explanation, counterfactual examples, similar examples, feature contribution, and feature importance (Lai et al., 2021; Liao & Varshney, 2021). Despite this, some studies have revealed a possible disadvantage in the idea of giving AI explanation, which is the risk associated with having an even stronger dependence on AI systems when the AI suggests something wrong (Bansal et al., 2021; Poursabzi-Sangdeh et al., 2021; Wang & Yin, 2021; Zhang et al., 2020). This is explained by the fact that there is no cognitive processing of AI descriptions since there is the possibility of quick heuristic due to the fact that people may decide to evaluate the trustworthiness and explainability when they are not even motivated or able to take time to analyze the AI response properly (Bertrand et al., 2022; Bućinca et al., 2020).

Some studies like Ma et al. (2024) used solution aims at making human dependence more appropriate through adjusting self-confidence. Another related study was conducted by He et al. (2023), where it discussed people often overrate themselves (so-called Dunning-

Kruger effect) and calibrates their own self-evaluation with the help of the tutorial. Nonetheless, their solution focused more on task-level self-assessment, but rational reliance involves judgments on a case-by-case basis on the adoption of AI recommendations (Zhang et al., 2020). Another related study was Ma et al. (2023), where it models the correctness likelihood (CL) with the case-specific human and AI, and compares them to enable an adaptive adjustment in the decision-making interface. Nonetheless, they emphasized mostly on the development of AI on the aspects of human understanding, but not human self-calibration. They also discovered that some users did not believe human CL as estimated by the system, making it problematic in its effect on their practice. In addition, they influenced user decisions by pushing the interface design and this could overstep user autonomy while questioning ethical issue. On the contrary, Ma et al. (2024) puts emphasis on the calibration of personal confidence in self-belief, not only on ensuring user freedom but also preventing any ethical concern related to AI nudges.

An individual's subjective perceptions are based on his/her confidence in the correctness of the ideas and capabilities. It is critical in judgment and openness to counsel, including influencing the desire to follow the suggestions of AI (Chong et al., 2022; Lu & Yin, 2021; Vodrahalli et al., 2022a). Self-confidence in humans is also correlated with credibility in many situations, such as the way children think about adults or the opinion of jurors towards expert witnesses. Self-confidence may be untrue to reality sometimes, and therefore cause underconfidence or overconfidence to both laypersons and experts (Duke, 2019; Turner et al., 2022). Risky decisions can be caused by overconfidence which is over-estimating oneself. On the other hand, self-underestimation characterized by underconfidence may result into missed opportunities. The incongruity of human self-confidence and actual accuracy has been extensively demonstrated in the empirical literature of decision-making in both clinical diagnosis and financial decision-making. For instance, Grežo et al. (2021) found that

overconfidence has a greater influence on financial decisions. These results illustrate the significance of proper self-evaluation.

Self-confidence calibration literature explores cognitive mechanisms and processes. Some studies revealed heuristics and mental biases leads to mis-calibration, including the effect of overconfidence, and the Dunning-Kruger effect. Metacognitive may cause manipulations in terms of the improvement of calibration, whereas cognitive methods are used to create moderate self-confidence. For instance, Moore (2020) evaluated the complexities of human confidence, and provides the factors that drive accurate judgments and the practical strategies, such as the application of feedback, varied perspectives, and growth attitude. Duke (2019) highlights the significance of taking risks and making decisions as bets, providing a strategy to evaluate the risks, uncertainty, and other possible results.

2.4.AI Usage and Its Influence on Managerial Decision Confidence

To understand the impact of trust, the researcher examined the implementation of trust by considering various situations and contexts, such as technology, organization, relationships, and decision-making (Harwood & Garry, 2017). The two major classifications of trust, such as cognitive and non-cognitive aspects, have been the focus of a few studies, which help explore people's behavior and thinking (Ferrario et al., 2020).

The implementation of trust was considered as belief or feeling help to achieve the goal with the help of system or another person with a definition "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" explored as widely accepted definition of trust helps to combine different ideas from earlier research (Hoffman et al., 2018).

The individual's knowledge, beliefs, emotions, and past experiences were shaped by trust, as illustrated from the perspective of human-computer interaction. Effective conflict resolution, team performance, and problem-solving provide a successful foundation of trust, particularly in teamwork. The negative consequences in an organization were caused by a lack of trust in the team, which impacts learning and cooperation within the team and increases misunderstandings, thereby affecting the team's performance (Tuncer & Ramirez, 2022).

The willingness of people to use the new technology was predicated on trust in human interactions. Task completion in an organization was effectively carried out based on user trust in using technology to complete the task reliably. In contrast, the use of technology by users was prevented due to a lack of trust. Users who are unsure about the performance of new technology resist its use. The successful and effective use of technology depends on the establishment of trust, which was considered essential for enhancing an organization (Łapińska et al., 2021).

The use of automated systems faces challenges in establishing trust, as evidenced by analyses across many studies. Without human control, AI was designed to operate independently (Xu et al., 2022). Trust in using AI depends on making the user feel assured about the transparency of the decisions made by AI, which helps users trust AI. The confidence in using an AI system was reduced by the occurrence of interpretability. The lack of clarity by users makes it hard for them to predict or understand AI decisions. To make AI use more friendly, a new framework and tools were introduced to address the challenges. Conversely, instead of addressing the challenges, most of the studies focus on improving the algorithm rather than designing an AI system that helps to meet the needs of the user. The need for more user-centered AI development highlighted in the study helps to explore the existence of a gap in the research (Rakova et al., 2021; Ferreira et al., 2021; Shneiderman, 2020b; Xu et al., 2019).

High-stake and low-stake decisions are the two major types of AI-based decision-making processes. The decisions taken by the human were, in most cases, supported by AI. An efficient environment in an organization was created through the integration of AI and humans working together. On the other hand, a few of the researcher states that consideration of the real possibility of AI making independent decisions. Each stage of AI preferred a different level of autonomy for automation. The system's performance improved with the appropriate level of autonomy at each stage (Trunk et al., 2020).

The unpredictable and complex nature of AI was made more efficient through the establishment of trust between humans and AI. The lack of trust in the implementation of AI causes a sense of risk. The implementation of AI with humans was made easier by establishing transparency for every action taken by AI with humans. The processes of problem-solving and decision-making were improved through the establishment of trust in the implementation of AI. Moreover, the implementation of AI focuses on enhancing human centered, trust worthy and decision-making understandable. The intentions of AI need to be made understood by use, which helps develop a shared understanding between machine and human. The enhancement of societies, economies, and long-term development depends on the establishment of trust with human and AI. The establishment of trust helps in the successful adoption of AI across the world. The potential and benefits of AI were diminished due to a lack of trust establishment (Tuncer et al., 2022).

Instead of examining the process of decision-making by AI, most research focuses on the final decision made by AI, predicated on analyses of previous studies on AI and trust. The AI-based decision-making system depends on the decision-makers. The feedback provided by decision-makers on using AI helps enhance the system. The long- and short-term strategic decisions in organizations were made by top-level managers in business settings. The

occurrence of strategic problems was addressed using AI, as 94% of business executives believed by 2018.

In contrast, only 18% of organization prefers to adopt AI in an organization in the same year. The implementation of AI understanding was considered a challenging task for the managers. The decisions or predictions made by AI were not understood by nearly 65% of managers in US companies. Trust in using AI in an organization was reduced by the lack of transparency and a user-friendly AI system (Xu et al., 2023). The occurrence of a usability problem linked to trust was considered a major problem caused by the use of AI in decision-making, as per the analysis of the research. Decision-makers prefer the implementation of AI to be user-friendly. In contrast, poor decisions were sometimes caused by trusting AI too much, accepting all recommendations without questioning, which led to over-reliance. Calibrating user trust helps balance the implementation of trust in an efficient way, leading to better decision-making outcomes (Tuncer & Ramirez, 2022).

2.5. Psychological Factors Affecting Decision Confidence

2.5.1. Trust in Artificial Intelligence

Based on the focus and context, the implementation of trust in an organization was explained in different ways (Sheridan, 2019). Meta-analysis was used to evaluate the implementation of trust based on technology, automation, and robots. The enhancement of trust was made evident through the analysis of the study, which reflects the way people interact with technology. The comfort of people in using and depending on technological systems was determined using trust (Hancock et al., 2021).

The use of virtual assistants and automated vehicles is rapidly increasing, making technology more important in society. The implementation of technology in an efficient way

depends on the establishment of trust, which was predicated by the analysis of research. The trust of the people helps in the efficient use of decision-support tools to manage extreme weather and other challenges. In contrast, establishing stability in the implementation of trust needs to be more focused on enhancing AI within an organization. The existence of security weaknesses was considered a major challenge in the implementation of virtual assistants like Alexa. The trustworthiness of AI implementation was impacted mainly due to the existence of security weaknesses, which harm users and cause them to lose confidence. In the case of self-driving vehicles powered by AI, the establishment of trust was considered mandatory. People need to ensure safety when using self-driving vehicles. The physical parts of the vehicles help to establish the trust of the people, which traditionally makes many people drive the cars comfortably.

In contrast, driving with vehicles integrated with AI requires a special type of trust to be established. The user needs to believe the algorithm that controls the vehicle's decisions and physical components. Moreover, uncertainty among people was caused by the unpredictable nature of AI in using AI-driven vehicles (Kaplan et al., 2023).

To establish trust with humans, AI needs a detailed analysis of the factors that impact human trust. In daily life, people interact with AI in many ways, but the study focuses only on related articles based on a certain type of AI, selected from research articles. The non-physical AI systems, self-driving vehicles, chatbots, and robots are the four major categories of AI. For each type of AI, the implementation and assurance of trust vary from one classification to another. The trust was influenced by anthropomorphism, which helped make a major difference in the use of AI. The researcher needs to focus on factors influencing user trust in developers, helping them design systems that are more reliable and easier for users to trust. The interaction

between humans and AI was enhanced through the identification of major factors influencing trust (Kaplan et al., 2023).

The human-related factors and AI-related factors are the two major types of factors influencing the trust of AI. The performance of a task, based on the consideration of personal factors, plays a significant role in understanding the features of human-related factors. On the other hand, the implementation of AI-related factors was classified into two major types: performance and contextual factors. The methodology used by AI to communicate with users and its reliability play a major role in the performance-related aspects. The difficulty of the assigned task and teamwork are considered significant contextual factors. The analysis of different types of AI systems needs to focus on each factor separately, and this needs to be analyzed by the studies. During the rapid spread of COVID-19 in many countries, the virus's spread was continuously monitored using AI (Tolmeijer et al., 2020).

Compared with humans, AI has the ability to identify the source of infection rapidly useful in fields like epidemiology. Proactively identifying disease with AI can save many lives and help control its spread. In contrast, harmful results were caused to patients due to a mistake in the AI algorithm and a lack of accuracy in the algorithm. The serious consequences were caused by the implementation of AI due to incorrect predictions based on the the data used. Implementing AI offers both benefits and challenges. The responsible use of AI helps to assure reliability and accuracy. Sethumadhavan (2019) stated that both trust and distrust are involved in the implementation of AI. Sometimes AI mistakes make people distrust the use of AI. People fear, doubt, and concern are considered significant factors that cause distrust in in the use of AI. More steps need to be taken to restore trust after failures in using the system. More strategies were framed to regain the user's confidence and reduce distrust. The perception and use of AI systems depend on shaping trust and distrust among people (Tolmeijer et al., 2020).

In contrast, sometime flaw in the AI system was caused due to over trust of AI system. The failure of AI in implementation causes various risks and harms to users. The mistakes made by humans were easily identified, but the process of accountability was considered a major problem in the implementation of AI. The single person was not able to take responsibility for the mistake made by AI. Moreover, the occurrence of failure in self-driving cars may cause serious problems, making it unclear who is responsible for the failure. Compared with the implementation of other technologies, the establishment of trust in using AI needs to be considered as mandatory to help prevent the harm caused to people. The use of AI was made more powerful through its digital and physical implementation. Based on the context, the AI was able to adapt quickly to new situations and respond differently. Before establishing trust with AI, people prefer a "wait and see" approach. The behavior of AI differs from one situation to another, making the "wait and see" approach ineffective. Over time, the AI system was able to learn and improve. The complete understanding of AI was affected by changes in behavior. The adaptability of AI was not desirable in defense and healthcare, as it impacts the lives of human beings. People preferred a stable, predictable system when using AI. The different inputs given to the system make even the non-learning AI system behave unpredictable creates challenges in the military sector (Hancock et al., 2021).

Sethumadhavan (2019) explores that the trust of the AI system was impacted by the occurrence of risk. Trust assurance becomes more important when risk is higher or consequences are serious. The presence of uncertainty in the system makes people think about establishing trust. The impact of trust was analyzed by influencing factors associated with AI (Kaplan et al., 2023).

2.5.2. *Perceived Reliability of AI Systems*

The best decisions were made using Decision Support Systems (DSS), which are computer-based tools used for efficient management of uncertain situations. Instead of replacing the human, the integration of a DSS system helps support human thinking. The implementation of DSS was made more effective with the integration of AI. The people were able to work together with AI, able to provide more reliable and collaborative solutions. The accuracy and validity were assured by the decisions made by the DSS (Javidan & Za, 2024).

The decisions made by people were enhanced through the integration of DSS, predicated on the analysis of research. The design of the AI system needs to consider psychological factors and human behavior. To support the decisions, the earlier model of DSS uses a fixed model that adopts predefined rules. The use of advanced techniques such as explainable algorithms and machine learning was used in the implementation of modern AI-based DSS. The clear, understandable solutions were provided by AI integrated with DSS. The major aim of AI-based systems was not to replace humans but to support them by offering useful insights (Haag, 2025; Phillips-Wren et al., 2019). Better and more effective decision-making was achieved through the integration of human judgment with AI. Phillips-Wren et al. (2019) state that the behavior and thinking of the people play a major role in the implementation of an effective decision support system. Various factors, such as risk attitudes, decision styles, and cognitive biases, play a major role in the effectiveness of a decision support system. Human thinking was enhanced with the integration of DSS. Additionally, more focus on the implementation of DSS on assuring interpretability and transparency helps establish balanced trust. Effective and accurate decision-making in an organization was achieved through the integration of AI with DSS.

The adaptable DSS was designed with a focus on balancing reliance and trust. The dependency of people in automation system was explored. The challenges were caused by both over-reliance on technology and a lack of trust in using it. The poor decisions were caused by overreliance on technology. The system's performance was affected by ignoring the AI's correct decisions. The achievement of a balanced level of trust was considered mandatory for ensuring AI is widely used across different industries. The decision quality was enhanced through the use of AI, ensuring a a balanced level of trust (Haag, 2025).

The overreliance of people on AI systems was supported by analyses of many studies (Bansal et al., 2021; Bućinca et al., 2021; Logg et al., 2019; Vasconcelos et al., 2023). Klingbeil et al. (2024) found that people's adoption of AI did not even match the situation. Wu et al. (2022) stated that in the healthcare sector, patients are less willing to accept painful treatments based on AI advice. Sometimes mistakes were caused by ignoring appropriate advice from AI (Harada et al., 2021).

The process of decision-making was impacted by both overreliance and under-reliance on technology, which predicated the need for a balanced use of AI. The serious outcomes of decision-making are evaluated using contextual factors. The trust and reliance on AI were evaluated based on stakeholder influence. People react strongly to high-risk situations, such as self-driving cars or healthcare, when AI decisions cause problems. Both over-trusting AI and under-reliance on AI pose challenges in implementation (Johnson, 2025).

Users understood the mistakes made by AI in low-risk situations and were able to trust the system again. Depending on the situation, people rely on AI. The occurrence of context helps build people's trust. In high-risk situations, the implementation of trust poses challenges and is sensitive to manage. On the other hand, in low-risk situations, people were able to adjust

to the trust easily (Freel et al., 2025). The establishment of reliance and trust differs from one to another. The behavioral outcome was predicted using reliance (Chiou & Lee, 2023).

The system's performance depends on the level of user support in DSS, achieved by focusing on establishing calibrated trust. The advice of AI helps users to act based on appropriate reliance (Poursabzi-Sangdeh et al., 2021; Schemmer et al., 2022). The establishment of the right level of trust helps to assure the appropriate functioning of the system. People over-trust AI, which leads to blind reliance on AI systems, causing challenges. The decision-making and performance processes were affected by excessive or insufficient trust in a system (Schemmer et al., 2022).

The impact of using automation and AI systems on trust was explored using real data, based on an analysis of research studies. The greater use of AI systems depends on the establishment of trust. In contrast, less user usage of the AI system was caused by low trust. Both modern AI-based decision support tools and traditional automated systems were supported by the establishment of trust, which helps enhance an organization (Hasija & Esper, 2022; Kim et al., 2021). Compared with human doctors, the medical decisions made by AI were less trusted by the people. The occurrence of high-risk situations in the healthcare sector leads to a lack of trust among people in the implementation of AI in healthcare (Juravle et al., 2020).

Shekar et al. (2024) found that AI-generated responses are considered more trustworthy and satisfactory by non-experts than doctor-generated responses. The reliance of people on AI systems depends on the establishment of trust, predicated on research. Choung et al. (2023) stated that AI-supported recommendations help enhance user trust. Kahr et al. (2024) stated that the use of an accurate AI system helps enhance trust and reliance. The interaction of the user with the system helps increase trust in the system over time. Moreover, the proper use of

AI in decision-making was ensured through the establishment of calibrated trust (Kim et al., 2021; Schemmer et al., 2022). The more useful AI advice was ignored due to a lack of trust from the people. Proper reliance on the system was established through balanced trust (Schemmer et al., 2022). The use of AI was less relied on by the experts, which helped increase trust (Dogru & Krämer, 2025; Küper et al., 2024).

2.5.3. *Risk Perception in AI-Assisted Decision-Making*

The implementation of AI was not explored by using a single definition (Duan et al., 2019). The European Commission defined the use of AI in decision-making. Both structured and unstructured data collected from the environment were analyzed using AI to help make decisions. To achieve specific goals, the system was able to choose the system (Vereschak et al., 2024). Decision-making in AI was supported by data gathering and analysis. The best decisions made by humans were made with AI integration, assisting the decision-making process. The implementation of AI in the decision-making process was not considered an opportunity to replace humans; instead, it helps support human decision-making by offering insights that make decisions more effective (Schmude et al., 2023).

AI provided more than one recommendation to decision-makers to help them make the right decisions. The final decision depended on humans if the system was not completely automated. Sometimes the decision maker's original opinion differs from the suggestion generated by AI, creating a conflict between AI decisions and human decisions. The effective use of recommendations by AI was impacted by a lack of transparency makes harder for the decision maker to trust the decisions made by AI (Lagioia & Contissa, 2020).

The decisions made by AI need to be expected, with clear recommendations that help understand the reasons behind the decision (Yu & Kohane, 2019). The identification of biases in the system poses challenges due to AI's lack of clarity. The level of trust in the system for

using AI in decision-making by people helps judge the quality of an AI recommendation (Wang & Du, 2018). The trust people place in AI for decision-making helps them believe the decisions made by AI. On the other hand, the own judgment of humans was considered.

In various sectors such as loan approval, public safety, and hiring, the use of AI helps make the best decisions by analyzing large volumes of data. People's lives were affected by AI's decisions. Trusted AI decisions help provide greater benefits to people. The establishment of trust with AI was analyzed by researchers and organizations, helping ensure fair, reliable and responsible decision-making (Board, 2019).

Two major themes are explored by human AI trust, predicated on the analysis of literature, which focuses on identifying factors influencing trust and understanding its meaning. The understanding of human AI trust was explored using theoretical studies (Jacovi et al., 2021). Based on the context, the use of AI in decision-making helps achieve the personal goal by establishing trust. The occurrence of risk and uncertainty is a major challenge in the implementation of AI for the the establishment of trust (Vereschak et al., 2021). The definition of trust in the use of AI in decision-making depends on three major factors: vulnerability, positive expectations, and attitude. Moreover, trust was classified as emotional and logical by some of the researchers (Ryan, 2020).

Glikson and Woolley (2020) identified several key factors that influence trust in AI through a review of the research. Various major factors related to the implementation of AI systems, such as transparency, performance or reliability, task characteristics, anthropomorphism, social behavior, and tangibility, were explored by studies in the context of AI systems. User interaction and evaluation of AI in the real world are major factors in the use of AI in healthcare decision-making. The establishment of trust was managed and understood through the implementation of AI in real-world contexts (Browne et al., 2022). The direct users

of the AI system were considered the main focus of the research related to human AI trust. The developers, organizations, managers, and other stakeholders was influenced by the establishment of trust. Browne et al. (2022) stated that the entire clinical AI deployment process in real settings was explored beyond the context of the trust factors related to new trust calibration points. The focus on a single type of stakeholder by human AI trust was explored by many of the studies. The Human-AI decision-making systems focus on factors related to stakeholders and users.

The use of AI-assisted decision-making systems focuses mainly on stakeholders and helps link the development of an organization. The AI practitioners, users, and decision subjects are the three major parties involved in an AI-based decision-making system. The system was designed and developed with the help of AI practitioners. The decisions were made more accurate with user input. The decisions taken impact the decision subjects. The creation and use of AI DSS depend on three groups: users, AI practitioners, and decision subjects. The rules and policies related to AI were developed with the help of regulators and policymakers by stakeholders. The role of stakeholders was not considered a major significant factor in the study (Yurrita et al., 2022).

Users of AI systems play a major role in establishing trust in human-AI decision-making (Lai et al., 2023). In the adoption of an AI system, understanding of user trust plays a major role, as it helps increase people's acceptance of AI in decision-making. The implementation of AI was made more reliable and easier by identifying factors that impact user trust, helping developers design an efficient system. Most studies focus on users of AI. The establishment of trust in AI depends on the user's experience. Moreover, considering only the user alone does not help establish complete trust in the system. Various factors, such as stakeholder needs, AI practitioners, decision subjects, and roles that influence trust and

expectations, play a major role in the establishment of trust with AI. The establishment of trust on user system depends on AI practitioners, decision subjects, and developers. The perspective of stakeholders needs to be considered to help understand the human AI trust with the inclusion of human-centered values in AI design (Yildirim et al., 2023; Yurrita et al., 2023). The different perspectives of stakeholders, such as fairness, AI ethics, and explanations, were explored by previous studies. The establishment of trust between humans and AI was not explored by the studies, but studies that explore various perspectives support the approach used in the research (Vereschak et al., 2024).

2.6. Behavioral Responses to AI-Assisted Decision-Making

2.6.1. *Automation Bias and Over-Reliance on AI*

In most human-AI interaction scenarios, explanations may be helpful, especially when reinforcing human analysis processes or creativity, instructing human-like processes (content moderation, translation, etc.), forecasting modeling predictions clearly, legal requirements, etc., The impact of an explanation based on different dimensions has been assessed by different studies, including whether the explanation enhances the trust in the AI by the users (Kunkel et al., 2019); helps developers debug their models (Kaur et al., 2020) or allows users to simulate the model predictions (Poursabzi-Sangdeh et al., 2021). Wang et al. (2019) focused on the situations of AI-assisted decision-making, when decisions are to be made by a human (like a judge), whereas an AI assistant (like a classification model) provides recommendations, and final decisions are to be made by a human (judge). In particular, performance is assessed in terms of the accuracy of the human-AI team. Although there are other metrics, end-to-end team assessment seem efficient due to following three reasons: (i) Firstly, a successful implementation of such a human-AI team should be deployed when there is a complementary performance. This allows to perform better than the AI and the human acting separately; (ii)

Secondly, a proxy assessment, which is helpful in determining whether humans would use it to predict model output), may cause other, false conclusions in their end-to-end performance compared to a proper evaluation (Bućinca et al., 2020); and (iii) Lastly, AI-assisted decision making is usually among the key reasons why AI explanations are needed.

Over the last few years, user studies have been utilized in many research to demonstrate that human accuracy improves when the AI system justifies its diverse tasks such as trivia answering, loan default prediction, and medical diagnosis. None of these studies found complementary performance to be effective, which in turn, resulted in worse performance than had AI operated alone. For example, Lai et al. (2020) investigated employees on a MTurk platform, where they argued SVM-based and BERT-based prediction models are provided deceptive hotel reviews in the form of inline-highlights. Nevertheless, models performed better than each employee. Another study by Zhang et al. (2020) observed the better performance of the models and measured the trust and quality calibration, where difference between the human and AI performances was having less impact. Nevertheless, their Gradient Boosted Trees model was 10 percent more accurate on their task of prediction of the income categories than were their own MTurk workers, which appeared to be marginally comparable. Moreover, their AI model was only partially ahead of the best team when operated independently.

The same line of performance is noticed in tasks other than classification. For example, in the study conducted by Poursabzi-Sangdeh et al. (2021), the regression models were applied to predict house prices by MTurk employees, where the models generated interpretations based on the most salient features. The error percentage was very low. In an earlier study by Feng et al. (2019), professional and amateur participants took part in Quiz Bowl based on suggestions provided by the Elastic Search system. The system justified its predictions with influential training examples, and inline highlights are used to justify the relationship between the question

and evidence. The non-occurrence of complementary performance in these cases can be attributed to at least two possible reasons. Firstly, the task design could have served as a barrier to collaborating: the former researchers thought of AI systems whose precision was significantly greater than that of the individual human, which resulted in a narrow range of complementary performance. For instance, this could have increased the chances that the human error was an overset of the AI error such that the human overseer was less likely to find a machine error. Secondly, it is not clear whether the collaboration mechanisms under study facilitate it even when the performance of the task can complement. The elements of collaboration such as the type of explanations, incentives, and the presence or absence of uncertainty in AI might push the human to less collaborative heuristics, such as always trust the AI or never trust the AI (Bansal et al., 2021).

2.6.2. Algorithm Aversion and Resistance to AI

With AI-supported decision-making leading to high-stakes decisions, it is important to make sure that human intuition and AI-provided suggestions are effectively integrated. Even though AI explainability is improving, there is still the problem of establishing the right dependence. Xu et al. (2025) discussed AI decision-support systems to improve human intuition by examining 84 studies to answer three questions such as "What design strategies can allow AI systems to facilitate the intuitive decision-making of humans without undermining decision-making autonomy?"; "What is the impact of AI presentation and interaction approach on human-AI collaboration, particularly trust reliance behavior and trust calibration?"; and "What are the practical and ethical implications of continuing to incorporate AI decision support systems in high-risk human decision-making, especially in terms of accountability, skill degradation, and trust calibration under various areas?". To answer this, the study used four strategic design choices, including context-aware task allocation dynamically

assigning responsibilities based on situational factors, allocation of dynamic tasks and responsibilities based on situational and contextual elements, adaptive user-focused designs that dynamically allocate tasks to individuals depending on the situation, and complementary role systems for improving human judgment rather than replacing them. The study found that uncertainty communication, interactive capabilities and visual presentation were important in calibration of trust, and simple visual highlight is much more effective than elaborate presentation and interactive techniques to avoid over-reliance. There is, however, a concern exists over performance paradox in which human-AI integration tend to perform worse than the best single agent whilst still outperforming human-only performance. The study showed that domain-specific calibration, integrated sociotechnical design that takes into consideration the calibration of trust and skill preservation together with proactive measures are key to successful AI integration in high-risk situations (Xu et al., 2025).

Human-AI Collaboration (HAIC) i.e., the combined work of AI and human, has become a necessity in numerous sectors that improves innovation, efficiency, and decision-making. Although the potential of HAIC is wider, it is still difficult to assess its activity due to the complex nature of its components. Fragiadakis et al. (2024) offered an in-depth discussion of current methods of evaluating HAIC and comes up with a new paradigm that can better evaluate these systems. A structured decision tree was developed in this study with an aim to choose the appropriate metrics depending on the specific HAIC modes (Symbiotic, Human-Centric, AI-Centric). The framework proposed may be considered as an attempt to delineate dynamic and reciprocal nature of HAIC as it allows incorporating quantitative and qualitative indicators and measure its influence and effectiveness. The practicality of this framework can be discussed in terms of its use in a variety of areas, such as education, finance, healthcare, and manufacturing, where each of them has its own set of difficulties and needs (Fragiadakis et al., 2024).

According to Castelo et al. (2019), consumers are less dependence on algorithms-based work that can still be carried out by humans, although algorithms usually do it better. This is due to the fact of having less trust and reliance on algorithms when they are supposed to perform the task that are considered to be subjective (and not objective) in nature. Nevertheless, they demonstrate that perceived task objectivity can be changed, where the trust in using algorithms for a particular task is increased when that task perceived objectivity is higher. Users are having misbelief that algorithms do not have adequate the skills for completing subjective tasks. Perceived affective human-likeness for algorithms need to be increased in order to employ these algorithms for subjective tasks. These findings can be backed by the four online lab study results conducted on more than 1,400 participants, as well as the two online field study results conducted on more than 56,000 participants. The findings offer inferences about the probability of consumers using algorithms and at what time, and the likelihood that marketers can maximize such utilization whenever it performs better than human beings do (Castelo et al., 2019).

With the growing integration of AI into the educational sphere of higher institutions, the subject of resistance to its implementation has become one of the key academic questions. In Allen's (2025) study, theoretical frameworks are discussed that can give researchers, educators, and graduate students an idea of the AI resistance in an academic context. Extrapolating the struggling experience of graduate students towards aligning research issues and theoretical studies, as well as the dynamic nature of the AI scholarship, highlights the necessity to provide stronger theoretical foundations. This study also showed the evolution of the major models of technology adoption, such as the Unified Theory of Acceptance and Use of Technology, Technology Acceptance Model, Theory of Planned Behavior, Theory of Reasoned Action, and Diffusion of Innovations, and discussed their own motivating factors or barriers for using AI. Quantitative methods are dominant in this discipline; however, Allen

viewed that more qualitative, participatory research methods are needed that place greater emphasis on lived experience (Allen, 2025).

2.6.3. Human-AI Interaction and Behavioral Adaptation

In the field of human and AI integration, the human and AI partners should share common work and coordinate them to reach a predetermined goals set. This interaction is dynamic depending on the duration of an interaction as the tasks, the patterns of collaboration and the composition structure of teams might vary with time. Individuals could apply the knowledge they acquire about the task, the partner, as well as the external environment to update their approach towards the task. To coordinate well, AI teammates need to learn to adjust to various behaviors and various team members (Ahmad et al., 2017). The important elements in the process of adapting are the ability to observe people and understand their behavior during an interaction (Nikolaidis et al., 2017) or over a sequence of repeated interactions (Shih et al., 2021). In the following section, we look at the interaction between human and robot or human and AI where an autonomous agent adapts to some salient feature of the behaviour of the human. The choice of such a feature suggests that the feature to which the agent is being adjusted is pertinent to whatever the goal of the interaction is. Adaptation parameters can be human intentions, physical factors, features that can be found in the cognitive aspect or acquired models of human behaviour depending on the nature of the interaction.

The AI teaming partners have to study their experiences with human team members in order to form a superior understanding of the team members. Inferring the goals of human partners is one way through which the agents exercising their behavior can comprehend it. The framework of goal recognition is often recognized as MDPs (Sutton & Barto, 2018). The problem of intent inference has been defined as either an inverse learning of reinforcement or an inverse optimal control. In goal inference, such as methods that use Bayesian considerations

are also common. The AI can infer the intent of the human partner which is which subtask the human partner wants to accomplish and can aid in an identical subtask. That is due to knowing the desired objectives would in turn direct the way a robot partner would revise its actions (Koert et al., 2019; Levine & Williams, 2018). Khoramshahi and Billard (2019) created a system of adaptive control to enable a robot to learn the desired task that a human partner is attempting to perform by keeping a belief distribution about each task and refining its beliefs according to the actions of a human. A switch in the task to what the human partner intends to do also activates the adaptation of the robot. The goals and the intentions of the human partner can also act as an indication according to which the robot adjusts to collaborative conduct.

Along with the inference of goals, cognitive or internal aspects of human partners are inferred and enable robot-to-human adaptation. Developing a model that learns how much a human can be adapted to their partner, Nikolaidis et al. (2017) created a computational formalism of mutual adaptation between a robot and a human partner in collaborative activity. The robot uses the metric of human adaptiveness in identifying how it can best work with the human partner and whether or not to direct the human partner through an improved approach. The mutually adaptive robot made the participants more adaptable in a user study, compared to a baseline cross-trained robot. The other cognitive element that determines behavior in a cooperative environment is the awareness and dislike of risk by humans. In Kwon et al. (2020), humans have risk-awareness, where people may vary in perceiving the difference between positive and negative rewards, and where they may vary in the level of aversion of negative rewards received. The state of mind of human partners observed by collaborative agents in Görür et al. (2018) happens in two steps. During the agent stage, the agent is preparing in advance the availability of the human and his or her ability to accomplish the task as well as the actual task. During the second stage, the robot will choose actions to be performed, namely, whether the robot should be helpful to the human or not. In one of the repeated conversational

talk, Hawkins et al. (2020) learn and adjust to human speaking conventions. The strategy builds on the fact that human beings develop new linguistic conventions by engaging in repeated interactions with partners in order to communicate better.

Human physical factors can guide robot adjustment in physical human robot interactions. Such internal factors include fatigue, which affects a person's ability to work hard in an activity. Peternel et al. (2018) adjusts the assistance of a robot to human motor exhaustion online. Electromyography is a way of quantifying the activity of the human muscle and once the fatigue levels reach a certain level the robot modifies its motion stiffness so as to take over the task completion leaving the human partner to put in fewer physical efforts. Zhang et al. (2020) take into consideration a human-robot physical cooperation during a manufacturing assembly scheduling issue. On the basis of the critical observation that robots' capability is generally constant, whereas human capability is generally variable, the system monitors the performance index of the human partner periodically and approximates the capability of the human. The ability of the human influences the ability to do the task required and a scheduler reacts to this ability and assigns more tasks to the robot companion. Nemec et al. (2018) identify robot control in a physical human-robot interaction adjusting on the measures of the speed and variance of human demonstrations.

2.7. Individual Differences in AI Adoption

2.7.1. Role of Managerial Experience

Practical wisdom is a concept based on the philosophy of Aristotle, and it involves making right decisions in particular situations and acting in the most desirable way in given circumstances. This idea represents the ability to make moral and practical decisions when an individual faces real-time, complex situation. Practical wisdom is often associated with self-awareness, processing in a balanced way, and ethical values. This means that, an individual

with practical wisdom knows how it is possible to use his knowledge, experience and make the best choice in this or that situation. Practical wisdom allows managers and leaders to properly analyze complicated situations, find the factors, and make responsible and ethical decisions, while taking into account the long-term outcomes. They are able to handle uncertainties and ambiguities, make good decisions in a difficult situation, and have innovative and creative solutions to problems using intuition and experience. Moreover, they interact well with their stakeholders and employees and incorporate them in making decisions. Other researchers have found that practical wisdom is one of the main factors in leadership and making ethical decisions (Akgün et al., 2019; Bratianu & Bejinaru, 2023a; Caniglia et al., 2023; Cugueró-Escofet & Rosanas, 2020a; Ferrero et al., 2020; Gluck, 2018; Kristjánsson et al., 2021; Trinh & Castillo, 2020; Winch & Hajikazemi, 2025).

Unlike practical wisdom, theoretical wisdom is more connected with profound knowledge and familiarity with widespread principles and concepts. It is applicable to the management education and psychological studies (Akgün et al., 2019). Despite the fact that theoretical wisdom does not directly affect the daily decision-making process, it could play a role in the application of practical wisdom although indirectly. Theoretical wisdom is also sometimes known as *sophia*, which entails a deep knowledge of the surrounding world as well as of human nature and the laws that govern them. Theoretical wisdom helps managers to have a wider scope on issues, which in turn, offers an ability to see them in bigger picture. This broader outlook can make them more predictive and develop the right strategies (Bratianu & Bejinaru, 2023b). Also, they can be better aware of human behavior, which can help them communicate more proficiently with their subordinates and implement philosophical and scientific concepts to come up with solutions and make judgments (Caniglia et al., 2023). For instance, managers who are also well versed in scientific formulations and the philosophical

concepts can be in a better position to think more critically about complex issues and make better decisions (Cuguro-Escofet & Rosanas, 2020b).

Organizational wisdom defines the organizational aptitude of using knowledge and experience in creating an innovation and better performance. The idea has been frequently linked to organizational learning, knowledge management, as well as organizational culture. Organizational wisdom helps organizations to leverage previous experiences and improve their products and processes. Organizational wisdom entails capability of an organization to learn out of the past experiences, learn and utilize the knowledge to improve performance and innovatively. The elements of this organizational wisdom include the production and preservation of organizational memory, knowledge sharing, and a culture that promotes learning and life-long learning. Organization wisdom will enable a company to learn through its historical experiences and will help it not to make the same errors. They are able to control knowledge and skills of their workers and utilize it to address problems and decision-making. Also, they may develop their organizational culture in order to promote learning, innovation, and constant improvement as they constantly upgrade their processes and products and respond to changes in the environment (Akgün et al., 2019; Bratianu & Bejinaru, 2023b; Cuguro-Escofet & Rosanas, 2020a).

Ethical wisdom also focuses on human virtues and moral principles and is used in various areas like ethical decision-making, crisis management, and ethical leadership. It assists managers to make ethical and responsible decisions within difficult circumstances. This idea is the ability to perceive and do what is right and ethical. Ethical wisdom helps organizational leaders and managers to be able to make responsible and ethical decisions even dealing with complex and high-stress situations. They are used as role models in ethical conduct in the organization, and they promote ethical culture, do justice to their workers and other

stakeholders, and meet their social responsibilities to the community and environment (Javadi & Damayanti, 2025).

2.7.2. Familiarity and Technological Competence with AI

The range of technologies that are able to address the surroundings and focus on the simulation of human intelligence describe the new generation of AI. The trustworthiness of employees in AI technology is a key element to the success of its implementation in organizations. Glikson and Woolley (2020) reviewed the distinction between AI and other technologies based on the available empirical studies exist on that time. The review focused on the factors that influence human trust in AI, carried out in various fields, and within the period of 20 years (2000-2020). AI was found to be in various forms such as robot, virtual, and embedded and the degree of machine intelligence (i.e., its capabilities) are viewed as crucial antecedents of the formation of trust on this study. Based on the review findings, the authors suggested a framework that describes the cognitive and emotional trust factors towards influencing users. This study found the significance of the reliability, transparency, tangibility, and immediacy behaviors in establishing cognitive trust exhibited by AI, and the anthropomorphism of AI specifically by enthusiastic trust. The study had some limitations to the present evidence base, including the variety of measures of trust and excessive reliance on small sample, short-term, and experimental studies, in which the formation of trust may vary in contexts of longer-term and high stakes fields (Glikson & Woolley, 2020).

One issue with human-AI team performance in seeking AI-assisted decision-making is that the humans need to use AI in the most appropriate way, as any uncertainties exist in both human and AI (Bansal et al., 2021; Buçinca et al., 2021; Lai et al., 2023; Schemmer et al., 2023). The overconfidence on AI negatively affects human-AI decision-making when the model will be imperfect or the information is not credible. Under-reliance, on the other hand,

is the inability of people to use proper AI recommendations and to take chances to work better. The primary emphasis in previous research has been on interventions that are centered on AI with the aim of encouraging proper reliance (Zhang et al., 2020). Specifically, the presentation of AI levels of confidence has been suggested to assist users in estimating the risks of accurate predictions (Ma et al., 2023; Vodrahalli et al., 2022b; Zhang et al., 2020). Also, providing explanations why AI outputs are produced is one of the popular methods of promoting conventional dependence (Bansal et al., 2021; Li & Yin, 2024; Wang & Yin, 2021; Zhang et al., 2020). However, there is a heterogeneous success of those AI-centric interventions, and it means that these methods do not necessarily contribute to better human-AI cooperation (Ma et al., 2023; Zhang et al., 2020; Zhao et al., 2023). Consequently, the increased attention has been paid to human self-confidence which is another major component of proper reliance (Chong et al., 2022; Ma et al., 2024; Mahmood et al., 2024; Vodrahalli et al., 2022a). According to the previous research, it is crucial to mention the role of self-confidence between human DMs as a determinant of the decision to use AI recommendations (Chong et al., 2022). Nonetheless, self-confidence has been a confined subject; it does not consider how it can be influenced, to reduce over- and under-reliance. Thus, in this paper, we put forward a hypothesis that self-confidence shaping may be one of the optionable approaches to the improvement of the human-AI team functioning.

AI-assisted decision-making has a major application in finance (Hase & Bansal, 2020; Zhang et al., 2020; Li & Yin, 2024; Vodrahalli et al., 2022b). Self-confidence in AI-assisted decision-making often seems efficient since it is a high-stakes field, where a mistake could potentially cost you a lot of money (Biran & McKeown, 2017; Lai et al., 2023), and due to its common overconfidence issue in people (Grežo, 2021). However, several tasks that are significantly examined in AI and aid in decision-making in finance, including income prediction, do not reflect the extremely high-stakes environment of finance (Lai et al., 2023;

Li & Yin, 2024). The studies that discuss investment decisions such as stock movement prediction, which may lead to significant losses (Biran & McKeown, 2017), and they all assume exclusive use of numerical data, disregarding textual information, such as corporate performance descriptions, which are extensively put into practice in the context of real investments (Takayanagi et al., 2025).

The speed and quality of decisions have evolved after the classical Simon's 1977 model, which aimed at breaking down the decision-making process, has been introduced with new technologies. Regarding data analytics, big data, and data-driven culture as they relate to the decision-making process, a large amount of literature was produced through multiple angles and across different spheres. On the aspect of speed and quality of decision taking, a number of studies have been conducted to examine the process of improvement, the time pressure among computer-supported groups, the competitiveness variability among the system of viable-services and complexity. Despite of the many research done in the field, studies relating data-driven culture with the speed and quality of decisions especially in the Albanian context, they are lacking. Hysa and Koldashi (2021) addressed these gaps and examined how data-driven culture impacts the decision-making' quality and speed with the purpose of the data-driven culture as a belief that all business units should be aligned with data use. This also ensure data is stored and people can access and operate to it. This study draws on the Huber's theory and focused on the impact of high information technology on the organizational design, intelligence and decision-making. According to Huber's theory, advanced information technology affects quality and speed of decisions. Unlike Huber, this study suggested that although organizations may employ the sophisticated information technology, in case it is not employed in a proper way and in the harmonious interaction with all business units, this technology has no benefits to the quality and speed of decisions (Hysa & Koldashi, 2021).

2.8.Theoretical Framework

2.8.1. *Technology Acceptance Model (TAM)*

The present study is grounded in the Technology Acceptance Model (TAM), which explains how individuals adopt and use technological systems (Xue et al., 2026; Lee et al., 2025). Originally proposed to examine user acceptance of information systems, TAM posits that users' behavioural intentions and actual usage are influenced by their cognitive evaluations of technology, particularly perceived usefulness and perceived ease of use (Xue et al., 2026).

In the context of AI-supported decision systems, TAM provides a foundational framework to understand how managers engage with AI tools in organizational decision-making (Song et al., 2025). However, due to the complex and autonomous nature of AI technologies, the traditional TAM model has been extended in contemporary research to incorporate additional psychological and contextual variables such as trust, perceived reliability, and risk perception (Mustofa et al., 2025; Khoso et al., 2025).

Within this study, AI-supported decision systems usage (AI-SDSU) represents the behavioural outcome of technology adoption (Song et al., 2025). Trust in AI and perceived reliability serve as key cognitive evaluations that enhance acceptance, while risk perception represents a negative evaluation that may inhibit usage and confidence (Khoso et al., 2025; Mustofa et al., 2025). These factors collectively influence managerial decision confidence, which extends beyond traditional TAM outcomes by capturing the psychological impact of technology on decision-making effectiveness (Song et al., 2025).

Furthermore, TAM supports the inclusion of individual differences such as familiarity with AI, as prior experience with technology enhances users' ability to interpret system outputs and increases their confidence in using such systems (Ibrahim et al., 2025). Thus, TAM

provides the primary theoretical foundation for explaining how AI usage and cognitive evaluations influence managerial decision confidence (Xue et al., 2026; Ibrahim et al., 2025).

2.8.2. Attribution Theory

Attribution Theory explains how individuals interpret events and assign causes to outcomes based on internal (personal ability, judgment) or external (situational or system-related) factors. In decision-making contexts, attribution processes play a critical role in shaping perceptions of responsibility, trust, and confidence.

In AI-assisted decision-making environments, managers must interpret whether decision outcomes are attributable to their own judgment or to AI system recommendations. This attribution process becomes particularly complex due to the “black box” nature of many AI systems, where the reasoning behind outputs is not fully transparent (Asatiani et al., 2020; Parlangeli et al., 2023; Stuart & Kneer, 2021; Sullivan & Fosso Wamba, 2022).

Attribution Theory is highly relevant to this study as it explains how managers form psychological evaluations of AI systems. Positive outcomes attributed to AI may increase trust and reliance, whereas negative outcomes attributed to AI may lead to resistance and reduced confidence (De Graaf & Malle, 2019; Guidi et al., 2021; Komatsu et al., 2021). Additionally, attribution biases such as self-serving bias and actor–observer bias influence how managers evaluate decision outcomes (Chen et al., 2024). This theory aligns with the study’s objectives by explaining:

- how trust in AI, perceived reliability, and risk perception are shaped through interpretation of AI outputs,
- how behavioural responses such as reliance and resistance emerge based on attribution patterns,

- and how managerial decision confidence is influenced by perceived responsibility for outcomes.

Thus, Attribution Theory provides a cognitive and psychological explanation of how managers interpret AI-supported decisions and develop confidence in their judgments.

2.8.3. *Signaling Theory*

Signaling Theory explains how individuals interpret signals under conditions of information asymmetry. Originally developed by Spence (1973) and later expanded by Connelly et al. (2010), the theory describes how signalers convey information to receivers through observable indicators, which are then interpreted to reduce uncertainty.

In AI-assisted decision-making, AI systems act as signal generators, providing outputs such as recommendations, predictions, and confidence scores. These outputs serve as signals that managers must interpret to make decisions. The clarity, consistency, and credibility of these signals influence how managers perceive the reliability and trustworthiness of AI systems.

Signaling Theory is particularly relevant in AI contexts where information asymmetry exists between the system and the user. Managers often lack full understanding of AI algorithms and must rely on observable outputs to evaluate system performance. Strong and clear signals enhance trust and perceived reliability, whereas ambiguous or inconsistent signals increase perceived risk and uncertainty (Guo et al., 2025; Machlev et al., 2021). This theory supports the study by explaining:

- how trust in AI develops through interpretation of system outputs,
- how perceived reliability is formed based on signal quality,
- how risk perception arises under conditions of uncertainty,
- and how behavioural responses such as reliance or resistance are influenced by signal interpretation.

Furthermore, the ability to interpret signals effectively is influenced by managerial experience and familiarity with AI, supporting their role as moderating variables in the study. Thus, Signaling Theory provides an information-processing perspective that explains how AI outputs influence managerial perceptions, behaviours, and decision confidence.

2.8.4. *Integrated Theoretical Framework*

The present study adopts an integrated theoretical framework combining TAM, Attribution Theory, and Signaling Theory to explain the psychological impact of AI on managerial decision confidence.

- The Technology Acceptance Model (TAM) explains how managers adopt and use AI systems and form evaluative beliefs regarding trust, reliability, and risk.
- Attribution Theory explains how managers interpret decision outcomes and assign responsibility, influencing trust, behavioural responses, and confidence.
- Signaling Theory explains how AI-generated outputs are interpreted as signals under uncertainty, shaping perceptions of reliability, risk, and trust.

Together, these theories provide a comprehensive explanation of how AI-supported decision systems influence managerial decision confidence through cognitive evaluations, information interpretation, and psychological processing. This integrated approach ensures that the study captures both technological and human dimensions of AI-enabled decision-making in organizational contexts.

2.9. Research Gap Identification

The need for the present research was justified by focusing on major factors, such as the contextual gap, a critical examination of existing studies, and the consideration of real-time implementation, which was explored in the rapid expansion of the literature on AI in

organizational decision-making. Many of the existing gaps were identified through the analysis of AI in organizational decision-making. The system's efficiency was improved by focusing on the technical aspects of AI, as many previous studies have, but by also addressing human factors related to AI. The research on managers' decision-making confidence with AI support was less explored. The psychological impact of AI on decision-making was explored by focusing on further research in this area.

The use of technology and performance was considered a major factor in most studies, creating a major gap in the existing research. The integration of human AI thinking and decision-making was less of a focus in the research. Prasanth et al. (2023) and Górká et al. (2025) stated that focusing more on speed, efficiency, and accuracy helps enhance AI's decision-making. Most studies focused on the technical implementation of AI in decision-making, lacking integration of human considerations. By ignoring the perspective of the human being, most studies consider the process of decision-making as a logical, data-based process. Managers consider psychological factors, such as perception, confidence, and judgment, in real situations when taking decisions. The managers' confidence in making decisions with AI increased as trust and reliability in the system were established. Confidence enhancement improves outcomes and enables managers to make strong decisions. The psychological impacts of AI need to be explored by analyzing a larger number of studies, which helps achieve the success of an organization and effective decision-making.

Various major factors impacting AI in decision-making related to humans, such as perceived reliability, trust, and risk perception, were explored separately, creating a gap that needs to be addressed by focusing on the integration of these factors. The complete framework of the study was ensured by the analysis of the integration of all the factors that needed to be focused on. Booyse and Scheepers (2024) further explore the assurance of transparency and

trust in the adoption of AI, while leaving other significant factors unaddressed. Baines et al. (2024) focused more on responsiveness from the user's perspective rather than on the major factors shaping AI's influence on decision-making. At a time, only a few factors are focused on by the study. But predicting the influence of human AI decision-making depends on integrating more psychological elements to work together. Many interconnected factors play a major role in complex decision-making. The manager's confidence in an organization was influenced by trust, reliability, and risk perception, and these factors need to be considered when making decisions using AI. A complete understanding of AI's impact on human thinking was not provided by using a comprehensive model that focused on integrating factors. The psychological factors influencing managerial decision-making need to be analyzed through more integrated research that considers all factors impacting human behavior.

The lack of consideration of the real organizational setting in analyzing the manager's behavior when using AI for decision-making creates a gap in the research, particularly regarding the organizational context. Instead of focusing on real-world managerial environments, major important factors associated with human-AI decision-making, such as algorithm version and automation bias, are explored using controlled experimental settings. The implementation does not ensure the external validity of the studies' findings. Without examining the major significant factors associated with the study, most studies focus on either overreliance or resistance to AI. The dynamic nature of behavioral responses needs to be further examined through research on behavioral coexistence over time. The techniques used by managers to balance reliance on AI with their own judgment and to build confidence in decision-making need to be explored.

In using AI, the lack of focus on individual differences among managers creates a significant gap. The adoption of technology by the people was influenced by managers'

familiarity and experience; these need to be analyzed more in the context of AI-based decision-making to enhance an organization. The experience manager resists to use AI since they rely more on past knowledge and intuition. The AI recommendations were more preferred by less experienced managers. The occurrence of uncertainty among managers was reduced by the familiarity with using AI technologies, which helped build trust in AI decisions; in turn, this enhanced managers' confidence in making decisions. Moreover, studies related to the behavioral aspects of managers with AI in decision-making need to be conducted in a more detailed and systematic way to provide valuable insights. The researcher focused very little on the relationship between AI use and decision-making impacting factors. The current finding was not applied to all types of managers due to a lack of examination of significant factors associated with AI use and confidence in decision-making. The overall understanding of AI's impact was expanded due to a lack of focus on major behavioral factors related to the study. The interaction between AI and influence on decision-making was explored, and more detailed, nuanced research was needed to predict individual characteristics.

The lack of connection between empirical studies and theoretical creates another important gap in the research. The understanding of the people was explored by focusing on theoretical concepts such as attribution theory and signalling theory, which help respond to information. The manager's interpretation of AI recommendations was explored using theories, but the decision-making process needs to be considered in the study. The use of results and observations is focused on most studies, which depend on empirical methods but lack the inclusion and comparison of related theories. Moreover, studies focusing more on theoretical concepts lack testing with real-world data. The usefulness of theories in practical situations cannot be predicted due to a lack of studies. The problem arose from the gap between practice and theory. The AI impact on manager thinking, decision-making, and behavior was understood through the proper integration of practice and theory. To develop a clear and complete

understanding of the psychological impact of AI, future research needs to focus on integrating theory with real-world evidence.

The manager's confidence was impacted by AI transparency and interpretability, which were not the focus of the studies, creating another important gap. Page and Kallapur (2025) stated that the results produced by the advanced generative AI model were not understood by many of the human-caused challenges. The AI's decision was hard for many managers to understand. The manager felt uncertainty due to a lack of understanding of the decisions made by AI. The reliance on AI recommendations and trust was affected by managers' lack of understanding. The major psychological factors related to the study, such as decision confidence, reliability, trust, and interpretability, need to be the focus. A manager's complete understanding of the decisions made by AI helps enhance confidence. To enhance trust and confidence in AI decision-making, more research was needed.

The focus on specific context and sector creates another major limitation in the study. The wide variety of organizational existence was not the focus of many studies; instead, most focused on AI in particular. The findings of the study were not suited to all types of business environments. The emerging countries were less focused on research than developed countries, creating a gap between organizations in different countries with various cultures. The adoption of AI and the decisions made were influenced by the fact that countries may have different cultures and resources. The more general and widely applicable insights were provided by focusing future research on the consideration of different countries, industries, and organizational contexts.

The lack of a complete and integrated framework creates a significant gap in the literature, as it focuses on behavioral and technological aspects of AI. The major studies focus only on the area of technical performance of AI impacting organizational outcomes. The impact

of managerial involvement in decision-making was affected by a fragmented approach. The combination of technology, behavior, and human thinking impacts the decision-making of managers in an organization. The development of a comprehensive model used in the study helps address the existence of a gap. Various factors, such as trust, risk perception, behavioral responses, perceived reliability, and individual differences associated with managers, were analyzed in the study. The study provides a deeper, more complete understanding through the integration of all elements. The limitations in previous research were addressed by the study, which provides valuable insights from theory and practice.

2.10. Conceptual Framework and Hypotheses Development

The conceptual framework below is adopted in this study (Figure 1):

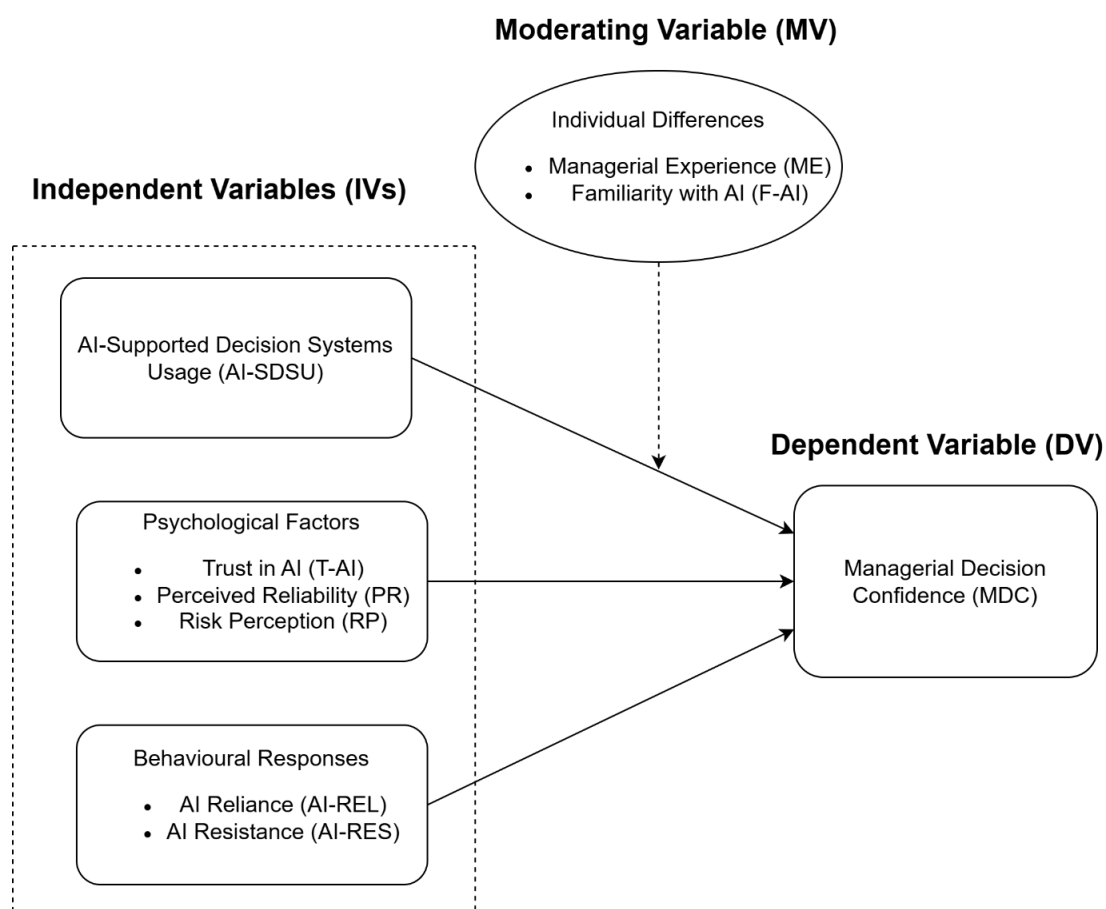


Figure 1:
Conceptual Framework (Satish Kondapareddy, 2026)

Research Variables:

Table 1 describes the chosen research variables of the study, including independent, moderating, and dependent variables:

Table 1: Research Variables

Independent Variables (IVs)	Moderating Variable (MV)	Dependent Variable (DV)
AI-Supported Decision Systems Usage (AI-SDSU)	Individual Differences • Managerial Experiences (ME) • Familiarity with AI (F-AI)	Managerial Decision Confidence (MDC)
Psychological Factors • Trust in AI (T-AI) • Perceived Reliability (PR) • Risk Perception (RP)		
Behavioural Responses • AI-Reliance (AI-REL) • AI-Resistance (AI-RES)		

2.10.1. AI-Supported Decision Systems Usage and Managerial Decision Confidence

(Satish Kondapareddy, 2026)

The Technology Acceptance Model (TAM) suggests that increased interaction with technological systems enhances users' familiarity, perceived usefulness, and confidence in utilizing such systems. In the context of AI, frequent use of AI-supported decision systems enables managers to better understand system outputs, interpret recommendations effectively, and integrate them into decision-making processes (Xue et al., 2026; Song et al., 2025).

Moreover, continuous exposure to AI systems reduces uncertainty and improves users' cognitive comfort with technology, which positively influences decision-related outcomes. As managers gain more experience with AI-supported decision systems, they are more likely to develop confidence in their decisions due to increased system understanding and reduced ambiguity. Therefore, it is expected that higher levels of AI-supported decision systems usage will positively influence managerial decision confidence.

***H1:** AI-supported decision systems usage (AI-SDSU) has a significant positive effect on managerial decision confidence (MDC).*

2.10.2. Trust in AI and Managerial Decision Confidence

Trust is a critical determinant in technology adoption and decision-making contexts. According to Attribution Theory, individuals develop trust based on how they interpret outcomes and assign responsibility for those outcomes. When managers perceive AI systems as reliable and capable, they are more likely to attribute successful outcomes to the system, thereby enhancing trust.

Additionally, Signaling Theory suggests that credible and consistent signals from AI systems strengthen users' trust under conditions of uncertainty. Empirical studies further confirm that trust significantly influences users' attitudes and acceptance of AI systems (Khoso et al., 2025; Mustofa et al., 2025). Higher trust reduces perceived uncertainty and enhances confidence in decision-making. Thus, managers who trust AI systems are more likely to exhibit higher levels of decision confidence.

***H2:** Trust in AI (T-AI) has a significant positive effect on managerial decision confidence (MDC).*

2.10.3. Perceived Reliability of AI and Managerial Decision Confidence

Perceived reliability refers to the extent to which users believe that AI systems provide accurate, consistent, and dependable outputs. From the perspective of Signaling Theory, AI-generated outputs act as signals that convey information about system quality. Strong, consistent, and accurate signals enhance perceived reliability, which in turn reduces uncertainty and improves decision confidence.

Furthermore, Attribution Theory suggests that when AI systems consistently produce reliable outcomes, users are more likely to attribute success to the system's capability, thereby reinforcing confidence in its outputs. Empirical research highlights that perceived reliability significantly influences user trust and acceptance of AI technologies (Khoso et al., 2025; Mustofa et al., 2025). Consequently, higher perceived reliability is expected to positively influence managerial decision confidence.

H3: Perceived reliability (PR) of AI has a significant positive effect on managerial decision confidence (MDC).

2.10.4. Risk Perception and Managerial Decision Confidence

Risk perception reflects the degree of uncertainty and potential negative consequences associated with using AI systems in decision-making. According to Attribution Theory, uncertainty and ambiguity in outcomes increase the likelihood of attributing negative consequences to external factors, thereby reducing confidence in decisions.

Additionally, Signaling Theory posits that unclear or inconsistent signals from AI systems increase perceived risk, which negatively affects users' trust and confidence. Empirical studies indicate that higher perceived risk reduces users' willingness to rely on AI systems and decreases confidence in decision outcomes (Lee et al., 2025; Khoso et al., 2025). Therefore, it

is expected that higher risk perception will negatively influence managerial decision confidence.

***H4:** Risk perception (RP) of AI has a significant negative effect on managerial decision confidence (MDC).*

2.10.5. AI Reliance and Managerial Decision Confidence

AI reliance refers to the extent to which managers depend on AI-generated recommendations when making decisions. Behavioural decision-making literature suggests that reliance on external decision support systems reduces cognitive effort and enhances decision efficiency, which can lead to increased confidence in decisions.

When managers appropriately rely on AI systems, they benefit from data-driven insights and reduced uncertainty, thereby improving their confidence in decision outcomes. However, reliance must be calibrated to avoid overdependence. Empirical studies indicate that appropriate reliance on AI systems enhances decision quality and user confidence (Bansal et al., 2021; Ma et al., 2023). Thus, higher levels of AI reliance are expected to positively influence managerial decision confidence.

***H5:** AI reliance (AI-REL) has a significant positive effect on managerial decision confidence (MDC).*

2.10.6. AI Resistance and Managerial Decision Confidence

AI resistance refers to the tendency of individuals to reject or avoid AI-generated recommendations. Behavioural decision-making research highlights that algorithm aversion can lead individuals to distrust AI systems, even when such systems provide accurate outputs.

Resistance to AI often arises from uncertainty, lack of understanding, or negative prior experiences, which reduce trust and increase cognitive conflict during decision-making. This conflict can lead to hesitation and reduced confidence in decision outcomes. Empirical evidence suggests that resistance to AI negatively impacts decision performance and user confidence (Castelo et al., 2019; Bansal et al., 2021). Therefore, higher levels of AI resistance are expected to reduce managerial decision confidence.

H6: AI resistance (AI-RES) has a significant negative effect on managerial decision confidence (MDC).

2.10.7. Moderating Role of Managerial Experience

Managerial experience plays a crucial role in shaping how individuals interpret and utilize AI systems. According to Attribution Theory, experienced managers rely more on established cognitive frameworks and prior knowledge when interpreting decision outcomes. This may influence how they attribute outcomes to AI systems versus their own judgment.

Experienced managers may exhibit greater skepticism toward AI recommendations due to reliance on intuition and past experience, which can moderate the relationship between AI usage and decision confidence. Conversely, they may also use AI more strategically when they recognize its value. Therefore, managerial experience is expected to moderate the relationship between AI-supported decision systems usage and managerial decision confidence.

H7: Managerial experience (ME) moderates the relationship between AI-supported decision systems usage (AI-SDSU) and managerial decision confidence (MDC).

2.10.8. Moderating Role of Familiarity with AI

Familiarity with AI reflects users' prior exposure, knowledge, and experience with AI technologies. According to TAM, familiarity enhances users' ability to understand and utilize technological systems effectively, thereby improving their confidence in using such systems (Ibrahim et al., 2025).

From the perspective of Signaling Theory, familiarity improves users' ability to interpret signals generated by AI systems, leading to better evaluation of system outputs. Users who are more familiar with AI are more likely to trust and rely on system recommendations, resulting in higher decision confidence. Therefore, familiarity with AI is expected to strengthen the relationship between AI-supported decision systems usage and managerial decision confidence.

H8: Familiarity with AI (F-AI) moderates the relationship between AI-supported decision systems usage (AI-SDSU) and managerial decision confidence (MDC).

2.11. Summary

This chapter reviewed existing literature on AI in organizational decision-making, focusing on its psychological and behavioral impact on managerial decision confidence. The literature highlights that AI-supported decision systems have transformed decision-making by enhancing data processing, improving accuracy, and enabling faster, data-driven decisions. However, most studies adopt a technology-centric perspective, with limited attention to human cognitive and behavioral aspects.

Managerial decision-making was examined through the lens of information processing and data-driven practices, emphasizing how AI reduces uncertainty but also introduces challenges related to interpretation and reliance. Managerial decision confidence emerged as a

critical construct influencing decision implementation, yet it remains underexplored in AI-related research.

The review identified key psychological factors affecting decision confidence, including trust in AI, perceived reliability, and risk perception. Trust and perceived reliability positively influence confidence by enhancing the credibility of AI outputs, whereas risk perception negatively impacts confidence due to uncertainty and perceived potential losses. Additionally, behavioral responses such as AI reliance and resistance play a crucial role, as managers may either over-rely on AI (automation bias) or resist it (algorithm aversion), affecting decision outcomes.

Individual differences, particularly managerial experience and familiarity with AI, were found to shape how managers interact with AI systems, acting as moderating factors. The chapter also incorporated Attribution Theory and Signaling Theory to explain how managers interpret AI outputs and form confidence judgments.

Overall, the literature reveals significant gaps, including the lack of integrated models addressing psychological, behavioral, and individual factors. This study addresses these gaps by proposing a comprehensive framework to examine the psychological impact of AI on managerial decision confidence.

Chapter 3:

Methodology

3.1.Introduction

The study assesses the psychological effects of AI on the confidence of managerial decisions, especially how AI-assisted decision systems can affect cognitive perceptions, trust, and behavioural responses while making decisions across organizations. The research is informed by a number of objectives, which include looking into how the use of AI-supported decision systems affects the confidence of the managerial decisions, exploring the impact of psychological variables like trust in AI, perceived reliability, and risk perception, and exploring behavioural reactions like AI reliance and resistance. A methodology chapter is meant to describe and justify the research procedures and methods used in order to fulfill the aim and objectives stated. It gives a detailed description of the research philosophy, approach, design, data collection methods, population, sampling, and data analysis methods applied in the research. The chapter provides transparency and rigour in the research process by clearly stating how data is collected, measured, and analysed to test the proposed hypotheses and also determines reliability and credibility for the research being conducted. According to this study, the research design adopted was quantitative research design, where primary data was collected through questionnaire survey from managers and decision-makers having AI-supported decision-making experience. In summary, the following sections are aimed at offering empirical data on the psychological and behavioural implication of AI in the sphere of managerial decision-making.

3.2. Research Philosophy

The research philosophy used in this study was positivism research philosophy, which is based on the assumption that reality is measurable, objective, and can be determined by means of statistical analysis and empirical observations. This design is commonly used by researchers who test hypotheses, make quantitative measurements of relationships between variables, and generalize the findings (Kaluarachchi, 2025). Positivism offers a more formal and scientific way of studying quantifiable constructs in the context of this study.

The main reason as to why positivism was chosen is due to the nature of the research objectives and hypotheses. The current research was structured to test pre-determined hypotheses (H1-H8) for examining correlational and causal associations between dependent, moderating, and independent variables. These variables are operationalized with the help of standardized measurement scales and measured with the help of structured questionnaire. This research design is backed up by positivism, which focuses on statistical validation, numbers, and objectivity, which enables the researcher to make valid and consistent conclusions. Moreover, the statistical methods of moderation and regression analysis with SPSS are consistent with the positivist paradigm in the importance of data-driven evidence over subjectivity. Positivism was relevant to the current study since it is concerned with the identification of relationships and patterns based on empirical information. As the study aims to comprehend the effect of AI use and psychological variables on the level of confidence in managerial decisions, it needs a way of systematically assessing these variables and evaluating their interactions. Positivism allows the researcher to isolate variables, test their moderating and direct impacts as well as assure that the results can be replicated and generalized to other similar organizational settings (Park et al., 2020).

Thus, positivist philosophy was the most suitable in this case since it shows how to use structured data collection, measurable variables, and strict statistical analysis. It makes the study reliable, objective, and scientifically sound and answers the research questions and tests the hypotheses proposed.

3.3. Research Approach

A deductive research methodology was adopted in this study to entail formulation of hypotheses using quantitative data that are based on the prevailing theories and subsequently conduct empirical tests for these hypotheses. This research methodology is a logical process that starts with theoretical backgrounds, hypothesis development, and ends with the data collection and statistical analysis. Within the framework of this study, the deductive approach was built based on the existing theories on technology adoption, behavioural decision-making, and trust in technology, all of which offer the conceptual foundation to comprehend the impact of AI on managerial decision confidence.

The main reason why the deductive approach was chosen is that the research objectives are structured, and there are clearly defined hypotheses (H1-H8). These hypotheses lay out the relationships anticipated among variables, including the use of AI-supported decision systems, the confidence of managerial decisions (the dependent variable), managerial familiarity and experience with AI usages (moderating variables), and behavioural (AI resistance and reliance) and psychological (risk perception, perceived reliability, trust in AI) variables. The deductive method was also appropriate since it enables the researcher to test these predetermined relationships in an objective and systematic way via statistical methods like moderation, regression, and correlation analysis using the SPSS. Moreover, the deductive methodology supports the positivist philosophy adopted in this research. Both focus on empirical validation, objectivity, and use measurable data to confirm or reject theoretical propositions (Abu-Alhaija,

2019). Deductive approach helped this research determining how the current theories are valid in the environment of AI-supported managerial decision-making, thus making the research a part of theory refinement and validation.

In summary, the most suitable research approach for the current study is the deductive one since it offers a rational, theory-based conceptualization of the studies of the relationships between usages of AI, behavioural responses, psychological variables, and managerial decision-making confidence. It guaranteed rigor in its methods and is able to objectively test hypotheses, which suits its quantitative nature and objective of the research.

3.4. Research Design

A quantitative research design was adopted in this research due to its objective, structured nature of exploring relationships among variables using statistical analysis. Since the current study aimed at quantifying the psychological effect AI has on managerial decision-making confidence through well-defined standardized measures and variables, this quantitative research design was most appropriate to conduct with. The research presupposed the testing of a number of predefined hypotheses (H1-H8), where statistical methods were used to analyze numerical data. This research design also helped the study ensuring objectivity, reducing biases, and offering generalizable and credible results on a larger sample of managers.

The rationale of using a quantitative design was that it is consistent with the aims of the research and the positivist philosophy that forms the basis of the study. Given that the study aimed at examining the impact of the use of AI-supported decision systems, behavioural reactions, and psychological variables on the managerial decision-making confidence, it is necessary to measure these variables and test the relations between them in an empirical way. A 5-point Likert scale was adopted for this design, which helped comparing the answers and identify trends and patterns across quantitative data. Also, statistical applications, including

SPSS, can be used to test hypotheses by methods like moderation and regression analysis, which are key towards attaining the objectives of the study.

The research also adopted a cross-sectional design, where the researcher involved in data collection at only one point in time from the research samples chosen. The design is appropriate as it enabled the researcher to obtain the prevailing behaviours, attitudes, and perceptions of managers towards AI-supported decision-making without the need to carry out an extended observation since the resources and time are limited. Furthermore, the study adopted a survey design, which involves a structured questionnaire as a primary data collection tool. Surveys are useful in obtaining standardized information of a relatively large sample of 200 to 300 respondents. A questionnaire was developed to give consistency in the responses, easy data coding and large-scale data analysis. They are also cost-effective and take less time particularly when conducted online and therefore, surveys are applicable in reaching managers of various organizations and industries.

3.5.Population and Sampling

3.5.1. Target Population

The study population included managers and organisational decision-makers who actively use or are exposed to AI-assisted decision systems in their work. The rationale for choosing them as population was due to the fact that they are directly engaged in the process of making decisions using AI. The targeted population guaranteed the relevance of the data used to address the research objectives, especially in the analysis of the effects of AI-based systems on decision-making behaviour and confidence in the actual organizational setting.

3.5.2. Sampling Technique

The sampling method used in this study was a non-probability method (purposive and convenience sampling). The convenience sampling was used due to its easy access nature from the respondents via organizational contacts, online platforms, and professional networks; whereas, purposive sampling guaranteed that only the respondents with the relevant experience of making decisions with the help of AI was the part of the study. The rationale behind non-probability sampling was the accessibility and time limitations that are inherent in practice and the necessity to focus on a certain group of respondents who have the required experience and knowledge in regards to AI systems. This method was efficient since the researcher can collect data of qualified respondents unlike probability sampling where a complete sampling frame and random sampling are required. This approach can restrict generalizability, although to a smaller degree, but this method is well-established in behavioural and organizational studies where the researcher is interested in a particular expertise as opposed to the random representation of the population.

3.5.3. Sample Size

To achieve generalizability, validity, and reliability for the findings of a study, an appropriate sample size needs to be determined. For quantitative research, especially conducted using moderation and regression analysis, one must have a sufficient sample size to attain adequate statistical power and reduce the bias in estimation. Accordingly, in the present research, the sample size is calculated based on the most commonly accepted formula created by Cochran (1977) and is applicable to large or unknown populations:

$$n_0 = \frac{Z^2 \times p \times (1 - p)}{e^2}$$

Where, ‘n’ means initial sample size, ‘Z’ denotes the Z-value (95% confidence level standard normal deviation = 1.96), ‘p’ denotes estimated population proportion (presupposed to be 0.5 to have the maximum variability), and ‘e’ means margin of error.

By substituting the values, the formula becomes:

$$n_0 = \frac{(1.96)^2 \times 0.5 \times (1 - 0.5)}{(0.05)^2} = 384.16$$

Thus, the ideal sample size was determined to be approximately 384 respondents. However, due to the specific focus on managers and decision-makers with exposure to AI-supported systems, and the use of convenience and purposive sampling techniques, achieving this ideal sample size was practically challenging. A total of responses was collected, and after conducting a rigorous data screening process (including removal of incomplete and inconsistent responses), a final usable sample of 280 respondents was retained for analysis.

Despite being lower than the ideal sample size, this sample is considered statistically adequate. According to the item-based rule of thumb, which recommends 5–10 respondents per questionnaire item, the present study with 32 items requires between 160 and 320 responses. The final sample size of 280 falls well within this acceptable range. Therefore, the sample size is deemed sufficient for conducting regression and moderation analyses, ensuring reliable and valid results.

3.6.Data Collection Method

Primary data was the optimal choice for data collection in this study, since it sought to collect original, pertinent, and precise data that directly originates out of respondents who are actively involved in managerial functions, and are currently working with AI-aided decision systems. Primary data collection method enabled the researcher to align the data collection tool

based on the research objectives, variables and hypotheses. The collection of original data is the fact that the study is guaranteeing that the information collected is very relevant, context-specific and representative of contemporary organizational practices relating to AI and decision-making. Moreover, the primary data collection allows for more control over the consistency, structure, and quality of the data collected, which is critical to performing rigorous statistical analysis.

A structured questionnaire survey was used as the main research instrument to collect these primary data. The questionnaire captured all the constructs in the conceptual framework that are important such as the usage of AI-supported decision systems, trust in AI, perceived reliability, risk perception, AI reliance, AI resistance, managerial experience, familiarity with AI, and managerial decision-making confidence. All these variables were being operationalized by a series of items, and measured using 5-point Likert scale with the lowest point strongly disagree and the highest point strongly agree. A structured questionnaire was being used to ensure that all respondents are receiving the same set of questions in a uniform format, thus improving the comparability and reliability of the responses.

The quantitative analysis was also improved through the structured form of questionnaires, since the responses can be being easily coded into numerical values which can be processed statistically with the use of SPSS. To make the questionnaire clear and logically structured, the questionnaire was categorized into various sections. In the first section, demographic data (gender, age, managerial experience, industry, etc.) was collected, and then the sections on the independent variables, moderating variables, and the dependent variable were included. This orderly system enabled respondents to comprehend the questions more readily and minimizing chances of being misleading or misunderstanding. Also, the close-

ended questions are reducing ambiguity and are making the responses comparable to all the sample.

The questionnaire was disseminated via several online resources, including Google Forms, email, and professional networking platforms and websites like LinkedIn. Such digital tools were chosen due to their convenient, efficient nature, and many professionals and managers are using it. The questionnaire was developed in Google Forms, which is offering a user-friendly interface, automatic records of data, and easy integration with data analysis tools. Direct outreach to possible respondents in organizations was carried out via email, and LinkedIn was used to reach out to professionals in various industries and geographical areas that have experience with AI-assisted decision-making systems. Online distribution presents a number of convenient benefits. Firstly, it is proving to be very economical, since it is doing away with the costs of printing, physical distribution and manual data entry. The survey is digital which also means that it is lowering the cost of the conventional data collection procedures, and therefore it is an appropriate option in academic research. Secondly, this process saves a lot of time, since it is making it possible to spread out the questionnaire to many respondents in a very shorter period. Real time responses are being collected, which enable the researcher to keep track of participation rates and make changes to boost response rates where needed. Furthermore, online platforms are making it easier and convenient to the respondents as they are able to take their own time to fill in the questionnaire and at their own convenient time. This adaptability increases the response rates and improves the data quality since respondents are not being restricted by location or time. Online surveys also have an advantage of anonymity, which motivated respondents to give sincere and objective responses, especially those relating to their perceptions and attitudes towards AI systems and decision-making processes. Another benefit is that it is guaranteeing standardized responses; thus, vital in ensuring the consistency of the data as well as reliability. The difference in responses is largely

due to the difference in perceptions and experiences of the respondents and not the inconsistencies of data collection process since all the respondents are being asked the same questions and response options. Such standardization increases the validity of the findings, and allows meaningful comparisons and statistical analysis of the various variables.

The process of data collection was needed to be developed in a manner that is understandable and easy. The questionnaire items were developed and worded in clear and simple language to prevent ambiguity. Clarity in instructions was being offered at the commencement of the survey to inform the respondents on how to fill in the questionnaire. The questionnaire was also be pre-tested among a small group of respondents to determine whether any difficulties can arise regarding the clarity, wording or structure of the questions. The pre-test feedback was being utilized to improve the questionnaire, where additional measures were being taken to ensure that the questionnaire was successfully measured the target constructs.

Moreover, a structured questionnaire is also in line with the quantitative nature of the study since it is facilitating the gathering of large amounts of data that can be analysed statistically to ascertain the hypotheses proposed. The Likert scale responses were converted into numerical data, which is appropriate to perform different statistical analyses, such as moderation statistics, regression analysis, correlation analysis, reliability testing, and descriptive analysis. This correspondence between the data collection procedure and the data analysis procedures is facilitating consistency and methodological soundness in the research procedure.

On the whole, the data collection method used in this research was under the process of carefully choosing and applying it to guarantee high quality, reliable, and relevant data is collected. The survey in a structured questionnaire form given online was proven to be efficient and effective in reaching a huge number of managers and decision-makers. The methodology

helped advancing the goals of the research as it allows measuring the important variables in a systematic manner and conducts a powerful statistical analysis. Consequently, the selected data collection strategy played a key role in guaranteeing the reliability and validity of the research results and thus provided a comprehensive insight into the psychological effects of AI on managerial decision confidence.

3.7. Instrument Design

The study's research objectives were assured of their efficiency through the instrument design used. The systematic collection of data for the study was ensured through the integration of various development tools, such as questionnaires, measurement methods, and survey instruments, which help ensure the reliability and validity of the data collected. All independent and dependent variables considered in the implementation of the conceptual framework, such as behavioral responses, psychological factors, and moderating variables, were carefully considered in the framing of the questionnaire for the evaluation of the study. Each question in the questionnaire was aligned with the research hypotheses (H1-H8), focused mainly on enhancing consistency and clarity. Confusion and ambiguity were reduced by framing the questionnaire so respondents could understand it, thereby improving the overall reliability and quality of the collected data.

The study's dimensions were captured in the questionnaire and organized into sections. Demographic details, including participant age, managerial experience, and industry type, are collected in Section A of the questionnaire. The researcher evaluated the influence of perceptions of AI and decision-making confidence on the respondent by using the demographic details collected (Araujo et al., 2020). The collection ensured the interpretability and generalizability of the study's findings regarding demographic data across diverse managerial profiles.

The evaluation of AI-supported decision systems (AI-SDSU) by managers was supported by Section B of the questionnaire. The reliability of Section B of the questionnaire was assured by previously validated studies, which helped construct it on a firm foundation in established literature. Various factors considered in the questionnaire, such as reliance on AI-generated insights, integration into daily workflow, and frequency of use, help evaluate managers' use of AI tools in the decision-making process, as predicated by the questionnaire used in Section B. Research objective 1, which was addressed by capturing the level of AI usage, provides a foundation for analyzing managerial decision-making confidence. The content validity of the study was assured by the use of validated measurement items, which helped ensure consistency with prior empirical research (Ramachandran et al., 2023; Zhang et al., 2025).

The manager's decision-making confidence was evaluated using Section C of the questionnaire, with consideration of psychological factors. The Risk Perception (RP), Trust in AI (T-AI), and Perceived Reliability (PR) play a major role in examining managers' confidence in decision-making. Based on the consideration of well-established studies, questions related to evaluating the trust of AI were considered in the questionnaire. The established developed scales help evaluate the measurement of Trust in AI (McGrath et al., 2025; Scharowski et al., 2025; Jian et al., 2000; Küper & Krämer, 2025). The overall trustworthiness, perceived integrity, and respondents' confidence in AI systems were evaluated using established scales. The consistency, accuracy, and dependability of AI outputs were evaluated using perceived reliability (McGrath et al., 2025; Scharowski et al., 2025; Alordiah, 2025). The concern related to negative consequences, potential errors, and uncertainty was evaluated based on risk perception associated with AI use (Zhou et al., 2025; Tagini et al., 2021). The use of AI was explored from both cognitive and emotional perspectives, highlighting factors such as trust, fear, and confidence in AI based on people's psychological perceptions.

The behavioral responses to AI were evaluated using Section D, considering two aspects: AI Reliance (AI-REL) and AI Resistance (AI-RES). The AI REL mainly focuses on evaluating managers' dependency on AI by considering questions derived from analyses of related studies, seeking support for tasks, and integrating it into the judgment (Castro et al., 2025; Klingbeil et al., 2024). Reluctance, skepticism, and avoidance behaviors toward AI systems are considered major behaviors that help measure AI resistance. The research objective 3 used in the study helped evaluate managerial decision confidence through behavioral engagement, using this Section. The balanced assessment of managerial interaction with AI technologies was ensured by including both positive and negative behavioral constructs (McGrath et al., 2025; Scharowski et al., 2025; Özdemir, 2025).

The Managerial Decision Confidence (MDC) dependent variable was the focus of Section E. MDC assessed decision confidence in organizational contexts. Various major factors associated with the study, such as the level of certainty, perceived effectiveness of decisions, and assurance, were evaluated. The primary study outcome variable, aligned with the central research objective, was ensured by capturing various major factors associated with the evaluation of MDC (Cau & Spano, 2025; Lorentz & Hilmola, 2012).

The Familiarity with AI (F-AI) moderating variable used in the study was evaluated using Section F. Based on the analysis of previous studies, the overall comfortable of using AI technologies and ability of interpretation AI output by the managers was evaluated by questionnaire helps in examining the moderating effects on the relationship between managerial decision confidence and AI usage provides deeper understanding into individual differences (Castro et al., 2025; Sahari, 2024).

A 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree was used to evaluate participants' responses to the questionnaire. The behavioral tendencies,

perceptions, and attitudes were captured in a structured manner using a Likert scale. The varying degrees of agreement and disagreement by the user were captured using a scaling technique, which is suitable for statistical analysis and helps capture attitudes, perceptions, and behavioral tendencies. The reliability and comparability of the findings were assured through the use of a Likert scale in the study.

Using the validated literature, information related to the questionnaire is retrieved. The content validity of the instrument used in the study was enhanced by consideration of prior related literature. The occurrence of measurement error related to the study was reduced by the adaptation of the questionnaire approach, which helped strengthen the study's reliability. The construct validity was further enhanced by the integration of multiple sources for each construct, which helps capture different dimensions of the variables.

The ordering of questions, the wording used in the questionnaire, and the order of questions are carefully designed. To enhance the respondent's understanding of the questionnaire, the language used was simple and clear, helping the respondent understand and interpret each question. The respondent was kept engaged by the structural features of the questionnaire, such as a logical sequence and starting with general information like demographics. Focusing on major topics such as the use of AI, behavioral responses, psychological perceptions, and decision confidence helps reduce fatigue when answering the survey and improves the accuracy and quality of responses.

The quantitative research approach used in the study, which plays a major role in the overall design of the research instrument, helps achieve the objectives of the study in an efficient manner. The reliability and validity of the study were assured by using a well-structured questionnaire, established with the integration of a measurement scale and a clear, logical format. The consideration of the complex nature of AI-supported decision-making was

ensured through the integration of various aspects, including technological, psychological, and behavioral factors, in the questionnaire. The overall quality and rigor of the research were assured by the study instrument, which provides a robust foundation for examining the psychological impact of AI on managerial decision-making confidence.

3.8. Data Analysis Techniques

The moderate sample size of 200 to 300 respondents was considered for the study, and the use of IBM SPSS Statistics software, efficient for handling quantitative data, helped assure reliability and efficiency. The examination of the relationship between variables and the hypothesis testing of the study were ensured with the use of IBM SPSS software, which helped the researcher organize the process and analyze the collected data. The study's assured calculation was ensured by SPSS, which helped generate clear output and interpretation of the results associated with the research framework.

3.8.1. Preliminary Analysis

The preliminary test was conducted by the researcher before performing the statistical analysis, which included data cleaning. Based on the consideration of major factors such as unusual values, duplicate entries, and inconsistent responses dataset used in the study was examined. The alignment of the expected questionnaire format with the participant's responses was ensured by the researcher. Missing values were either replaced with the average or incomplete cases were removed to manage missing data. The overall validity of the research was impacted by improper cleaning and handling of missing values. The dataset was further focused for statistical testing in the initial stage of data analysis, which was considered a preliminary analysis of the study.

3.8.2. *Descriptive Statistics*

The key characteristics of the dataset were evaluated using descriptive statistics, followed by preliminary analysis used in the study. The measurement items were evaluated based on the mean, standard deviation, minimum, and maximum values calculated from all measurement values. The demographic variable in the study was evaluated using a frequency distribution. The central tendency of responses was assured with the consideration of the mean value. The variability around the mean was measured using the standard deviation. The general response pattern of the study was identified by the analysis used; this helps assure that the data adequately represent the construct under study. Before proceeding with inferential analysis, descriptive statistics provide a foundational understanding of the study.

3.8.3. *Normality Analysis*

The normal distribution used in the study helps ensure the consideration of the advanced statistical tests used by the researcher. The use of the Kolmogorov–Smirnov test helps examine the normality assumption used in the study. The abnormal distribution of the data used in the study was confirmed by a significance value less than 0.05 (Field, 2018). The deviations from normality were caused by the consideration of Likert-scale data and moderate sample sizes in the behavioral research.

The reliability of the study was assured through the use of regression and correlation analyses. The composite use of variables in the study helps ensure the efficient use of parametric techniques rather than individual items. The occurrence of minor deviations and normality results was interpreted in light of the sample's impact on the normality result of the study. The sample size used in the study helps evaluate the results of the normality test. The practical survey conditions were ensured while maintaining methodological rigor.

3.8.4. Common Method Bias (CMB)

The occurrence of bias was assessed using common method bias (CMB), as the study relies on self-reported questionnaire data collected from a single group of respondents. The majority of the dataset's variance was evaluated using Harman's Single Factor Test. Factor analysis helps examine the entire set of measurement items used in the study. The occurrence of bias was not considered a serious concern if the first factor accounts for less than 50% of the total variance (Aguirre-Urreta & Hu, 2019). The existence of a relationship between the variables used in the study was confirmed using Harman's Single Factor Test. The credibility and reliability of the findings were enhanced by considering data collected from real sources, and the genuine use of variables in the study was assured.

3.8.5. Reliability Analysis

The use of Cronbach's Alpha by the researcher helps ensure the reliability and consistency of the questionnaire used in the study. The reliability of the questionnaire was assured with a Cronbach's Alpha value of 0.7 or higher. All key words used in the study, such as behavioral responses, managerial decision confidence, and behavioral responses, are evaluated using the Cronbach's Alpha test. The consistency of the study was compromised by removing questions, thereby reducing its overall reliability. The accuracy of the data used in the study was assured through the Cronbach's Alpha test, which helps to assure reliability (Hair et al., 2019).

3.8.6. Validity Analysis

The existence of relationships among variables was examined using Exploratory Factor Analysis (EFA), which helped provide meaningful factors associated with the study. The instrument's accuracy in the study was ensured through validity analysis. The sustainability of

the data used in the study was evaluated using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. Factor loadings with an association with the factor and values above 0.50 are considered acceptable (Hair et al., 2019).

The Composite Reliability (CR) and Average Variance Extracted (AVE) are assessed to assure convergent validity and construct reliability. The consistency of the item was assured; a value higher than 0.70 indicates good reliability. Convergent validity was established with Average Variance Extracted (AVE) values above 0.50. The statistical reliability and theoretical appropriateness were assured by the use of both CR and AVE in the study, which helps make the research findings more accurate.

3.8.7. Correlation Analysis

The behavior of the variables used in the study was accurately predicted using Pearson's correlation analysis. The existence of strength and direction between the variables used in the study was predicted. The existence of a strong relationship between the variables was confirmed by the values of +1. The value of -1 in the results indicates that one variable increased and the other decreased. The correlation coefficient values range from -1 to +1. The nonexistence of a relationship between the variables was indicated by a value of 0 (Kafle, 2019).

The existence of a relationship between variables was initially assessed using correlation analysis. The interaction between the variables was proactively predicted using early insights before conducting more advanced analyses, such as regression. The existence of a relationship between the variables was confirmed, and the use of multicollinearity was assessed to determine its impact on the accuracy of regression results. The presence of multicollinearity was ensured by considering correlation values below 0.70. A clearer understanding of the relationships among variables was assured through the correlation

analysis, which helped the researcher gain a clearer understanding in the context of AI-supported decision-making.

3.8.8. Regression Analysis

The integration of SPSS with regression analysis helps to test the proposed hypothesis (H1-H6) used in the study. The direct impact of the independent variables on managerial decision confidence was examined using separate regression models. The strength and significance of each independent variable used in the study, such as AI-supported decision systems usage, trust in AI, risk perception, AI reliance, perceived reliability, and accuracy, were evaluated using regression analysis. The clear understanding of each independent variable was provided to the researcher by the use of regression analysis, which helps influence managerial decision-making and supports the validation of the study hypothesis (Kafle, 2019).

The strength and direction of the relationship between the variables used in the study were provided using coefficients, which indicate the statistical relevance and the hypothesis supported for the study. The R-squared and adjusted R-squared values help evaluate the overall effectiveness of the model. The test's accuracy was assured through the use of a diagnostic test. The presence of autocorrelation was evaluated using the Durbin–Watson statistic. The closeness among the variables was evaluated using VIF values. The validity of the proposed relationships was assured using regression analysis.

3.8.9. Moderation Analysis

The moderation analysis is conducted using the PROCESS macro (Version 5.0) to help evaluate the moderating effects proposed in H7 and H8, specifically the Model 1 developed by Hayes (2018). The existence of relationships between moderating variables, such as familiarity with AI and managerial experience, was explored using moderation analysis. The occurrence

of multicollinearity was reduced, and the use of analysis helped improve accuracy and interpretation. The interaction between the moderating and independent variables was ensured by creating a macro process that automatically generates the interaction. To generate confidence intervals, the use of the bootstrap technique was recommended, which helps increase the robustness and reliability of the study. The moderation was supported by the statistical significance of the interaction effect; the relationship varied across different levels of the moderator. The non-significant interaction effect confirmed the absence of moderation.

3.9. Ethical Considerations

The research was conducted in an honest and professional way, with ethical considerations implemented. The research needs to adhere to strict ethical guidelines throughout the entire research process due to the involvement of human participants, such as managers and decision-makers, in the study (Ali et al., 2025). The participant needs to be clearly informed about the purpose of the study and the type of questions to be asked through the informed consent. A brief explanation of the research objectives used in the study, provided to the respondent at the beginning of the questionnaire, helps increase the respondent's confidence. Respondents need to be assured that their responses will be used only for academic purposes. The respondent provided a clear understanding that only those participants who voluntarily agreed to take part in the study were included.

The study needs to ensure that the consideration of voluntary participation of the respondent helps ensure the respondent takes part on their own. The participant was clearly informed that the involvement was optional and that they had the freedom to withdraw from participation at any time without facing any negative consequences. Throughout the research process, the researcher needs to ensure the respondent's comfort and respect. The study fosters trust by allowing participants to make independent decisions. The overall quality of the data

was assured through respondents' honest, accurate, and unbiased answers (Ndubuisi & FNisafetyE, 2025).

The confidentiality and anonymity of all respondents need to be assured, as they play a major role in the implementation of ethical considerations. The details revealing the participant's personal identities, such as name, contact details, and organizational identifiers, need not be collected by the participant in aggregated form; all responses from the participant need to be recorded and analyzed. The respondent's privacy was safeguarded with the use of an aggregated form encourage participant to share genie participations (Asogwa & Sinthumule, 2025).

3.10. Limitations of Methodology

Even though the study uses a structured and rigorous methodological approach, it is impacted by limitations in the research method and design. The major limitation of the study was the vulnerability of the data to biases arising from self-reported data collected through questionnaires. Due to the existence of response bias, participants have a chance to either overestimate or underestimate the use of an AI system (Akbulut et al., 2023). Data collected at a single point in time affects the study's cross-sectional design. The long-term effects of the variable associated with the study were not captured, and no relationships between variables were identified as major; another limitation of the study. The deeper insights were provided by a longitudinal approach (Neiroukh et al., 2025). The non-probability sampling method used to select the participants of the study was based on selecting respondents based on ease of use and relevance to the study, rather than on random selection.

3.11. Summary

In summary, this methodology chapter provided a detailed description of the research method that examined the psychological effects of AI on the managerial decision-making confidence. It presented the major methodological decisions of choosing the positivist research philosophy and the deductive research approach, which are in line with the aim of testing existing hypotheses and testing relationships between measurable variables. The research design used was quantitative research design and a cross-sectional survey strategy was also used in the study, which allowed the researcher to collect data in a systematic manner using a cross-sectional survey strategy and managers and decision-makers using AI-supported decision systems. Non-probability sampling has been explained by the accessibility and relevance of the sample size (300 respondents) and the structured questionnaire instrument was developed to provide valid and reliable measurement of all constructs. The rationale of a quantitative approach has been strongly supported throughout the chapter as it is offering a systematic, objective, and statistically sound framework of examining the connection between AI use, psychological aspects, behavioural reactions and managerial decision confidence. The consistency of responses was ensured by the use of a 5-point Likert scale and a standardized questionnaire, whereas rigorous data analysis was ensured by using statistical SPSS tools using techniques like descriptive statistics, reliability and validity tests, correlation, regression and moderation analysis. These methodological decisions are such that the research is generating empirical and generalizable results that are based on quantitative evidence. In general, this chapter laid a strong groundwork towards the next phase of the research. Data analysis and findings will be discussed in the next chapter where the data obtained will be analysed systematically with the help of SPSS and the results of statistical tests will be presented and discussed in terms of the hypotheses of the research. Such a shift will allow the study to shift

towards a methodological design to empirical evaluation and eventually lead to a more profound comprehension of the role of AI in influencing managerial decision confidence.

Chapter 4:

Results

4.1. Introduction

This chapter presents the empirical results shows data obtained is analyzed to investigate the psychological effect of AI on confidence in decision-making by managers. This analysis is accomplished as per the objectives of the research and hypothesis as stated in the earlier chapters. The major objective of the chapter is to give a critical and objective assessment of the association between the AI-assisted system of making decisions and its usage, psychological elements, behavioral reactions, and decision confidence of managers based on the quantitative analysis.

The chapter starts by giving a background of the demographic characteristics of the respondents and the background of the sample composition. The preliminary data analyses, such as descriptive statistics, normality testing, reliability analysis, common method bias testing and exploratory factor analysis, to determine the appropriateness and the quality of the data to be used in further statistical analyses.

Correlation analysis is then accomplished to determine the strength and the direction of relationships between the key variables. The constructs are correlated, and then hypothesis testing will be accomplished. The chapter outlines regression analyses to test the direct relationships suggested and moderation analysis to test the role of individual differences, namely, managerial experience and familiarity with AI.

All hypotheses are addressed systematically, and the findings are discussed as per the objectives of the research. The chapter ends with a conclusion of the main findings that will be used as a foundation to discuss in the following chapter.

4.2. Demographic Characteristics

The section of the demographic categories shows the collective profile of respondents who participated in the survey session. The demographic variables mainly analysed through the age of respondents, gender, industry type, and managerial experience. These structures provide an overview of the conformation of the sample and allow the researcher to assess the importance of respondents to the students' contexts.

4.2.1. Age

Table 2 and Figure 2 show the age distribution of the respondents. The outcomes show that a large portion of the population belonged to the 25 to 34 years age limit, accounting for 33.9% of the total sample. Respondents between the ages of 35 and 44, who made up 28.9% of the sample, came next. 18.6% of respondents were between the ages of 45 and 54, while 10.4% were younger than 25. Respondents who were 55 years of age or older made up the smallest group, accounting for 8.2% of the respondents being examined.

Table 2: Age of Respondents. (Satish Kondapareddy, 2026)

Age (years)	Frequency	Percent
Below 25	29	10.4
25-34	95	33.9
35-44	81	28.9
45-54	52	18.6
55 and above	23	8.2
Total	280	100.0

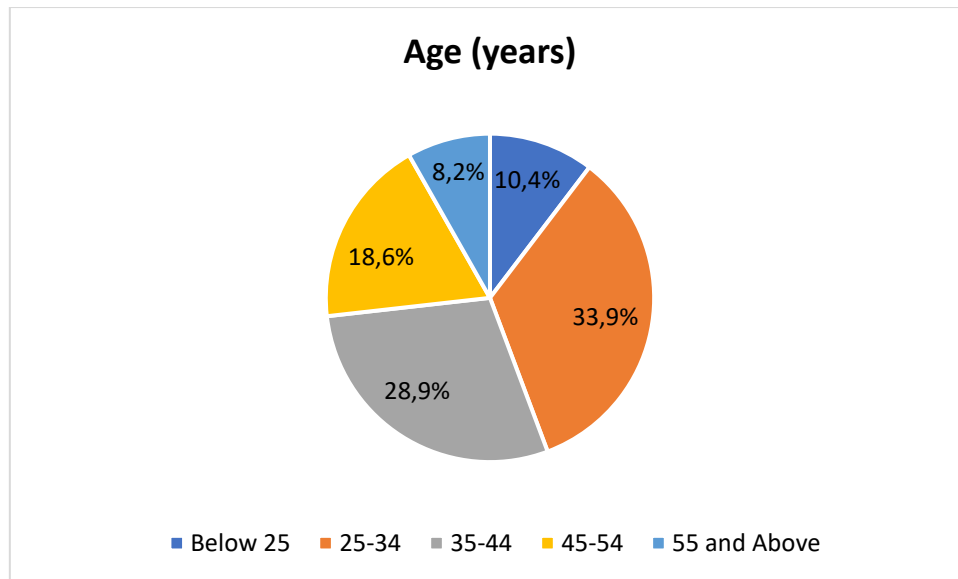


Figure 2: Age of Respondents (Pie-Chart). (Satish Kondapareddy, 2026)

The findings show that most of the respondents are categorised in the early-to mid-career stages, which is suitable for the researcher to focus on the managerial decision-making in business. The high representation of respondents from the 25 to 44 age range shows that the study gets the perceptions of managers about the AI-supported decision-making process. Along with that, older respondents' inclusion supports the adversary of managerial perspectives within the sample.

4.2.2. Gender

Table 3 and Figure 3 display the gender breakdown. According to the results, 40.4% of respondents were female, and 51.8% of respondents were male. An additional 7.9% of the chosen responders would rather remain silent.

Table 3: Gender of Respondents (Satish Kondapareddy, 2026)

Gender	Frequency	Percent
Male	145	51.8
Female	113	40.4
Prefer not to say	22	7.9
Total	280	100.0

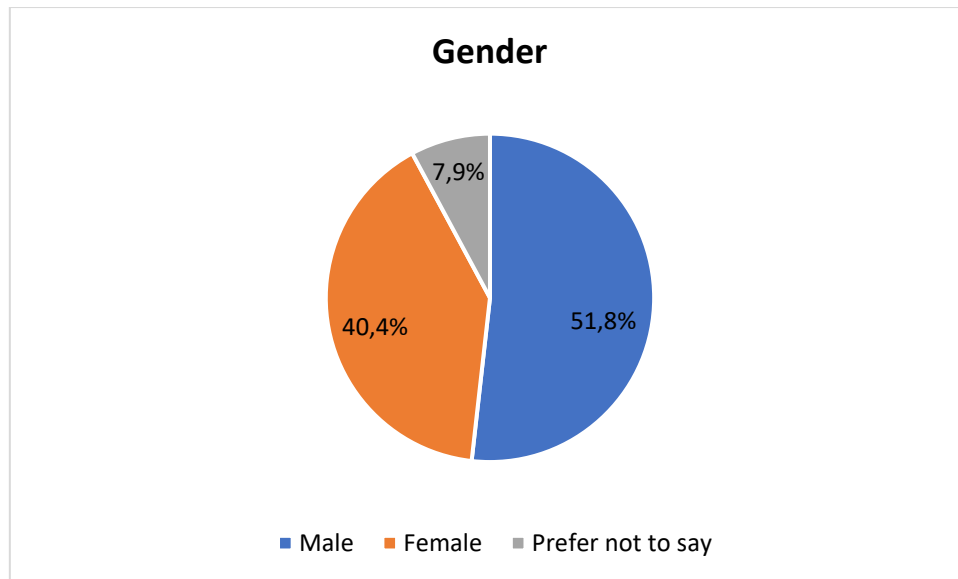


Figure 3: Gender of Respondents (Pie-Chart). (Satish Kondapareddy, 2026)

The outcome shows that in the survey, both male and female respondents participated. In this survey, male participants outnumber female participants, but the diversity shows that both males and females have experience working in managerial positions, and studying can provide different perspectives. Incorporating respondents who chose not to reveal their gender also demonstrates ethical consideration and encourages respondents to feel comfortable taking part in the poll.

4.2.3. Industry Type

Table 4 and Figure 4 show the respondents' distribution across different industries. Almost 30.7% of the participants belonged to the IT and software development sector, 21.8% of respondents belonged to business consulting services, 15.4% in the finance sector, 16.4% in the healthcare and 13.2% belonged to the manufacturing sector. The results show that only 2.5% of respondents were categorised in the other section,

Table 4: Industry Type of Respondents (Satish Kondapareddy, 2026)

Industry Type	Frequency	Percent
IT & Software	86	30.7
Finance	43	15.4

Healthcare	46	16.4
Manufacturing	37	13.2
Business Consulting Services	61	21.8
Others	7	2.5
Total	280	100.0

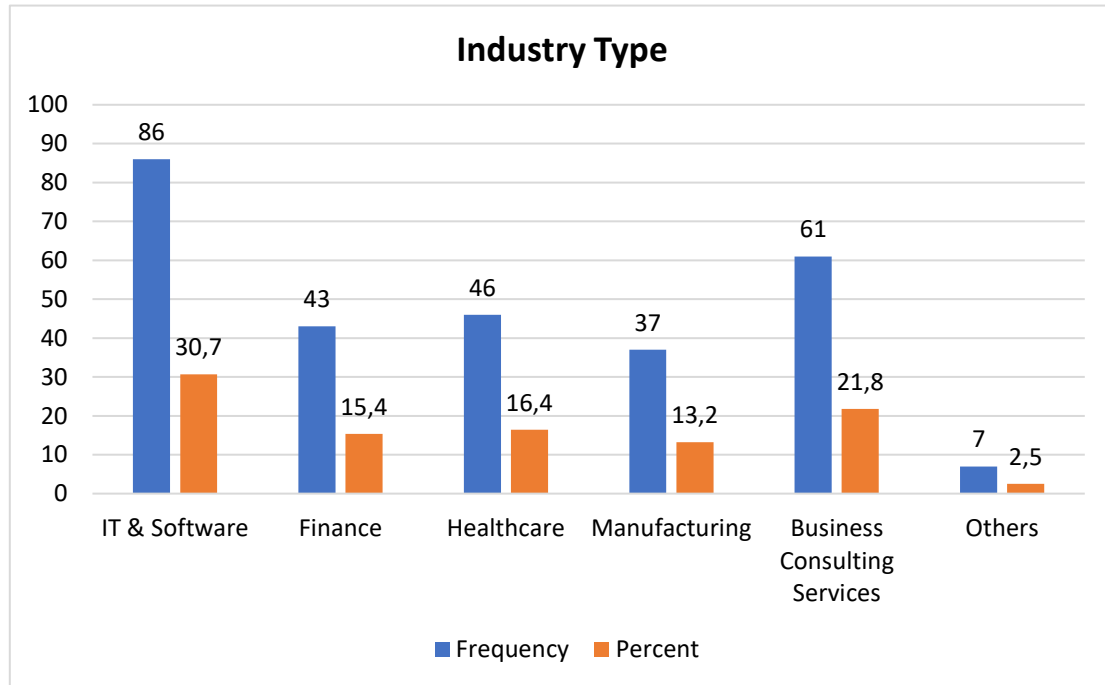


Figure 4: Industry Type of Respondents (Bar Chart). (Satish Kondapareddy, 2026)

The findings present that the high proportion of respondents belonged to IT and software development sectors which highlights that the AI technologies integration in the technology driven sectors, along with that inclusion of the respondents from finance, manufacturing section sectors healthcare shows that study include indifferent organisation contexts here AI technologies integrated with the aim of inducing the decision-making process. the diversity is the surveys shows the findings applicability and presents the comprehensive understanding of the behavioural and psychological effects of using AI among the managers across the different industries.

4.2.4. Managerial Experience

Table 5 and Figure 5 show the managerial experiences of the respondents. From the findings, it has been found that the 33.9% of the respondents have 3 to 7 years, 24.3% of the respondents have 8 to 12 years, 20% of the respondents have more than 12 years' experience.

Table 5: Managerial Experience of Respondents (Satish Kondapareddy, 2026)

Managerial Experience (years)	Frequency	Percent
Less than 3	61	21.8
3 to 7	95	33.9
8 to 12	68	24.3
More than 12	56	20.0
Total	280	100.0

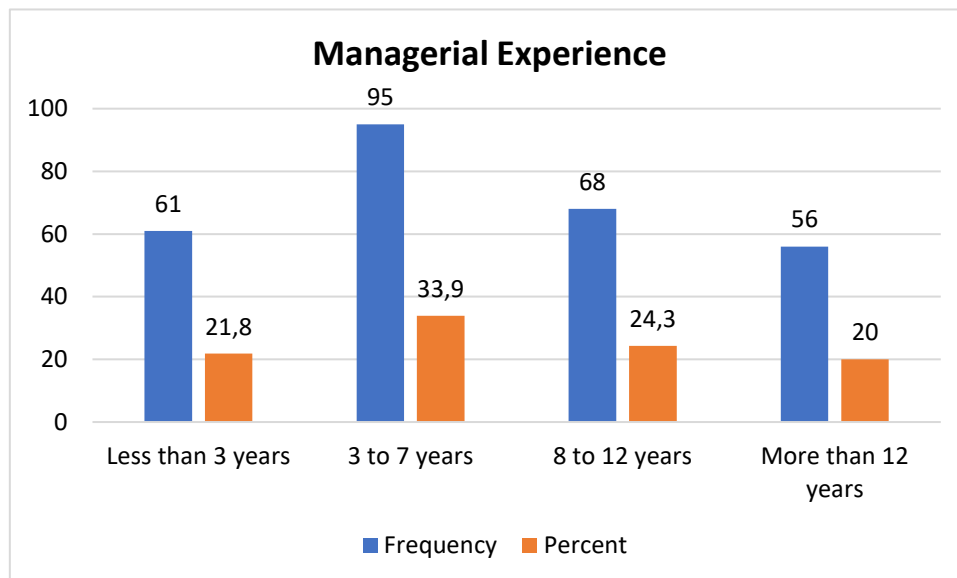


Figure 5: Managerial Experience of Respondents (Bar Chart). (Satish Kondapareddy, 2026)

From the findings, it has been found that the distribution mainly indicates that early-career individuals are highly seasoned professionals. The high concentration within the 3 to 12 years' experience range shows that a significant portion of the respondent population consists of managers who have contributed to the AI-driven decision-making process and are familiar with the AI application in businesses. Along with that, the presence of the highly experienced managers adds more strategic and established perspectives to the study.

Overall, the demographic profile findings show that the sample is appropriately diverse and helps in examining the managerial perception and confidence in AI integration in the decision-making process in different sectors.

4.3. Preliminary Data Analyses

In this study, different initial analyses have been carried out before the proposed hypothesis with the aim of checking the suitability and quality of the data. These mainly comprise testing for normality, descriptive statistics, reliability analysis, checking for the mutual method bias, and exploratory factor analysis. When taken as a whole, these procedures helped guarantee that the data were suitable for more inferential statistical analysis.

4.3.1. Descriptive Statistics

Table 6 shows the descriptive statistics for all the measurement factors that are included in this study. For each of the factors, mean, median, and standard deviation values were formulated. The outcome shows that all the factors recorded a minimum of 1 and a maximum value of 5, and that confirms that responded has been used the Likert five-point scale. This finding shows that factors help to capture the variability, respond perception, and do not face the floor or ceiling issues.

Table 6: Descriptive Statistics of all Variables (N=280) (Satish Kondapareddy, 2026)

Variables	Minimum	Maximum	Mean	Std. Deviation
AI-SDSU1	1	5	2.96	1.299
AI-SDSU2	1	5	2.86	1.246
AI-SDSU3	1	5	2.74	1.261
AI-SDSU4	1	5	2.93	1.272
T-AI1	1	5	2.91	1.274
T-AI2	1	5	2.95	1.239
T-AI3	1	5	2.87	1.287
T-AI4	1	5	3.03	1.329
PR1	1	5	2.71	1.241
PR2	1	5	2.74	1.295

PR3	1	5	2.78	1.317
PR4	1	5	2.93	1.270
RP1	1	5	2.95	1.328
RP2	1	5	2.95	1.258
RP3	1	5	2.90	1.290
RP4	1	5	3.03	1.257
AI-REL1	1	5	2.96	1.307
AI-REL2	1	5	2.75	1.197
AI-REL3	1	5	2.88	1.261
AI-REL4	1	5	2.94	1.208
AI-RES1	1	5	2.87	1.227
AI-RES2	1	5	2.71	1.299
AI-RES3	1	5	2.98	1.287
AI-RES4	1	5	2.81	1.247
F-AI1	1	5	2.87	1.266
F-AI2	1	5	2.96	1.251
F-AI3	1	5	2.80	1.265
F-AI4	1	5	3.08	1.283
MDC1	1	5	2.89	1.298
MDC2	1	5	2.95	1.215
MDC3	1	5	2.96	1.264
MDC4	1	5	2.97	1.311

Note: AI-SDSU = AI-Supported Decision Systems Usage; T-AI = Trust in AI; PR = Perceived Reliability; RP = Risk Perception; AI-REL = AI Reliance; AI-RES = AI Resistance; F-AI = Familiarity with AI; MDC = Managerial Decision Confidence.

The mean values of the 32 items have been calculated, and findings show the range between 2.71 and 3.08. It shows that respondents agreed on moderate and not strongly positive or negative. The highest mean value is 3.08, recorded for F-AI4, and it suggests that the familiarity aspect with AI is rated as higher by the managers. Additionally, T-AI4 and RP4 showed somewhat stronger compatibility with comparatively higher mean values (3.03). On the other hand, PR1 and RES2 have a mean value of 2.71, which is followed by AI-SDSU3 and PR2 at 2.74. These values show lower agreement on some of the perspectives on AI resistance, perceived reliability, and AI-supported system usage.

The standard deviation ranges between 1.197 and 1.329, which indicates a moderate level of dispersion around the mean value. It means most of the responses were placed in the middle; the answers of the respondents were unclear. From the findings, it has been found that

T-AI4 had a high SD value, like 1.329, which shows that respondents agree on the different points about the trust-related questions. On the contrary, some of the items related to AI-SDSU, AI-REL, AI-RES, and MDC have the SD values of 1.25, which shows a good level of change in responses. The construct level, the mean value in Table 6 shows moderate opinions of respondents, AI SDSU had the mean value of 2.87, T-AI had 2.94, PR had 2.79, RP had 2.96, AI-REL had 2.88, AI-RES had 2.84, F-AI had 2.93, and MDC had 2.94. Respondents were neither strongly favorable nor strongly detrimental, according to these figures. Overall, the findings demonstrate that the answers are fair and provide a basic knowledge of the data prior to more in-depth research.

4.3.2. Normality Analysis

The Kolmogorov–Smirnov test has been carried out for all the items with the aim of checking whether the data met the normality assumptions, and the results are presented in the following sections. The results show that all the variables have a significance value of 0.000, which indicates that the null hypothesis was rejected for all the items. This result suggests that each item's related responses do not follow the normal distribution.

From the findings, it has also been found that the outcome appropriately captures the responses given in the Likert scale, particularly when the sample size is large. In this study, the sample size is 280, which is considered a large dataset. Due to these, statistical methods can be used even if the gathered data is not seamlessly normal. In this real research, analysis models like Pearson correlation, linear regression, and moderation analysis, which are acceptable in different areas, are true while the data does not show any issues, and the analysis relies on the scores rather than the individuals' variables.

Table 7: Normality Test for all Variables (Satish Kondapareddy, 2026)

Variables	Kolmogorov-Smirnov		
	Statistic	df	Sig.
AI-SDSU1	0.206	280	0.000
AI-SDSU2	0.178	280	0.000
AI-SDSU3	0.200	280	0.000
AI-SDSU4	0.165	280	0.000
T-AI1	0.188	280	0.000
T-AI2	0.170	280	0.000
T-AI3	0.168	280	0.000
T-AI4	0.185	280	0.000
PR1	0.199	280	0.000
PR2	0.187	280	0.000
PR3	0.188	280	0.000
PR4	0.158	280	0.000
RP1	0.153	280	0.000
RP2	0.161	280	0.000
RP3	0.162	280	0.000
RP4	0.168	280	0.000
AI-REL1	0.187	280	0.000
AI-REL2	0.218	280	0.000
AI-REL3	0.182	280	0.000
AI-REL4	0.190	280	0.000
AI-RES1	0.189	280	0.000
AI-RES2	0.216	280	0.000
AI-RES3	0.198	280	0.000
AI-RES4	0.198	280	0.000
F-AI1	0.176	280	0.000
F-AI2	0.165	280	0.000
F-AI3	0.194	280	0.000
F-AI4	0.166	280	0.000
MDC1	0.156	280	0.000
MDC2	0.171	280	0.000
MDC3	0.181	280	0.000
MDC4	0.178	280	0.000

Note: AI-SDSU = AI-Supported Decision Systems Usage; T-AI = Trust in AI; PR = Perceived Reliability; RP = Risk Perception; AI-REL = AI Reliance; AI-RES = AI Resistance; F-AI = Familiarity with AI; MDC = Managerial Decision Confidence.

In this study, the lack of perfect normality is not considered a serious issue. This information can be included with the aim of conducting analysis, as the sample is large (280),

and a selected statistical method can manage small deviations from normality. The study uses different items with the aim of measuring each concept and combining these variables into a score, which usually improves the distribution of data. Therefore, the normality test result does not stop using further analyses and does not impact the reliability of findings.

4.3.3. Common Method Bias (CMB)

The study depends on the self-reported questionnaire data collection process and gathered data from a single group of respondents, and for that, it is significant to measure the potential presence of common method bias (CMB). In order to do this, Harman's Single Factor Test has been conducted, and the results are shown in the following section.

Table 8: Common Method Bias (CMB) using Harman's Single Factor Test (Satish Kondapareddy, 2026)

Component	Initial Eigenvalues	% of Variance	Cumulative %
1	7.285	22.765	22.765
2	3.236	10.111	32.876
3	2.477	7.742	40.618
4	1.817	5.677	46.296
5	1.742	5.444	51.739
6	1.576	4.924	56.664
7	1.458	4.557	61.220
8	1.106	3.455	64.675

The results show that the first section clarified 22.765% of the total variance. This value is lower than any common threshold of 50%. It shows that in the datasets, there are no single factors that influenced the data. In other words, the findings show that the data are not significantly affected by a single factor, so the bias can be reduced in the results. From the findings, it has also been found that the variance has been spread across several items, which shows that common procedure bias is not the major issue in this research; it refers to the connection between the items that are real and not affected by the way data were gathered. As a result, the data can be regarded as trustworthy and appropriate for additional statistical

examination. Overall, the results confirm that the study's findings are reliable and may be confidently applied to the subsequent phases of research.

4.3.3. Reliability Analysis

Cronbach's Alpha has been used to conduct the regression analysis and helps the study determine the internal consistency of measurement scales. The outcome is shown in Table 9. From the perspective of the social sciences, the acceptable value of Cronbach's Alpha is 0.70, which indicates that each of the items within a construct account for the same underlying concept.

Table 9: Reliability Test using Cronbach's Alpha (Satish Kondapareddy, 2026)

Construct	No. of Items	Mean	Std. Deviation	Cronbach's Alpha
AI-SDSU	4	2.87	1.006	0.802
T-AI	4	2.94	1.043	0.829
PR	4	2.79	1.005	0.792
RP	4	2.96	0.982	0.764
AI-REL	4	2.88	0.973	0.789
AI-RES	4	2.84	1.005	0.805
F-AI	4	2.93	1.015	0.815
MDC	4	2.94	1.046	0.840

Note: AI-SDSU = AI-Supported Decision Systems Usage; T-AI = Trust in AI; PR = Perceived Reliability; RP = Risk Perception; AI-REL = AI Reliance; AI-RES = AI Resistance; F-AI = Familiarity with AI; MDC = Managerial Decision Confidence.

The results indicate that all eight constructs met or exceeded the acceptable level. Cronbach's Alpha values for AI-SDSU were 0.802, T-AI was 0.829, PR was 0.792, RP was 0.764, AI-REL was 0.789, AI-RES was 0.805, F-AI was 0.815, and MDC was 0.840. This outcome shows satisfactory to strong internal consistency across all the constructs included in the research. Among all the concepts, the high values recorded for MDC, like 0.840, and that refers that these items help in measuring the managerial decision confidence, which is considered highly consistent. T-AI and F-AI also present strong reliability, which means systems like trust in AI and familiarity with AI are connected. The lowest values are recorded

for RP, like 0.764, which is above the acceptable level and suitable for further analysis. Overall, these results show that measurement tools are appropriate for this study, and the scale is mainly considered for AI usage, behavioural, psychological factors, managerial decision confidence, and familiarity with the AI technology are consistent. So all the constructs are kept for further analysis.

4.3.5. Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) was conducted to assess instrument construct validity and to determine whether the measurement variable loaded suitably onto the planned factors. Using Composite Reliability (CR) and Average Variance Extracted (AVE), the analysis assessed sample adequacy, factor loadings, and construct reliability and validity.

4.3.5.1. KMO Test for a Sample Adequacy

It is important to determine whether the data sets are appropriate before factor analysis; the KMO TST has been conducted. This is mainly assessed by using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity, and result presented in the following section:

Table 8: KMO and Bartlett's Test for a Sample Adequacy (Satish Kondapareddy, 2026)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.859
Bartlett's Test of Sphericity	Approx. Chi-Square	3497.815
	df	496
	Sig.	<0.001

The KMO values in the research were 0.859, which shows “a high level of sample adequacy”. Generally, the KMO values are above 0.80, which is considered very good. It refers to the connection among the variable are strong to create reliable factors. It also presents that the correlation and the sample size are appropriate for the factor analysis. Bartlett's Test of Sphericity is also significant with a chi-square value of 3497.815, degrees of freedom (df) =

496, and $p < 0.001$. A significant result indicates that the correlation matrix is not an identity matrix and that the variables are linked to one another. This validates the application of factor analysis. All things considered, these findings demonstrate that the dataset is suitable for exploratory factor analysis. The items have sufficient common variance to extract major factors, as confirmed by the high KMO value and significant Bartlett's test.

4.3.5.2. Factor Loadings

Table 11 shows the factors leading to all eight constructs. Through the factor loading analysis, the connection among items and corresponding factors can be determined. To generate the values of the factor loading, 0.50 is considered as the acceptable value, while values more than 0.70 are considered as a high contribution of constructs to the latent concepts.

Table 9: Factor Loadings (Satish Kondapareddy, 2026)

Variable	Factor Loading
AI-SDSU1	0.729
AI-SDSU2	0.803
AI-SDSU3	0.722
AI-SDSU4	0.742
T-AI1	0.808
T-AI2	0.729
T-AI3	0.722
T-AI4	0.755
PR1	0.764
PR2	0.767
PR3	0.685
PR4	0.752
RP1	0.720
RP2	0.768
RP3	0.700
RP4	0.731
AI-REL1	0.734
AI-REL2	0.760
AI-REL3	0.773
AI-REL4	0.734
AI-RES1	0.725
AI-RES2	0.756
AI-RES3	0.784
AI-RES4	0.789

F-AI1	0.795
F-AI2	0.794
F-AI3	0.778
F-AI4	0.792
MDC1	0.671
MDC2	0.722
MDC3	0.690
MDC4	0.731

Note: AI-SDSU = AI-Supported Decision Systems Usage; T-AI = Trust in AI; PR = Perceived Reliability; RP = Risk Perception; AI-REL = AI Reliance; AI-RES = AI Resistance; F-AI = Familiarity with AI; MDC = Managerial Decision Confidence.

From the findings, it has been found that all the items had the factor loading above the minimum value. The values of the factors loading range from 0.671 to 0.808, and the values show that all the constructs are suitable for the analysis. The factor loadings were between 0.722 and 0.803, recorded for AI-SDSU, and the value shows that all four items contribute well to account for the construct. With loadings ranging from 0.722 to 0.808, the T-AI goods clearly reflected the idea of trust in AI. In the context of the PR, the loading ranged from 0.685 to 0.767, and for RP, the values range from 0.700 to 0.731. These values are satisfactory, and it presents that the item measured these concepts properly. Similarly, AI-RES ranged from 0.725 to 0.789 while AI-REL had loadings between 0.734 and 0.773. This suggests that unambiguous and accurate measurements of behavioral response variables were made.

The findings show that the F-AI construct presented a strong outcome with the factor loading ranging between 0.778 and 0.795, and this value shows that, in this study, the familiarity with AI has been tested effectively. In the context of the MDC, factor loading ranges from 0.671 to 0.731. Despite having the lowest rating (0.671), MDC1 was still appropriate and did not require removal. Overall, each item's loadings on the corresponding constructions were good. This demonstrates the validity and dependability of the measurement instrument. As a result, no components were eliminated, and the entire model was retained for additional examination.

4.3.5.3. Construct Reliability and Validity

In order to assess the measurement model quality, Composite Reliability (CR) and Average Variance Extracted (AVE) analysis have been conducted for each of the constructs, and outcome has been presented in the following section. In this case, the Composite reliability plays an effective role in evaluating the internal consistency of a latent construct. On the other hand, AV considers the aim of assessing the convergent validity by accounting for the variance amount obtained by the construct relative to measurement errors.

Table 10: Construct Reliability using Composite Reliability (CR) and Validity using Average Variance Extracted (AVE) (Satish Kondapareddy, 2026)

Construct	No. of Items	CR	AVE
AI-SDSU	4	0.837	0.562
T-AI	4	0.840	0.569
PR	4	0.831	0.552
RP	4	0.820	0.533
AI-REL	4	0.838	0.564
AI-RES	4	0.849	0.584
F-AI	4	0.869	0.624
MDC	4	0.797	0.496

Note: AI-SDSU = AI-Supported Decision Systems Usage; T-AI = Trust in AI; PR = Perceived Reliability; RP = Risk Perception; AI-REL = AI Reliance; AI-RES = AI Resistance; F-AI = Familiarity with AI; MDC = Managerial Decision Confidence; CR = Composite Reliability; AVE = Average Variance Extracted.

The outcome shows that all the included constructs have the CR or composite reliability values above 0.70. All the constructs in the studies are reliable. AI-SDSU had a CR of 0.837, T-AI had 0.840, PR had 0.831, RP had 0.820, AI-REL had 0.838, AI-RES had 0.849, F-AI had 0.869, and MDC had 0.797. These values mainly indicate that all the constructs in the study have strong internal consistency, even though it is better than what was present in Cronbach's alpha.

For the AVE or average variants extracted, the recommended value is 0.50 or higher than 0.500. the outcome shows that the results show that AI-SDSU had an AVE of 0.562, T-AI

had 0.569, PR had 0.552, RP had 0.533, AI-REL had 0.564, AI-RES had 0.584, and F-AI had 0.624. All these values are above the acceptable value of 0.50, which means that all the constructs have strong convergent validity.

The AVE value of MDC is 0.496, which is slightly below 0.50, but the items are still kept in the research because its CR value is 0.797, which is more than 0.70, and its factor loading value is also acceptable. Since that AVE value is very close to 0.50, it can be considered as an acceptable factor when it is combined with the other factors with good reliability.

Overall, the AVE and CR outcomes present a strong measurement model. The constructs are reliable, and most of the constructs show strong validity. The instrument of the study is appropriate for further analysis, such as regression, correlation, and moderation.

4.4. Correlation Analysis

In this study, the Pearson correlation analysis has been carried out to examine the direction and strength of the connection among the study items. In this case, the correlation matrix outcome is presented in the following table. This analysis provides an overview of preliminary evidence related to the relationship among items like familiarity with AI, AI-supported decision systems usage, psychological factors, managerial decision confidence, and behavioural responses.

Table 11: Correlation Test (Satish Kondapareddy, 2026)

Correlations		AI-SDSU	T-AI	PR	RP	AI-REL	AI-RES	F-AI	MDC
AI-SDSU	Pearson Correlation	1	0.348**	0.334**	-0.132*	0.341**	-0.103	0.211**	0.415**
	Sig. (2-tailed)		0.000	0.000	0.028	0.000	0.084	0.000	0.000
T-AI	Pearson Correlation	0.348**	1	0.376**	-0.294**	0.310**	-0.195**	0.135*	0.484**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.001	0.024	0.000

PR	Pearson Correlation	0.334**	0.376**	1	-0.221**	0.206**	-0.187**	0.205**	0.471**
	Sig. (2-tailed)	0.000	0.000		0.000	0.001	0.002	0.001	0.000
RP	Pearson Correlation	-0.132*	-0.294**	-0.221**	1	-0.045	0.392**	-0.107	-0.364**
	Sig. (2-tailed)	0.028	0.000	0.000		0.456	0.000	0.074	0.000
AI-REL	Pearson Correlation	0.341**	0.310**	0.206**	-0.045	1	0.041	0.150*	0.377**
	Sig. (2-tailed)	0.000	0.000	0.001	0.456		0.497	0.012	0.000
AI-RES	Pearson Correlation	-0.103	-0.195**	-0.187**	0.392**	0.041	1	-0.049	-0.363**
	Sig. (2-tailed)	0.084	0.001	0.002	0.000	0.497		0.411	0.000
F-AI	Pearson Correlation	0.211**	0.135*	0.205**	-0.107	0.150*	-0.049	1	0.125*
	Sig. (2-tailed)	0.000	0.024	0.001	0.074	0.012	0.411		0.036
MDC	Pearson Correlation	0.415**	0.484**	0.471**	-0.364**	0.377**	-0.363**	0.125*	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.036	
**. Correlation is significant at the 0.01 level (2-tailed); *. Correlation is significant at the 0.05 level (2-tailed).									

Note: N=280; AI-SDSU = AI-Supported Decision Systems Usage; T-AI = Trust in AI; PR = Perceived Reliability; RP = Risk Perception; AI-REL = AI Reliance; AI-RES = AI Resistance; F-AI = Familiarity with AI; MDC = Managerial Decision Confidence.

The outcome shows that the AI SDSU has a significant and positive association with the MDC ($r = 0.415$, $p < 0.01$), and it suggests that when business managers use AI-integrated DC and make the system more frequently, their confidence in making decisions increases. Trust in AI or T-AI also shows a positive and strong relationship with the MDC ($r = 0.484$, $p < 0.01$). In the same way, the PR is also positively linked with the MDC ($r = 0.471$, $p < 0.01$). These outcomes show that way in the business managers have the belief to use AI and consider it as one of the most effective and reliable to they feel more confident about making decisions to achieve business goals.

On the contrary, the Risk Perception- RP has a significant but negative relationship with the MDC ($r = -0.364, p < 0.01$), it refers that when business managers perceive that AI technology is risky, their confidence in using this technology declines. Resistance or AI-RES shows the negative association with MDC ($r = -0.363, p < 0.01$), and it suggests that managers who face the issues of using AI feel less confident to make decision by using this technology. On the other hand, the AI Reliance or AI-REL has a positive connection with the MDC ($r = 0.377, p < 0.01$), which suggests that manager that depending more on AI technology have higher confidence.

Familiarity with AI or F-AI is the moderating variable in the study, which shows a positive but weak connection with the MDC and suggests that the knowledge regarding AI technology slightly improves the confidence among managers, but the impact of taking effective decisions cannot be strongly compared to the other factors. The correlation table also presents the link between different independent variables of this study. AI-SDSU is positively linked with the T-AI, PR, AI-REL, and F-AI. It shows that improvement in the use of AI is connected with gaining more trust, reliance, and familiarity. The RP or risk perception is positively linked with the AI-RES or AI resistance and negatively related to the PR and trust in AI. It refers to the fact that when business managers see more risk in using AI, they resist AI more. Crucially, not a single correlation value above 0.70. This demonstrates that multicollinearity is not a significant issue. Overall, the findings support switching to regression analysis and align with the study's anticipated direction.

4.5. Data Analysis for RO1

H1: AI-supported decision systems usage (AI-SDSU) has a significant positive effect on managerial decision confidence (MDC).

Table 14 suggests that there is a moderate positive correlation between the use of AI-supported decision systems and managerial decision confidence, and this is indicated by a value of 0.415 as the R value. The model predicts about 17.3% of variance ($R^2 = 0.173$) in managerial decision confidence, indicating that the use of AI plays a significant role, but not necessarily in predicting decision confidence in managers. The adjusted $R^2 = 0.170$ value helps to verify the stability and consistency of the model.

The regression model as a whole is statistically significant, since the F-value of 58.002 ($p < 0.001$) is statistically significant. It shows that the model is better fitted than a model with no predictors and that the use of the AI-supported decision systems is a substantial predictor of managerial decision confidence.

This relationship is further supported by the coefficient. The unstandardized coefficient ($B = 0.432$) is used to show that a one-unit change in the usage of AI-supported decision systems causes a one-unit change of 0.432 units in the managerial decision confidence. The moderate strength of this positive effect is confirmed by the standardized beta coefficient ($\beta = 0.415$). The t-value of 7.616 ($p < 0.001$) shows that effect is significant and not by chance.

The VIF of 1.000 indicates that there is no multicollinearity in the model, whereas the Durbin–Watson of 2.002 indicates that there is no autocorrelation problem.

Table 12: Regression Analysis for H1 (AI-SDSU $\rightarrow$ MDC) (Satish Kondapareddy, 2026)

Statistics		Value
Model Summary	R	0.415
	R Square (R^2)	0.173
	Adjusted R^2	0.170
	Std. Error	0.953
	Durbin–Watson	2.002
ANOVA	F-value	58.002
	p-value	<0.001
Coefficients	Constant (B)	1.701
	AI-SDSU (B)	0.432

	Std. Error	0.057
	Beta (β)	0.415
	t-value	7.616
	p-value	<0.001
	VIF	1.000

The results indicate that increased application of AI-based decision systems leads to increased confidence of managers in their decisions. H1 is supported.

4.6. Data Analysis for RO2

Research Objective 2: The impacts of the major psychological variables, trust in AI, perceived reliability, and risk perception on the confidence of managerial decisions. Each of the factors was separately regressed.

H2: Trust in AI (T-AI) has a significant positive effect on managerial decision confidence (MDC).

Table 15 indicates that there is a moderate positive relational score between trust in AI and managerial decision confidence, with an R value of 0.484. The model also captures 23.5% of the variance ($R^2 = 0.235$) in managerial decision confidence, which is greater than AI usage alone in RO1. The adjusted R^2 value (0.232) confirms the robustness of the model.

The outcomes of the ANOVA show that the model is statistically significant ($F = 85.164$, $p < 0.001$), which proves that the trust in AI is an important predictor of managerial decision confidence. The regression coefficient of trust in AI is positive ($B = 0.486$), meaning that the higher the more the decision confidence. The standardized beta coefficient ($\beta = 0.484$) indicates that trust in AI has a strong effect on managerial confidence in comparison to other variables.

The t-value of 9.228 ($p < 0.001$) supports the fact that the correlation is statistically significant. The VIF of 1.000 means that there is no multicollinearity problem, and the Durbin–

Watson of 1.893 does not indicate any severe cases of autocorrelation. Such results suggest that those managers who view AI systems as trustworthy have more confidence in their decision-making. H2 is supported.

Table 13: Regression Analysis for H2 (T-AI $\rightarrow$ MDC) (Satish Kondapareddy, 2026)

Statistics		Value
Model Summary	R	0.484
	R Square (R^2)	0.235
	Adjusted R^2	0.232
	Std. Error	0.917
	Durbin–Watson	1.893
ANOVA	F-value	85.164
	p-value	<0.001
Coefficients	Constant (B)	1.514
	T-AI (B)	0.486
	Std. Error	0.053
	Beta (β)	0.484
	t-value	9.228
	p-value	<0.001
	VIF	1.000

H3: Perceived reliability (PR) of AI has a significant positive effect on managerial decision confidence (MDC).

Table 16 results show that perceived reliability also impacts managerial decision confidence positively, though this effect is moderate. This model resulted in an R value of 0.471 and a value of 0.222, indicating that the perceived reliability accounts for R^2 value is 2.2% of the variance in managerial decision confidence. The adjusted R^2 (0.219) is indicative of the consistency of the model.

The results of the ANOVA indicate that the model is statistically significant ($F = 79.391$, $p < 0.001$), which means that perceived reliability is a high predictor of decision confidence. The regression coefficient ($B = 0.491$) indicates that a one-unit increase in perceived reliability increases managerial decision confidence by 0.491 units. The standardized beta ($\beta = 0.471$) has a strong positive impact.

The t-value of 8.910 ($p < 0.001$) indicates statistical significance. The value of VIF is 1.000, which means that the research does not have multicollinearity problems, and the value of Durbin–Watson is 1.912, which means that the residual values are not too dependent.

Such results indicate that managers who believe that AI systems are predictable and reliable have more confidence in their decisions. Thus, H3 is supported.

Table 14: Regression Analysis for H3 (PR → MDC) (Satish Kondapareddy, 2026)

Statistics		Value
Model Summary	R	0.471
	R Square (R^2)	0.222
	Adjusted R^2	0.219
	Std. Error	0.924
	Durbin–Watson	1.912
ANOVA	F-value	79.391
	p-value	<0.001
Coefficients	Constant (B)	1.573
	PR (B)	0.491
	Std. Error	0.055
	Beta (β)	0.471
	t-value	8.910
	p-value	<0.001
	VIF	1.000

H4: Risk perception (RP) of AI has a significant negative effect on managerial decision confidence (MDC).

The regression outcomes of H4, which are in Table 17, show that there is a moderate negative association between risk perception and confidence in managerial decision-making, as shown by an R value of 0.364. The model indicates that 13.3% of the confidence in managerial decisions-confidence are explained ($R^2 = 0.133$), which is low in relation to trust and perceived reliability but remains significant. The adjusted R^2 (0.130) suggests an acceptable stability of the model.

The results of ANOVA indicate that the model is significant ($F = 42.542$, $p < 0.001$). The regression coefficient of risk perception is negative ($B = -0.388$), which means that the higher the perceived risk, the lower the managerial decision confidence. The standardized beta ($\beta = -0.364$) indicates a weak negative impact.

The negative relationship with a t-value of -6.522 ($p < 0.001$) is statistically significant. The value of VIF at 1.000 shows that there are no multicollinearity problems, whereas the Durbin -Watson value is 1.990, indicating that there are no problems with autocorrelation.

These findings suggest that managers are less confident in their decision-making when they feel AI systems are risky or uncertain. H4 is supported.

Table 15: Regression Analysis for H4 (RP $\rightarrow$ MDC) (Satish Kondapareddy, 2026)

Statistics		Value
Model Summary	R	0.364
	R Square (R^2)	0.133
	Adjusted R^2	0.130
	Std. Error	0.976
	Durbin–Watson	1.990
ANOVA	F-value	42.542
	p-value	<0.001
Coefficients	Constant (B)	4.089
	RP (B)	-0.388
	Std. Error	0.059
	Beta (β)	-0.364
	t-value	-6.522
	p-value	<0.001
	VIF	1.000

The results on RO2 suggest that positive perceptions of AI (trust and perceived reliability) have a positive impact on the degree of confidence in managerial decisions, whereas negative perceptions affect it negatively.

4.7. Data Analysis for RO3

Research Objective 3 was to examine the effects of behavioral reactions to AI-assisted decision-making on managerial decision confidence at AI reliance and AI resistance. To test this objective, two regression analyses were done, which were related to H5 and H6.

H5: AI reliance (AI-REL) has a significant positive effect on managerial decision confidence (MDC).

Table 18 showed that AI dependence has a moderate positive correlation with managerial decision confidence, with an R value of 0.377. These coefficient of determination values ($R^2 = 0.142$) indicate that AI dependence is associated with an ability to explain 14.2% of the variation in managerial decision confidence. The adjusted R2 (0.139) is an indication that the model has an acceptable explanatory strength and is not overfit.

The model as a whole is statistically significant with an F-value of 46.039 ($p < 0.001$). This proves that AI dependence is a significant factor in predicting confidence in decision-making in management and that the model is better than a predictor-free model.

The regression coefficient of the AI reliance is positive ($B = 0.405$), which implies that a one-unit change in AI reliance would lead to a one-unit change in managerial decision confidence. The standardized beta ($\beta = 0.377$) indicates a moderate positive impact, which means that dependence on AI systems is a significant factor in the development of managerial confidence. This effect is statistically significant since its t-value is 6.785 ($p < 0.001$).

VIF of 1.000 implies that there is no concern of multicollinearity, and a Durbin–Watson value of 1.907 implies no autocorrelation problems with the residuals.

These results suggest that managers who actively rely on AI-based information are more likely to be confident in their decisions. This implies that managers who are more dependent on AI would report greater confidence in making decisions, which can be due to the perceived analytical assistance of AI systems. H5 is justified.

Table 16: Regression Analysis for H5 (AI-REL → MDC) (Satish Kondapareddy, 2026)

Statistics		Value
Model Summary	R	0.377
	R Square (R^2)	0.142
	Adjusted R^2	0.139
	Std. Error	0.970
	Durbin–Watson	1.907
ANOVA	F-value	46.039
	p-value	<0.001
Coefficients	Constant (B)	1.774
	AI-REL (B)	0.405
	Std. Error	0.060
	Beta (β)	0.377
	t-value	6.785
	p-value	<0.001
	VIF	1.000

H6: AI resistance (AI-RES) has a significant negative effect on managerial decision confidence (MDC).

Table 19 regression results show that AI resistance is moderately negatively associated with managerial decision confidence with a value of 0.363. The R^2 is 0.131, which indicates that AI resistance can account for 13.1% of the variance in managerial decision confidence. The adjusted R^2 (0.128) shows that the model is stable and reliable.

The outcomes of the ANOVA indicate that the model is statistically significant ($F = 42.075$, $p < 0.001$) and proves that the AI resistance is a predictive variable with a significant meaning in managerial decision confidence. The regression coefficient of AI resistance is negative ($B = -0.377$), which means that one unit of resistance change causes the confidence in managerial decisions to decrease by 0.377 units. The standardized beta ($\beta = -0.363$) indicates

a moderate negative impact, which indicates the negative influence on the level of confidence created by resistance.

This relationship is statistically significant, as the t-value of -6.487 ($p < 0.001$) indicates. The VIF value is 1.000, which implies no multicollinearity problems, and the Durbin–Watson value is 2.038, which implies that there is no autocorrelation issue.

These results indicate that managers who are characterized by resistance toward AI systems, such as skepticism, reluctance, or avoidance, were less confident in their decision-making. Thus, H6 is supported.

Table 17: Regression Analysis for H6 (AI-RES $\rightarrow$ MDC) (Satish Kondapareddy, 2026)

Statistics		Value
Model Summary	R	0.363
	R Square (R^2)	0.131
	Adjusted R^2	0.128
	Std. Error	0.976
	Durbin–Watson	2.038
ANOVA	F-value	42.075
	p-value	<0.001
Coefficients	Constant (B)	4.014
	AI-RES (B)	-0.377
	Std. Error	0.058
	Beta (β)	-0.363
	t-value	-6.487
	p-value	<0.001
	VIF	1.000

The results of RO3 reveal that behavioral reactions to AI have a significant impact on managerial decision confidence. Although AI reliance boosts confidence, AI resistance reduces it, meaning that the attitudes and behaviors of managers towards AI systems are very important in decision-making. The comparatively close values of the beta coefficients of the AI reliance ($\beta = 0.377$) and AI resistance ($\beta = -0.363$) indicate that both positive and negative behavioral responses have similar strength, but in opposite directions. These findings indicate that it is

necessary to enhance positive behavioral interactions with AI systems in order to extract the maximum benefits in the context of organizational decision-making.

4.8. Data Analysis for RO4

Research Objective 4 aimed to determine the extent to which the relationship between the use of AI-supported systems used in decision making and managerial decision confidence is mediated by individual differences, managerial experience and familiarity with AI. To test the hypotheses H7 and H8, the interaction effects and the moderation analysis were conducted.

H7: Managerial experience (ME) moderates the relationship between AI-supported decision systems usage (AI-SDSU) and managerial decision confidence (MDC).

Moderation results (Table 20) show that the global model is statistically significant, with an R value of 0.428 and an R^2 value of 0.183, indicating that the model accounts 18.3% of managerial decision confidence variance. The fact that the F-value is 20.628 ($p < 0.001$) proves that the overall regression model is not meaningless.

The most important thing in moderation analysis is the interaction term. The interaction effect between the use of AI-supported decision systems and management experience (AI-SDSU $\times$ ME) resulted in a coefficient of $B = 0.073$ and a standardized beta of $\beta = 0.073$. The t-value of 1.314 and p-level of 0.190 show that this interaction is insignificant.

The interaction term ($\Delta R^2 = 0.005$) is not great, indicating that the addition of the managerial experience does not significantly enhance the explanatory power of the model. Even though the direct impact of the use of AI-supported decision systems is still positive and significant ($B = 0.429$), the experience of the manager does not have a significant impact on this relation.

These results indicate that the influence of the AI-assisted systems of decision-making on managerial confidence in decision-making can be relatively similar at various levels of managerial experience. H7 is not supported.

Table 18: Moderation Analysis for H7 (AI-SDSU $\times$ ME $\rightarrow$ MDC) (Satish Kondapareddy, 2026)

Statistics		Value
Model Summary	R	0.428
	R Square (R^2)	0.183
	ΔR^2 (Interaction)	0.005
	F-value	20.628
	p-value	<0.001
Coefficients	Constant (B)	2.943
	AI-SDSU (B)	0.429
	ME (B)	-0.072
	Interaction (AI-SDSU $\times$ ME)	0.073
	Std. Error (Interaction)	0.055
	Beta (β Interaction)	0.073
	t-value (Interaction)	1.314
	p-value (Interaction)	0.190

H8: Familiarity with AI (F-AI) moderates the relationship between AI-supported decision systems usage (AI-SDSU) and managerial decision confidence (MDC).

The results for H8, presented in Table 21, show that the overall model is statistically significant, with an R value of 0.418 and an R^2 value of 0.175, indicating that the model explains 17.5% of the variance in managerial decision confidence. The overall model is significant as the F-value is 19.524 ($p < 0.001$).

The same as with H7, the effect of interaction between the use of AI-supported decision systems and familiarity with AI (AI-SDSU $\times$ F-AI) is insignificant. The coefficient of interaction is $B = 0.033$, and the standardized beta is $\beta = 0.033$, $t = 0.573$, and $p = 0.567$. This implies that the level of familiarity with AI does not have a major impact on the strength.

The value of the ΔR^2 at 0.001 is another indication that the interaction term is adding very little value to the model. Familiarity with AI has a small positive direct relationship ($B = 0.039$), but it is not a moderating variable in this relationship.

These findings indicate that the effect of the AI-supported decision systems' use on the managerial decision confidence does not hinge on the familiarity levels of managers with AI technologies. The same benefits of AI use as far as confidence in the decisions they take is concerned. Thus, H8 is not supported.

Table 19: Moderation Analysis for H8 ($\text{AI-SDSU} \times \text{F-AI} \rightarrow \text{MDC}$) (Satish Kondapareddy, 2026)

Statistics		Value
Model Summary	R	0.418
	R Square (R^2)	0.175
	ΔR^2 (Interaction)	0.001
	F-value	19.524
	p-value	<0.001
Coefficients	Constant (B)	2.935
	AI-SDSU (B)	0.423
	F-AI (B)	0.039
	Interaction ($\text{AI-SDSU} \times \text{F-AI}$)	0.033
	Std. Error (Interaction)	0.057
	Beta (β Interaction)	0.033
	t-value (Interaction)	0.573
	p-value (Interaction)	0.567

The RO4 results show that individual differences do not moderate the association between the use of AI-supported decision systems and managerial decision confidence. Managerial experience and familiarity with AI were assumed to have any impact on this relationship, the findings indicate that the moderating effects of both variables are not statistically significant.

This indicates that the positive effect of AI-aided decision systems use on managerial decision confidence is more or less consistent at various experience and familiarity levels. The

lack of moderation effects suggests that AI systems can be widely applicable to increase decision confidence in spite of individual variations among managers.

4.9. Hypotheses Testing

Table 22 summarizes the results of the hypothesis testing, which are the results of the regression and moderation analyses carried out in the previous sections.

Table 20: Summary of Hypotheses Testing (Satish Kondapareddy, 2026)

Hypothesis	Relationship	Test Used	β	t-value	p-value	Decision
H1	AI-SDSU $\rightarrow$ MDC	Simple Linear Regression	0.415	7.616	<0.001	Supported
H2	T-AI $\rightarrow$ MDC	Simple Linear Regression	0.484	9.228	<0.001	Supported
H3	PR $\rightarrow$ MDC	Simple Linear Regression	0.471	8.910	<0.001	Supported
H4	RP $\rightarrow$ MDC	Simple Linear Regression	-0.364	-6.522	<0.001	Supported
H5	AI-REL $\rightarrow$ MDC	Simple Linear Regression	0.377	6.785	<0.001	Supported
H6	AI-RES $\rightarrow$ MDC	Simple Linear Regression	-0.363	-6.487	<0.001	Supported
H7	AI-SDSU $\times$ ME $\rightarrow$ MDC	Moderation (Regression Interaction)	0.073	1.314	0.190	Not Supported
H8	AI-SDSU $\times$ F-AI $\rightarrow$ MDC	Moderation (Regression Interaction)	0.033	0.573	0.567	Not Supported

The findings suggest that six out of eight hypotheses suggested are substantiated. The use of AI-supported decision systems (H1) indicates a strong positive role in the decision confidence of the managers, which proves the necessity of AI application in the decision-making process. Similarly, the relationship between trust in AI (H2) and perceived reliability (H3) is also significant as it is positive, and it underlines the importance of the psychological perception in determining the managerial outcomes.

The opposite is true in risk perception (H4), where it shows a strong negative impact, meaning that greater perceived uncertainty in the context of AI decreases confidence in decision-making. The effects on behavioral responses are also significant, as AI reliance (H5) positively affects the decision confidence, and AI resistance (H6) affects it negatively.

The hypotheses of moderation (H7 and H8) are not proven. Neither managerial experience nor familiarity with AI significantly moderates the relationship between AI-supported decision systems usage and managerial decision confidence. The effect of AI use on decision confidence is similar at various levels of experience and familiarity. The results strongly support the direct correlations of the conceptual model and disapprove the moderating influences.

4.10. Summary

This chapter gave the empirical results of the study by analyzing data obtained from 280 respondents with the application of different statistical methods. The findings present a detailed insight into the correlations among the use of AI-supported decision systems, the psychological variables, behavioral reactions, and the confidence of managers in their decisions.

The initial analyses ensured the data were appropriate to proceed with additional statistical testing. Descriptive statistics have shown moderate levels of agreement in all the variables, and the normality tests were significant, but acceptable due to the sample size. The reliability analysis showed that all constructs had a high internal consistency as indicated by Cronbach's alpha, which was above the recommended value. Also, the validity was determined using exploratory factor analysis with satisfactory factor loading, KMO values and composite reliability scores. The single-factor test by Harman ensured that the common method bias was not an issue of great concern.

The analysis based on correlation showed that there were significant relationships between the main variables, which justified the theoretical assumptions. Regression outcomes also revealed that the use of AI-supported decision systems, trust in AI, perceived reliability, and AI reliance have positive effects on managerial decision confidence. Conversely, the perception of risk and resistance to AI have a negative impact on the level of confidence.

The moderation analysis showed that managerial experience and knowledge of AI are not important factors that would affect the correlation between AI use and decision confidence. This implies that the utility of AI-based decision systems does not vary much between managerial profiles.

Comprehensively, the results point to the relevance of psychological and behavioral aspects to influence managerial decision confidence in AI-driven settings. The findings can serve as a good empirical basis for the discussion that will be discussed in the following chapter.

Chapter 5:

Discussion

5.1. Introduction

The current chapter is a detailed discussion and interpretation of the empirical results in Chapter 4. Although the last chapter was devoted to the presentation of statistical results, the aim of the chapter is to critically evaluate those findings with reference to the objectives of the research, theoretical framework and literature available. The discussion will seek to present more in-depth information on how AI can affect the confidence of managers in their decision-making by using patterns of use, perceptions, and behavioural reactions.

The main aim of this research was to investigate the psychological influence of AI-based decision system on decision confidence among managers. In particular, the researchers examined the direct impact of the use of AI-supported decision systems, the main psychological determinants, including trust in AI, perceived reliability, and risk perception, behavioural outcomes, such as AI reliance and AI resistance. Moreover, the research question of whether the relations between AI use and managerial decision confidence are moderated by individual differences, i.e. Managerial experience and familiarity with AI, was investigated.

The findings have been interpreted in a systematic way in this chapter as per the research objectives. It starts with the discussion of the findings connected with direct effects of the use of AI-supported decision systems on the confidence of managerial decisions. This is then followed by an in-depth discussion of the psychological factors, with a focus on the effect of positive perceptions (trust and reliability) and negative perceptions (risk) in increasing and decreasing decision confidence respectively. This chapter then looks at behavioural reactions

to AI, the opposite roles that a reliance on AI and a resistance to AI play in determining managerial outcomes.

Moreover, the chapter analyzes the moderating impacts of managerial experience and knowledge of AI. Though those factors were predicted to affect the correlation between AI use and decision confidence, the results show that the moderating influences were not statistically significant. This unexpected result is critically analysed to provide theoretical and practical explanations.

Besides the discussion of the findings in terms of the objectives of the study, this chapter also places the results in the context of the academic discourse by comparing the results with previous studies in the areas of AI adoption, technology acceptance and decision-making behaviour. Implications are then made both in theory and in practice to indicate what the study contributes to the body of knowledge and practice.

On the whole, the chapter presents a critical link between the empirical findings and theoretical knowledge and provides valuable insights on the impact of AI-driven decision environments on managerial confidence. The conclusions and recommendations in the next chapter are based on the insights gained in this chapter.

5.2. Discussion of Research Objective 1: AI-Supported Decision Systems Usage and Managerial Decision Confidence

The first research problem aimed to examine the effects of using AI-based decision systems on the confidence of the managers with regard to their decisions. The results suggest that the use of AI-supported decision systems can considerably and positively influence managerial decision confidence. It means that those managers who tend to use AI tools in order to make their decisions will probably be more confident in their decision. This fact supports

the main argument according to which AI is slowly becoming more a part of the organizational processes not only as a technical tool, but also as a decision-support system that enhances the depth of analysis, reduces uncertainty, and supports the activity of managers making decisions (Davenport and Ronanki, 2018; Jarrahi, 2018; Shrestha et al., 2019).

This finding can be explained within the framework of the Technology Acceptance Model (TAM), which describes how users use and embrace technological systems through cognitive appraisals in terms of usefulness and ease of use. In the current scenario, AI-based decision systems seem to be highly instrumental technologies due to their ability to offer managers with information-driven insights, predictive analytics, and real-time information that enhance the quality of decisions (Xue et al., 2026; Song et al., 2025). Such an interpretation is also aligned with the previous research, which stressed that the use of AI in organizational decision-making turns traditional decision processes that are based on judgment into more systematic and evidence-driven decision processes (Page and Kallapur, 2025; Shrestha et al., 2019; Joshi, 2025).

The existence of the positive correlation between AI use and confidence in the managerial decisions could also be explained by the fact that AI alleviates uncertainty and ambiguity. The conventional decision-making process usually demands managers to work incomplete information, time constraints and multifaceted environments. As explained, the contemporary organizations are working in VUCA environment, where volatility, uncertainty, complexity and ambiguity are major threats to managerial judgment. To deal with these conditions, AI-assisted systems are used to process vast amounts of data, discover concealed patterns and create predictive recommendations, which would otherwise be hard to obtain through human cognition (McAfee and Brynjolfsson, 2017; Mohammed et al., 2025; Zhang

and Dafoe, 2019). This will lead managers to believe their decisions to be informed, accurate and defensible hence, enhance confidence in their judgment.

This finding is further supported by the decision-support literature. The literature on business intelligence, analytics, and decision support systems supports that organizational information-processing capacity is enhanced and the quality of decisions is improved with the availability of high-quality, timely, and relevant information (Srinivasan and Swink, 2018; Appelbaum et al., 2017; Dubey et al., 2021; Yu et al., 2021a, b). Incorporating AI-assisted systems into the managerial processes increases the informational processing capacity of the decision-makers, decreases equivocality and uncertainty, and assists managers to make judgments based on facts, as opposed to intuition-based judgments (Aben et al., 2021; Szukits and Móricz, 2024). The current discovery thus supports the argument that AI-enabled systems are not just instruments of operation, but strategic facilitators of assertive managerial response.

The other significant interpretation is associated with the cognitive augmentation. It was emphasized that AI is increasingly becoming an instrument, which supports human cognitive abilities, as opposed to substituting them (Shrestha et al., 2019). The beneficial impact of AI use on managerial decision confidence in this study implies that managers receive a psychological reward by using AI as an augmenting resource. It helps to prove that AI can help managers reach an analytical level further, help them to consider scenarios and react to complex issues more quickly and more wisely (Wilson and Daugherty, 2018; Lehto et al., 2021). The result is thus consistent with the larger human-AI collaboration viewpoint, wherein AI performs best when acting as a decision-support partner, and not as a decision-making replacement of managerial decision-making.

Meanwhile, the discovery must be taken with a grain of salt. Though the usage of AI-supported decision systems is a significant boost to the confidence of managerial decisions,

this does not influence the variation in confidence fully on its own. This has theoretical significance since it was repeatedly stated that the confidence in decisions in AI-enabled settings is not dictated solely by the use, but also by psychological judgements including trust, perceived reliability, and risk perception and behavioural reactions including reliance and resistance (Glikson and Woolley, 2020; Hancock et al., 2021; Khoso et al., 2025; Mustofa et al. That is, the results imply that AI implementation gives the technological basis of confidence, yet its full effects are conditioned by the perception of the system and behavioural response of managers to it.

On the whole, the results of Research Objective 1 indicate that the introduction of the AI-supported decision systems into the managerial processes has a beneficial impact on decision confidence. This confirms the central assumption made that AI is transforming the process of organizational decision-making not only due to its technical efficiency, but also by affecting the quality of managerial judgment (Davenport and Ronanki, 2018; Siau and Wang, 2020). It also promotes the thesis that AI implementation has implications beyond mere system utilization to the post-implementation outcomes, which include confidence, assurance, and readiness to make decisions (Xue et al., 2026; Ibrahim et al., 2025). Therefore, the use of AI-supported decision systems can be considered a structural facilitator of managerial decision assurance in modern companies. Despite a massive enhancement in the confidence of managerial decisions when using AI-supported decision systems, the impact was relatively lower as compared to trust in AI and perceived reliability. This implies that managers cannot be confident that they can build this confidence solely by using the system; they need to feel that the system is reliable and can be trusted. Therefore, technological exposure can provide a basis of confidence, although it seems that psychological acceptance enhances it.

5.3. Discussion of Research Objective 2: Psychological Factors Influencing Managerial Decision Confidence

Research Objective 2 sought to examine the implications of the critical psychological elements trust in AI, perceived reliability and risk perception on managerial decision confidence. The results suggest that these psychological factors are very crucial in determining the perceptions and use of AI-based decision systems by managers. In particular, trust in AI and perceived reliability were discovered to positively influence the managerial decision confidence significantly, and risk perception had a significant negative influence. These findings are a solid confirmation of the claim that the psychological effect of AI goes beyond the performance of the technical systems and has a direct effect on managerial thinking and trust (Frenkenberg and Hochman, 2025; Riva et al., 2025; Kim and Lee, 2024).

The constructive impact of trust in AI on managerial decision confidence indicates that when managers have a perception that AI systems are reliable, safe, and can provide reliable results, they will be more inclined to become confident in the decisions made with the support of these systems. The result coincides with the existing literature, as trust has been found to be a key factor of human engagement with automation, technology, and AI-assisted decision-making (Hancock et al., 2021; Glikson and Woolley, 2020; Kaplan et al., 2023). It also endorses more recent AI-centered TAM extensions that demonstrates that trust is not just a precursor of technology uptake, but a central channel by which users attain positive attitudes and productive interactions with AI systems (Khoso et al., 2025; Mustofa et al., 2025). Trust, in the current scenario, seems to be decreasing hesitation and facilitating the incorporation of AI recommendations into the decision-making process of managers, increasing decision confidence. Out of all the direct predictors analyzed within the study, trust in AI was found to be the most significant positive predictor of managerial decision confidence. It means that the

trust in AI-assisted decisions is not so much based on exposure to the system as on the perception by managers about the credibility, reliability, and trustworthiness of the system.

This observation is also in line with the theoretical reasoning of Attribution Theory and Signaling Theory constructed. By using Attribution Theory, the managers who have trust in AI systems might be more likely to perceive AI outputs as valid and valuable contributors to effective decision-making instead of being uncertain external inputs. Trust can be a measure of the perception of AI outputs as powerful and valid signals in a state of information asymmetry, through Signaling Theory. There is enhanced confidence in both instances as the managers are ready to trust the system as a valid and reliable source of support in the uncertain decision environment.

Likewise, perceived reliability was also established to have a positive effect on managerial decision confidence that is strong. This shows that, in cases where AI systems are considered to be consistent, accurate and reliable over time, managers have a higher level of assurance using them as tools of decision-support. This aligns with the earlier research, which has stressed that the increasing use of AI in organizations does not only hinge on its accessibility and the availability of the systems, but also whether the managers think that the outputs can be trusted in the decisions taken in the real world (Zhang and Dafoe, 2019; Shrestha et al., 2019). It is also consistent with previous research indicating that trust in a system is enhanced by the consistency of its performance, resulting in more positive user satisfaction, enhanced trust calibration, and acceptance of AI-assisted decisions (Phillips-Wren et al., 2019; Haag, 2025; Kahr et al., 2024). A trustworthy AI system lowers unpredictability and cognitive conflict, thus, offering the predictability required to take managerial action.

In contrast, risk perception was found to have a significant negative effect on managerial decision confidence. It means that managers that perceive AI systems as risky,

opaque, or even prone to making errors, are less certain about AI-assisted decisions. This result is a direct response to the issues of previous studies about the lack of transparency in the AI-assisted organizational decision-making, ambiguity in accountability, and bias (Regona et al., 2026; Li and Huang, 2020; Wilson and Daugherty, 2018). It is also consistent with the arguments that highlighted user reluctance and mistrust caused by the lack of understanding, inadequate transparency, and ambiguous cues of AI (Lagioia and Contissa, 2020; Vereschak et al., 2021; Board, 2019). By doing so, perceived risk appears to have a negative impact on confidence since it increases the risk of uncertainty about the safety of utilizing AI outputs to make important decisions.

The main implication of these results is that the confidence of the managerial decisions depends on the balance between positive and negative attitudes towards the AI systems. Confidence is enhanced by trust and perceived reliability as they are indicators of competence, consistency, and usefulness. Risk perception undermines confidence as it is an indicator of uncertainty, vulnerability, and potential adverse outcomes. This proves the point that the reaction of managers towards AI is psychologically dualistic: on the one hand, managers are drawn to the analytical power of AI; on the other hand, they are wary of its obscurity, potential risks, and potential failure (Fryer et al., 2020; Park et al., 2021; Gerlich, 2023).

Overall, the results of the Research Objective 2 point to the fact that psychological factors play a central role in explaining how managerial confidence in decision-making in an AI-enabled environment. The positive perceptions of trust and reliability add to the level of confidence significantly to the negative perceptions of risk which reduce confidence. These results support the overarching thesis statement that successful implementation of AI in organizations entails more than just the technical capacity to achieve but also psychological assurance that AI is a trustworthy, reliable, and low-risk decision-making companion. Together,

these findings imply that the trustworthiness of managerial judgments is extremely affected by psychological evaluations of AI, and human cognition of AI can be as critical, or even more crucial, than the technological process.

5.4. Discussion of Research Objective 3: Behavioural Responses to AI and Managerial Decision Confidence

Research Objective 3 investigated the effects of behavioural reaction to AI-assisted decision-making, namely AI reliance and AI resistance, on managerial decision confidence. The results show AI dependence has a strong positive impact on the confidence in managerial decisions, and AI resistance has a strong negative impact. These findings support the opinion that behavioural responses constitute a significant process by which AI influences managerial outcomes (Araujo et al., 2020; Bankins et al., 2024; Park and Yoon, 2025).

The positive effect of AI reliance means that managerial users who depend on the information provided by AI are more sure about their decisions. This corresponds to the established tuned dependence and acceptable use of AI recommendations in the literature that proves that confidence can be enhanced with the help of AI being perceived by the users as an assisting source to their personal decision-making (Bansal et al., 2021; Ma et al., 2023; Schemmer et al., 2023). The result is also part of the argument that AI can be applied as a cognitive enhancing tool by allowing the analysis and reducing uncertainty and enhancing decision readiness (Shrestha et al., 2019; Wilson and Daugherty, 2018). When the managers are directed by the outputs of AI, it does not mean that they are delegating but are adding an additional level of analysis that adds to their sense of certainties about their decisions.

This finding also aligns with the literature on human–AI collaboration reviewed. Studies have indicated that proper reliance on AI guidance correlates with enhanced human-AI coordination, enhanced task support, and effective interpretation of the decision context (Lai

et al., 2021; Wischniewski et al., 2023; Xu et al., 2025). Reliance, in the current research, seems to indicate behavioural openness to work in collaboration with AI, which consequently leads to the increased managerial confidence. Nevertheless, this beneficial impact must be taken to mean constructive or moderated dependence as opposed to un-critical dependence. The over- or un-critical use of AI can generate other risks in decision-making, although in the current results, reliance seems to be an indicator of productive behavioural interactions with AI-based systems.

Conversely, the managerial decision confidence was shown to be negatively affected by AI resistance to a large degree. This aligns with the idea of algorithm aversion, i.e. people will reject or avoid AI recommendations, even though they can be helpful or correct (Castelo et al., 2019; Allen, 2025). Resistance can be based on technological, discomfort, lack of understanding of the logic behind AI, lack of trust, or perceived threat to managerial autonomy. The fact that managers might be underusing AI has already been posited due to the fear of holding them responsible, the fear of losing control, or dislike of opaque systems (Li and Huang, 2020; Regona et al., 2026). The current results demonstrate such resistance as not only an obstacle to usage, but also a direct obstacle to decision confidence.

Together, the findings suggest that there is significance in behavioural engagement with AI. Reliance and resistance are neither good nor bad reactions; they identify the possibility of AI-based systems to be psychologically helpful to managers. Where dependency establishes transparency to data-driven enhancement, opposition restricts the analytical benefits of AI and raises reliance on unfinished or system of judgment. By doing so, the trust of managers in decision-making is boosted when AI is positively involved and negative when AI is opposed.

In general, the findings of Research Objective 3 indicate that behavioural responses play a vital role in determining managerial decision confidence in AI-facilitated settings. They

affirm that the efficacy of the AI-assisted decision system is not only based on the quality of the system, but also the readiness of the managers to collaborate with AI as a valuable decision support source.

5.5. Discussion of Research Objective 4: Moderating Role of Managerial Experience and Familiarity with AI

Research Objective 4 intended to study the hypothesis that individual differences, namely, managerial experience and familiarity with AI, mediate the association between AI-supported decision systems use and managerial decision confidence. Surprisingly, the results show that neither managerial experience nor familiarity with AI can be considered as significant moderators of this relationship. Whereas the two variables were both theoretically anticipated to affect the way the managers use AI systems and gain confidence in them, the findings indicate that the moderating variables are not statistically significant.

The fact that managerial experience did not have a significant moderating impact means that the positive correlation between the use of AI-supported decision systems and managerial decision confidence is relatively similar across managers of different levels of experience. This is a rather surprising outcome since the studies implied that more experienced managers can be more inclined to intuition and the existing cognitive schemas but less experienced managers might have to be more dependent on AI assistance (Junior Ladeira et al., 2026). Nevertheless, the current results indicate that the advantages of AI-assisted systems can be wide enough to have an impact on the groups of managers.

The same tendency can be noticed regarding familiarity with AI. The discussion about TAM in particular, implied that the more familiar people are with AI, the more outcomes related to technology should be enhanced since previous exposure can enhance understanding, trust, and interpretative capacity (Ibrahim et al., 2025; Xue et al., 2026). However, the findings

indicate that knowledge of AI does not have a significant impact on the effect of using AI on decision confidence. Another potential reason is that modern AI-powered decision systems might already be user-friendly and accessible enough to diminish the role of familiarity in the past, an explanation that aligns with the low-code, no-code, and more democratized AI tools (Siau and Wang, 2020; Regona et al., 2026).

Such insignificant moderation results can thus be used to suggest that AI-based decision systems operate in a fairly inclusive way and provide the benefits of decision support to a wide range of managerial profiles. Instead of demanding a lot of prior background or technical knowledge, such systems can offer standardized support in analytics that can easily be deciphered by managers of other backgrounds. The given interpretation aligns with the general literature on AI adoption, indicating that system design, transparency, and usability may decrease barriers previously related to individual differences (Lee et al., 2025; Mustofa et al., 2025).

Overall, the results of Research Objective 4 show that the experience and understanding of AI do not play a crucial role in the strength of the relationship between the use of AI-supported decision systems and the confidence of managers in their decision in the given research. This finding provides a major twist to the literature: the conceptual relevance of individual differences, however, may be less modulated than expected in organizations where AI systems are increasingly standardized, more available, and more a part of the everyday decision-making process. One possible explanation is that AI-assisted decision systems may now be homogenized enough in an organizational setting that there is less discrepancy in how that managers become confident by using systems. It is also possible that organizational processes, training structures, or system interfaces can decrease the impact of individual variations, and the effects of AI use will be relatively similar among managers.

5.6. Theoretical Implications

There are a few significant theoretical contributions of the results of this study to the literature concerning the adoption of AI, technology acceptance, and managerial decision-making. The study contributes to the existing knowledge on managerial decision confidence as a unique product in AI-facilitated organizational environments by incorporating technological, psychological, and behavioural aspects.

First, the research builds the Technology Acceptance Model (TAM) by demonstrating that the use of AI-based decision systems has a considerable positive effect on the confidence of managerial decisions. TAM has always been concentrated towards the field of behavioural intention, acceptance and actual system usage. Contrastingly, the current research goes beyond the adoption and use to study the post-adoption cognitive outcomes. In this respect, the research elaborates TAM as a model of adoption behaviour into a model that assists in explaining cognitive outcomes of decisions as well. The results indicate that the perceived usefulness in the use of AI systems does not just promote adoption, but also enhances trust in the decisions made with the help of the technology.

Second, this research indicates that managerial decision confidence is not a technological only product but is multidimensional and is influenced by technology use, psychological appraisals and behavioural involvement. This is a significant contribution in terms of theory since other studies have tended to analyse system usage, trust, or behavioural response independent of each other. The current study demonstrates that the confidence of decision-making is the effect of the combination of these dimensions. The use of AI offers the basis, evaluative acceptance is based on psychological perceptions, and behavioural engagement is used to determine whether managers, in fact, gain cognitive benefit using the

system. This combined view provides a more detailed explanation of AI-aided decision-making in comparison to single-theory and single-variable modes.

Third, the research is relevant to the body of research on trust in technology by demonstrating that not only is trust in AI an antecedent of adoption, but also that perceived reliability is a direct predictor of decision-related consequences. The fact that trust in AI has become the most significant positive predictor of managerial decision confidence has theoretical significance as it can imply that psychological acceptance of AI can be more important than simply use. This contributes to the theoretical connection between cognitive assessments of AI systems and the effectiveness of the managerial decision-making process, building on the previous research on trust in automation and intelligent systems (Hancock et al., 2021; Glikson and Woolley, 2020).

Fourth, the research adds to the literature on behavioural decision-making as it empirically confirms the role of AI reliance and AI resistance. The results indicate that positive behavioural engagement leads to confidence and negative behavioural engagement reduces confidence. This complements and builds upon the existing research on automation bias, algorithm aversion, and calibrated reliance (Bansal et al., 2021; Castelo et al., 2019). More to the point, it demonstrates that behavioural reactions are not simply the effects of using technologies; they are the processes where AI utilisation is converted into the consequences of making decisions.

The paper also generalizes the Attribution Theory to the case of human-AI work. Attribution Theory describes the way people attribute causes and responsibility of outcomes. When working in AI-assisted environments, managers can attribute successful decisions to their expertise, AI inputs, or a combination of the two. The current results indicate that increased levels of trust and perceived reliability correlate with more positive ratings of AI-

aided outcomes, thus enhancing confidence, and increased perceived risk correlates with more reserved ratings that decrease confidence. It builds upon Attribution Theory by demonstrating the working of causal interpretation and perceived legitimacy when both the human and algorithmic support of responsibility exist in part.

Likewise, the research is also relevant to Signaling Theory since AI outputs are viewed as informational signals, which serve to inform managerial decisions in the face of uncertainty. Information asymmetry in AI-empowered decision-making is commonplace as the managers do not have all the knowledge regarding the inner workings of the system. In this case, trust and perceived reliability are strong, credible indicators, and risk perception is a weak or ambiguous indicator. The results thus expand Signaling Theory by demonstrating the influence of AI-generated signals on cognitive and behavioural reactions on organizational decision-making.

Another contribution is the realization that the experience of a manager and knowledge of AI did not play a crucial role in moderating the relationship between AI use and decision confidence. This undermines the suppositions that individual traits are obligated to be a high-quality boundary-condition factor in technology-related consequences. Rather, the data indicate that modern AI-enhanced tools could be convenient enough and easy to use, and thus minimize the disparity in terms of experience or previous knowledge. This offers a practical amendment to the literature and indicates that the role of individual differences might be context-dependent as compared to the presumed past.

Lastly, the paper supports the general perspective of AI as an aid to the decision-making process instead of a substitution of human decision-making. The findings show that AI enhances the certainty of decisions by decreasing uncertainty, aiding in analysis, and boosting informational capacity. This is in line with modern views that highlight human-AI

complementarity and adds to theoretical insights into collaborative decision-making within AI-driven contexts.

In general, the theoretical implications of the current investigation are that it can help to bridge several areas and offer a coherent explanation of the impact of AI on managerial decision confidence. The study provides a solid base of future research and application of AI adoption, organizational behaviour, and decision sciences by connecting AI application, psychological assessment, engagement in behavioural activities, and confidence in a single framework.

5.7. Practical Implications

The results of this research can have some valuable practical implications on the organizations, managers and even developers of AI-supported decision systems. With AI technologies becoming increasingly a part of the decision-making process of organizations, it is necessary to understand how they affect the confidence of managers to achieve the best possible outcomes and guarantee the successful implementation process.

First, the results highlight the importance of encouraging the use of AI-supported decision systems within organizations. Since the use of AI was found to significantly increase the confidence in decision-making by managers, companies must be keen to promote the use of AI systems within managerial tiers. It could be accomplished by investing in AI infrastructure, embracing AI tools in the day-to-day operation, and by creating an environment in which data-driven decisions are made. As soon as the managers get the AI-powered tools, they will be more sure of their choices and this can have a positive impact on the overall performance of the organization.

Second, trust and perceived reliability of AI systems as a need is observed in the paper. Some of the best predictors of managerial decision confidence were also perceived reliability and trust in AI, which suggests that managers should trust that AI outputs are accurate and reliable. Transparency, consistency, and quality of systems should be prioritized in the implementation of AI in organizations. This can be through transparent descriptions of how AI systems get their recommendations, the accuracy of their data and system consistency. Managers can also gain an advantage by training programs and awareness to better learn about AI capabilities and increase trust and decrease uncertainty.

Third, the adverse effect of risk perception and AI resistance imply that organizations have to take proactive care towards the issues and challenges associated with the adoption of AI. Managers might identify the risk of errors, lack of transparency, or other adverse effects of using automated systems, which may be perceived as risks. To address such anxieties, companies ought to adopt risk management measures, such as validation measures, human control and well-defined accountability framework. Moreover, the resistance should be decreased by promoting the positive attitude to AI through communication, training, and demonstrating the real-life advantages of AI systems in decision-making situations.

The other important implication is associated with promoting positive behavioural interaction with AI systems. The results indicate that the use of AI increases decision confidence, and resistance decreases it. It means that it is not enough to introduce AI systems, and the organizations should make sure that the active and effective use of the systems is performed by the managers. It can be done by ensuring AI tools are embedded in decision-making processes, ensuring easy to use interfaces, and by providing constant support to the users. It is also important to promote the culture of cooperation between human judgment and AI insights to maximize the value of these technologies.

The results also indicate that AI systems can be successfully applied in various managerial profiles because the managerial experience and the understanding of AI did not have a significant moderating effect on the correlation between AI use and decision confidence. This means that companies do not have to necessarily restrict AI usage to managers who are very experienced or technically knowledgeable. Rather, AI systems can be configured and implemented in a manner that will be reachable and useful to a large group of users. This facilitates the scalability of AI implementation and emphasizes the need to create easy-to-use and intuitive systems that can be easily used by managers of different expertise.

In addition, organizations are advised to prioritize training and development initiatives that can boost technical and psychological preparedness toward the adoption of AI. Although the knowledge of AI was not a mediating variable, the overall awareness and comfort with AI technologies have the potential to increase engagement and lessen resistance. The training regimes must not be based solely on the instruction on AI systems usage, but the way to analyze the results, evaluate risks, and apply AI insights to decision-making.

Lastly, to the developers of AI systems, the results demonstrate the significance of creating reliable, transparent, and user-friendly systems. The developers ought to work on enhancing system accuracy, giving explainable output and making the system easy to use. Technical performance and user perception help developers develop AI systems that are more apt to be trusted, adopted, and utilized successfully by managers.

Generally, the combination of technological capability, user trust, and positive behavioural engagement is the key to the successful implementation of AI-supported decision systems, as the practical implications of this study point to. Those organizations that effectively tackle such aspects have more chances to increase the confidence of managerial decisions and attain improved decision-making performance within AI-enabled settings.

5.8. Summary

This chapter gave a detailed discussion and interpretation of the empirical findings of Chapter 4. The main aim was to clarify the impact of AI-assisted decision systems on managerial decision confidence based on the use of technology, psychological perception, and behavioural reactions and also investigate the contribution of individual differences.

It has started by outlining that the application of AI-supported decision systems has a strong positive impact on managerial decision confidence. This means that the inclusion of AI in the decision-making processes will improve the confidence and quality of decisions made by managers by eliminating the level of uncertainty and giving them insights that are supported by data. The results also revealed that psychological factors are extremely significant in influencing decision confidence. Precisely, the confidence in AI and perceived reliability were identified to impact positively on managerial confidence, whereas risk perception affected it negatively. These results emphasize the importance of how managers perceive AI systems in determining their effectiveness.

The research further found out that behavioural reactions have a great influence on the confidence of managerial decisions. It was established that AI reliance increased confidence and AI resistance decreased it, emphasizing the significance of management attitudes and interactions with AI systems. These results indicate that positive and negative behavioural dispositions towards AI may contribute significantly to the decision-making results.

The moderating effect analysis indicated that none of the variables managerial experience and familiarity with AI significantly change the relationship between the use of AI-supported decision systems and the confidence of managers in their decisions. This means that the advantages of AI applications are comparatively similar irrespective of the profiles of the

managers, which means AI systems could be successfully applied by a wide group of users despite their experience or level of familiarity.

Another significant contribution of the chapter was to define major theoretical contributions by extrapolating the existing models of technology acceptance and decision-making by incorporating the psychological and behavioural factors. Practical implications were addressed to emphasize how organizations might build managerial confidence by encouraging AI adoption, fostering trust, perceived risks, and encouraging positive interaction with AI systems.

Altogether, the results of the research enable a more in-depth comprehension of factors that affect the confidence of managers to make decisions in AI-based settings. The knowledge gained in this chapter is the basis of the final conclusions and recommendations in the next chapter and thus completes the analytical development of the research.

Chapter 6:

Conclusion

6.1. Introduction

This chapter is the final part of the research because it summarizes the major findings, describes the limitations, and gives research directions. Although Chapter 4 was devoted to the empirical analysis and Chapter 5 provided the detailed discussion of the results, the aim of this chapter is to integrate the general results of the research in a summary and well-organized format. It seeks to draw the key findings of the research conducted on the psychological influence of AI on the confidence of managers on their decisions.

The research question was on the impact of the use of AI-supported decision systems, psychological (belief in AI, perceived reliability, and risk perception) and behavioural (AI reliance and AI resistance) factors on the confidence in managerial decisions. Besides this, the study has examined the presence of individual differences, in this case experience in the management field and familiarity with AI, which mediate these relationships. Combining these dimensions, the research affords an in-depth insight into decision-making in AI-enabled organizational contexts.

This chapter is divided into four sections. First, it includes an overview of the important data results in accordance with the research goals. This is then followed by the discussion of the limitations which might have affected the results. The chapter concludes with recommendations as to future research to expand the present study. Lastly, it ends with a brief conclusion on the whole contributions and the importance of the research.

6.2. Summary of Data Findings

This section briefly summarizes the major empirical findings of the study and organized them according to the objectives of the research. The purpose is to compile the key findings in the statistical analyses in the form of synthesis but not to repeat the detailed interpretations, which were already presented in Chapter 5.

Regarding Research Objective 1, the authors investigated how the use of AI-supported decision systems impacts the confidence of managers in their decisions. It found that there was a positive and significant correlation between the use of AI and the confidence in decisions. Managers who made regular use of AI-aided tools in decision-making processes stated their increased confidence in the decisions. This implies that AI systems can be considered effective decision-support tools, as they can make access to appropriate information easier, minimize uncertainty, and give data-driven information. Nonetheless, this relationship had moderate explanatory power meaning that although AI usage is a key predictor, it is not the only predictor of managerial decision confidence.

Regarding the Research Objective 2, the researchers examined how the effects of the main psychological variables, i.e., the trust in AI, the perceived reliability, and the perception of risk influence the degree of confidence in managerial decisions. The results demonstrated that both trust in AI and perceived reliability have significant positive effects on decision confidence. When managers see AI systems as credible and trustworthy, they will have more confidence in decisions that are backed by AI systems. Out of these variables, trust in AI had the highest impact on decision confidence among managers. Conversely, risk perception was detected to have a strong negative impact. This suggests that managers feel less confident in making decisions when they view AI systems as risky or uncertain. These results emphasize

the significance of cognitive appraisals in influencing the managerial reactions to AI technologies.

In relation to Research Objective 3, the researchers examined how behavioural responses, namely AI reliance and AI resistance, affect the confidence of managers in making decisions. The results indicated that the dependence on AI has a very strong positive impact on decision confidence which implies that managers who actively rely on AI-generated information are more likely to be confident about their decisions. On the other hand, AI resistance was observed to influence negatively, which means that the unwillingness or doubt towards AI systems makes managers less confident. The findings also indicate that reliance and resistance equally have similar kind of effects, but their impacts are in opposite directions. This highlights the significance of behavioural involvement in defining the usefulness of AI-enhanced decision-making.

In regard to Research Objective 4, the authors examined the modulating role of managerial experience and familiarity with AI on the correlation between the use of AI-supported decision systems and managerial decision confidence. The results showed that managerial experience and awareness of AI do not have a significant moderating role in this relationship. Despite the fact that both variables were predicted to impact the way that managers engage with AI systems, the findings indicate that the positive impact of AI utilization on the decision confidence is similar at all levels of experience and familiarity. The effects of the interactions were not significant, and the extra variance covered by these moderators was not large. It means that advantages of AI-supported decision systems are universal and do not depend on the personal differences between managers.

Altogether, the empirical evidence shows that managerial decision confidence in AI-supported contexts is conditioned by an interplay of the use of technology, psychological

perceptions, and behaviours. The use of AI, trust, perceived reliability, and AI reliance are positive contributors that increase the confidence in the decisions, whereas risk perception and AI resistance are negative contributors that decrease it. Conversely, personal differences in experience and familiarity do not have a significant effect on these relationships. These results give a good and systematic insight into the factors that determine the confidence of managerial decisions, and are the foundation of the final conclusions and recommendations given in the latter sections.

6.3. Limitations of the Study

Although this study has led to the creation of valuable insights, it is important to note that it has a number of limitations, which can affect the interpretation and generalizability of the results.

First, the research design used was cross-sectional research design in which data were gathered at one time. Although this is appropriate in determining relationships among variables, it does not allow us to make causal inferences. These results thus show that there are correlations between AI use, psychological variables, behavioural reactions, and confidence in management decision-making and not cause and effect relationships. Future research using longitudinal designs would help in obtaining more information regarding the development of these relationships over time.

Second, the research involved self-reports based on the use of questionnaires. Even though the technique is common with behavioural research, it is likely to be biased because it can result in response bias like social desirability bias and common method variance. It is possible that respondents answered as they perceived things to be like and not necessarily what they experience. Nevertheless, Harman's single-factor test was used which meant that the common method bias was not a significant issue in this research.

Third, the sample of 280 respondents is sufficient in terms of statistical analysis, but it might restrict the generalizability of the conclusions. Though the sample was representative of various industries, the representation was not completely even with a relatively greater representation of technology related sectors. This can affect how far the results can be applied to other industries with varied levels of AI adoption.

The other limitation is based on the scope of variables in the study. Although the study included major technological, psychological, and behavioural variables, other variables which could have been of interest like organizational culture, leadership support and AI system characteristics were not analysed. These components can also be important determinants of managerial decision confidence and might be of extra explanatory value when incorporated in future research.

Moreover, the research concentrated on decision confidence among managers as the main dependent variable, instead of the actual decision quality/performance. Although confidence is a significant cognitive outcome, it does not always imply that the decisions are correct or the best. Thus, the results are to be viewed in the framework of perceived confidence as opposed to objective effectiveness in making decisions.

Lastly, the research failed to take into consideration the fast technological shifts within AI systems that could affect user perceptions and behaviours in the long term. With the further development of AI technologies, trust, reliability, and usability may also shift and can influence the work of managers in dynamic respects. Also, single-source data might involve some endogeneity issues and this could be eliminated in future researches by using multi-source or objective methods of data collection.

On the whole, these drawbacks do not discredit the validity of the study, but they do point out some significant factors that should be remembered when analyzing the results.

Overcoming these constraints in future studies can help to deepen the insights into AI-aided decision-making in the organizational setting.

6.4. Future Research Directions

Based on the results and limitations of this research, recommendations are made on the directions of future research to develop the knowledge base of AI-assisted decision-making and managerial decision confidence.

To begin with, upcoming research may be based on a longitudinal research design in order to determine how the relationships determined in this research change over time. As the current study is cross-sectional, it only provides a picture of the managerial perceptions and behaviours. The longitudinal studies would enable the researchers to monitor the changes in trust, reliance, resistance, and decision confidence as managers will become more familiar with AI systems or technologies will be more advanced.

Second, it is possible to use experimental research designs to determine causality relationships in a more definite way. The variables that could be controlled to observe their direct impact on managerial decision confidence in controlled experiments include AI system reliability, transparency, or risk levels. These methods would give more solid evidence on causality and will assist to confirm the relationships found in this research.

Third, it is possible that the future research would investigate other moderating and mediating variables not covered in the current study. As an example, the organizational culture, leadership support, technological infrastructure, and AI literacy may have an effect on the interactions between the managers and AI systems. These variables may offer more in-depth insights into the contextual circumstances in which the use of AI influences the confidence in the decisions.

The other significant direction would be to look at industry-specific situations. Although, in this research, the respondents represented a variety of sectors, future studies may consider a particular industry, like healthcare, finance, or manufacturing, to learn how the introduction of AI and its effect on the confidence of decisions differ across the organizational setting. These researches would make the findings more contextually relevant and applicable.

The connection between decision confidence and actual decision performance by managers can also be explored in future studies. Although the current study was a psychological outcome of confidence, it would be quite interesting to determine whether augmented confidence related to the use of AI would lead to better decision accuracy or organizational performance. This would assist in establishing the relationship between AI-aided confidence and objective decision effectiveness.

Also, it may be worthwhile to investigate how explainable AI (XAI) and transparency of the system influence the perceptions of managers. With the increasingly complex AI systems in place, the way explainability affects trust, perceived reliability, and decision confidence may serve as an interesting addition to the body of knowledge to help enhance AI technology and practice.

Lastly, future research might include cross-cultural studies to address the impact of cultural differences on AI perceptions, trust, and decision-making behaviour. As the perception of technology and risk differs among cultures, such researches may give a more global insight into AI adoption and its influence on managerial decision confidence.

To conclude, the results of the current study should be extended in future research by increasing the number of methodological approaches, adding more variables and studying different contexts. Such guidelines will help to create a more detailed and multifaceted perspective of AI-assisted decision-making in organizations.

6.5. Conclusion

The current study aimed to research the psychological effects of AI on the confidence in managerial decisions through the roles of AI-supported decision systems use, psychological perceptions, behavioural reactions, and individual differences. The results present some definitive evidence that AI is an important factor in determining the level of confidence in managerial decisions in a modern organizational setting.

The findings indicate that the application of AI-based decision systems has a positive impact on the managerial confidence in decision-making, which suggests that AI can be a powerful instrument to improve decision-making. Moreover, psychological aspects including AI trust and perceived reliability were determined to bolster decision confidence, whereas risk perception has an adverse impact. These results show the significance of the perception of managers towards AI systems in their effectiveness and impact.

It was also found that behavioural responses are key, where AI dependency increased confidence and AI resistance decreased it. This highlights the importance of managerial mindsets and involvement in ensuring the maximization of AI technologies benefits. Conversely, personal factors, namely, the background in management, and AI knowledge, did not have a significant impact on the correlation between AI use and confidence in decision-making. This implies that AI-enabled decision systems can be broadly uniform to various managerial profiles.

In general, the research adds to the better comprehension of how technological, psychological and behavioural variables interplay and impact on the degree of confidence in managerial decision-making in AI-enabled situations. The results underline that successful AI adoption cannot be entirely reliant on technological capabilities but requires the establishment of trust, minimization of perceived risks, and a positive behavioural response among users.

At a time when AI is more and more integrated into organizational decision-making, this paper highlights the fact that the real worth of AI is not just the analytical features of AI, but also its applicability in influencing managerial thinking and belief. By revealing that psychological perceptions and behavioural involvement are the key factors along with the use of technology, the research shows the necessity of human-centric approach towards the implementation of AI. Finally, the results support the idea that the future of decision-making cannot be human versus AI, but human-AI partnership, where technology will augment, but not replace, managerial judgment.

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Appendix 1: Survey Questionnaire

The Psychological Impact of AI on Managerial Decision Confidence: A Behavioral Study

This survey aims to examine how AI-supported decision systems influence managerial decision confidence, along with psychological and behavioral factors associated with AI usage.

Your responses will remain confidential and will be used strictly for academic research purposes. There are no right or wrong answers—please respond honestly based on your experience.

Estimated time: 8–10 minutes.

SECTION A: DEMOGRAPHIC INFORMATION

1. Age (years)

- Below 25
- 25–34
- 35–44
- 45–54
- 55 and above

2. Gender

- Male
- Female
- Prefer not to say

3. Industry Type

- IT / Technology
- Finance
- Healthcare
- Manufacturing
- Services

- Other

4. Years of Managerial Experience

- Less than 3 years
- 3–7 years
- 8–12 years
- More than 12 years

Please indicate your level of agreement using the following scale:

1 = Strongly Disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Strongly Agree

SECTION B: AI-SUPPORTED DECISION SYSTEMS USAGE (AI-SDSU)

(Adapted from Zhang et al., 2025)

Code	Item	Scaling				
		1	2	3	4	5
AI-SDSU1	I frequently use AI-supported systems in my work					
AI-SDSU2	AI tools are integrated into my decision-making process					
AI-SDSU3	I use AI-generated outputs when evaluating managerial options					
AI-SDSU4	I regularly interact with AI systems to support work-related decisions					

SECTION C: TRUST IN AI (T-AI)

(Adapted from McGrath et al., 2025; Scharowski et al., 2025; Jian et al., 2000)

Code	Item	Scaling				
		1	2	3	4	5
TAI1	I am confident in the AI system					
TAI2	The AI system provides a sense of security in decision-making					
TAI3	The AI system behaves with integrity in decision-making					
TAI4	I can trust the AI system					

SECTION D: PERCEIVED RELIABILITY (PR)

(Adapted from McGrath et al., 2025; Scharowski et al., 2025)

Code	Item	Scaling				
		1	2	3	4	5
PR1	The AI system is reliable					
PR2	The AI system produces consistent results					
PR3	The AI system performs accurately across situations					
PR4	I can depend on the AI system's outputs					

SECTION E: RISK PERCEPTION (RP)

(Adapted from Zhou et al., 2025)

Code	Item	Scaling				
		1	2	3	4	5
RP1	Using AI in organizational decision-making involves significant risk					
RP2	AI-supported decisions can lead to negative consequences					
RP3	Errors in AI outputs could result in serious problems for decision outcomes					
RP4	Relying on AI for decisions may lead to unfavorable outcomes for the organization					

SECTION F: AI RELIANCE (AI-REL)

(Adapted from Castro et al., 2025)

Code	Item	Scaling				
		1	2	3	4	5
AI-REL1	I turn to AI frequently when I need information for decisions					
AI-REL2	I prefer to carry out some decision-related tasks with the help of AI					
AI-REL3	I frequently use AI to resolve doubts or answer work-related questions					
AI-REL4	AI strongly influences my managerial judgments					

SECTION G: AI RESISTANCE (AI-RES)

(Adapted from McGrath et al., 2025; Scharowski et al., 2025)

Code	Item	Scaling				
		1	2	3	4	5
AI-RES1	I feel suspicious of the AI system's intent, action, or output					
AI-RES2	I am wary of relying on the AI system					
AI-RES3	I believe the AI system may produce harmful outcomes					
AI-RES4	I am reluctant to depend on the AI system in decision-making					

SECTION H: FAMILIARITY WITH AI (F-AI)

(Adapted from Castro et al., 2025)

Code	Item	Scaling				
		1	2	3	4	5
F-AI1	I understand how AI systems generally work					
F-AI2	I can distinguish between objective and biased information generated by AI					
F-AI3	I am able to judge whether AI-provided information is relevant to my work					
F-AI4	I am prepared to identify possible errors or biases in AI outputs					

SECTION I: MANAGERIAL DECISION CONFIDENCE (MDC)

(Adapted from Cau & Spano, 2025)

Code	Item	Scaling				
		1	2	3	4	5
MDC1	I feel confident in the decisions I make when using AI-supported systems					
MDC2	I am certain about the correctness of my decisions when AI support is available					
MDC3	I feel assured about the outcomes of decisions made with AI support					
MDC4	I feel highly confident in decisions supported by AI-generated insights					