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AI-Assisted Decision-Making and Psychological Experiences of Organizational Leaders

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Abstract:
The increasing integration of artificial intelligence (AI) tools into organizational decision-making has significantly transformed leadership practices. While AI offers efficiency, speed, and analytical support, concerns have emerged regarding its psychological and cognitive implications for leaders. The present study examines the relationship between AI-assisted decision-making, cognitive load, reflective capacity, and leadership confidence among organizational leaders. Using a quantitative research design, data were collected from a sample of 60 working professionals in leadership roles across various organizational sectors. Standardized, validated self-report measures were used to assess AI-assisted decision-making, perceived cognitive load, reflective capacity, and leadership confidence. Descriptive statistics, independent sample t-tests, and correlational analyses were employed to analyze the data. The findings indicate that greater reliance on AI-assisted decision-making is associated with reduced cognitive load but shows mixed relationships with reflective capacity and leadership confidence. The results suggest that while AI tools may ease cognitive demands, excessive dependence may influence leaders' reflective engagement and confidence in judgment. The study highlights the importance of balanced human–AI collaboration and reflective leadership practices in contemporary organizational contexts. Implications for leadership development and future research are discussed.

Keywords: Artificial intelligence, AI-assisted decision-making, cognitive load, reflective capacity, leadership confidence, organizational leadership.

INTRODUCTION

Artificial intelligence (AI) is increasingly embedded in organizational decision-making processes, reshaping how leaders interpret information, evaluate alternatives, and exercise judgment. Contemporary organizations rely on AI-enabled systems for forecasting, risk assessment, performance analytics, and strategic planning, positioning AI as a critical cognitive partner rather than a passive tool (Davenport & Ronanki, 2018). As AI systems move closer to the core of leadership decision-making, questions arise not only about efficiency and accuracy but also about their psychological impact on leaders.

Leadership decision-making is inherently complex and cognitively demanding. Leaders are required to integrate diverse information sources, manage uncertainty, and remain accountable for outcomes that affect multiple stakeholders. Prior research in human–automation interaction suggests that advanced decision-support technologies alter how individuals allocate attention, process information, and maintain control over decisions (Parasuraman, Sheridan, & Wickens, 2000). In this context, AI-assisted decision-making represents a significant shift in how cognitive work is distributed between humans and intelligent systems.

One psychological construct central to leadership decision-making is cognitive load, defined as the mental effort required to process task-relevant information. While AI tools are often promoted as mechanisms for reducing cognitive burden, recent studies suggest that AI may simultaneously introduce new cognitive demands related to system monitoring, trust calibration, and interpretation of algorithmic outputs (Endsley, 2017). Understanding how AI affects cognitive load among leaders is therefore essential.

Beyond cognitive demands, effective leadership requires reflective capacity—the ability to critically examine one's assumptions, reasoning, and emotional responses. Reflective thinking enables leaders to learn from experience, navigate ethical dilemmas, and adapt to changing contexts (Schön, 1983). Concerns have emerged that increasing reliance on AI systems may encourage cognitive offloading, potentially diminishing reflective engagement if AI outputs are accepted without scrutiny (Raisch & Krakowski, 2021).

Leadership confidence represents another key psychological dimension in AI-mediated decision contexts. Confidence in decision-making influences risk-taking, accountability, and leadership presence. Emerging evidence suggests that AI recommendations can shape human confidence, either reinforcing self-belief or undermining it when discrepancies arise between human judgment and algorithmic output (Lee et al., 2025). This raises important questions about how leaders maintain confidence while sharing cognitive authority with AI systems.

Despite growing interest in AI and leadership, empirical research examining the combined psychological effects of AI-assisted decision-making on cognitive load, reflective capacity, and leadership confidence remains limited, particularly in non-Western organizational contexts. The present study seeks to address this gap by examining these psychological variables among organizational leaders using AI-assisted decision tools.

REVIEW OF LITERATURE

AI-assisted decision-making involves the use of algorithmic systems that augment human judgment by analyzing data, identifying patterns, and generating recommendations. Davenport and Ronanki (2018) emphasized that AI adoption in organizations has shifted from experimental applications to core managerial functions. Jarrahi (2018) conceptualized this shift as human–AI symbiosis, arguing that effective decision-making emerges from collaboration rather than substitution.

Recent leadership-focused studies have examined how AI reshapes authority and accountability. Raisch and Krakowski (2021) described an "automation–augmentation paradox," wherein AI enhances decision quality while simultaneously challenging managerial autonomy. Scoggins (2025) further highlighted that leaders using AI-supported systems often experience tension between algorithmic recommendations and personal judgment, influencing perceptions of responsibility and control.

Cognitive Load Theory posits that human cognitive capacity is limited and that excessive mental effort can impair decision quality (Sweller, Ayres, & Kalyuga, 2011). AI tools are frequently designed to reduce cognitive load by automating information processing; however, empirical findings indicate mixed outcomes. Endsley (2017) reported that advanced automation can increase cognitive load when system behavior is difficult to interpret or predict.

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Recent empirical work has emphasized the role of AI transparency in shaping cognitive load. Khan et al. (2025) found that opaque AI systems increased perceived mental effort and decision fatigue among users, whereas transparent systems supported cognitive clarity. These findings suggest that AI does not inherently reduce cognitive load; rather, its cognitive impact depends on system design and user engagement.

Reflective capacity is central to professional judgment and leadership development. Schön (1983) described reflective practice as the ability to think critically during and after action, enabling adaptive expertise. In AI-supported environments, reflective capacity may be challenged by tendencies toward cognitive offloading. Gerpott, Lehmann-Willenbrock, and Voelpel (2023) observed that reliance on intelligent systems can reduce active cognitive engagement if users defer excessively to algorithmic outputs.

Conversely, research suggests that AI systems designed to prompt explanation and comparison can enhance reflective thinking. Buçinca et al. (2024) demonstrated that human-centric AI decision aids encouraged users to question recommendations and engage more deeply with decision rationales. These findings highlight the importance of reflective capacity as a moderating factor in AI-assisted decision-making.

Leadership confidence influences decision ownership, persistence, and interpersonal influence. Bandura's self-efficacy theory provides a foundational framework for understanding confidence in leadership roles (Bandura, 1997). In AI-mediated contexts, confidence calibration becomes critical. Lee et al. (2025) found that frequent interaction with generative AI systems affected users' confidence in their own judgment, particularly when AI outputs were perceived as highly authoritative.

Human–AI interaction research suggests that mismatches between AI confidence and human confidence can lead to over-reliance or under-utilization of AI tools (Parasuraman et al., 2000). Scoggins (2025) further noted that leaders' confidence may fluctuate as they negotiate autonomy and accountability in AI-supported decisions.

Although prior research has examined AI adoption, cognitive load, reflective thinking, and leadership confidence independently, limited empirical work has explored their combined relationships within AI-assisted leadership decision-making. Moreover, most existing studies focus on Western contexts or technical performance outcomes rather than psychological experiences. The present study seeks to contribute to this emerging body of literature by empirically examining the relationships among AI-assisted decision-making, cognitive load, reflective capacity, and leadership confidence among organizational leaders.

RESEARCH QUESTIONS

1. Is there a relationship between AI-assisted decision-making and cognitive load and its dimensions (mental demand, physical demand, temporal demand, performance, effort, and frustration) among leaders?
2. Is there a relationship between AI-assisted decision-making and reflective capacity and its dimensions (self-reflection and insight) among leaders?
3. Is there a relationship between AI-assisted decision-making and leadership confidence among leaders?

4. Is there a relationship between cognitive load and its dimensions (mental demand, physical demand, temporal demand, performance, effort, and frustration) and leadership confidence among leaders?
5. Is there a relationship between reflective capacity and its dimensions (self-reflection and insight) and leadership confidence among leaders?

RESEARCH OBJECTIVES

1. To study the relationship between AI-assisted decision-making and cognitive load and its dimensions (viz. mental demand, physical demand, temporal demand, performance, effort, and frustration) among leaders.
2. To examine the relationship between AI-assisted decision-making and reflective capacity and its dimensions (viz. self-reflection and insight) among leaders.
3. To examine the relationship between AI-assisted decision-making and leadership confidence among leaders.
4. To study the relationship between cognitive load and its dimensions (viz. mental demand, physical demand, temporal demand, performance, effort, and frustration) and leadership confidence among leaders.
5. To study the relationship between reflective capacity and its dimensions (viz. self-reflection and insight) and leadership confidence among leaders.

HYPOTHESES

H1. There will be a significant relationship between AI-assisted decision-making and cognitive load and its dimensions
(Ai) mental demand,
(Aii) physical demand,
(Aiii) temporal demand,
(Aiv) performance,
(Av) effort, and
(Avi) frustration among leaders.

H2. There will be a significant positive relationship between AI-assisted decision-making and reflective capacity and its dimensions
(Ai) self-reflection and
(Aii) insight among leaders.

H3. There will be a significant positive relationship between AI-assisted decision-making and leadership confidence among leaders.

H4. There will be a significant negative relationship between cognitive load and its dimensions
(Ai) mental demand,
(Aii) physical demand,
(Aiii) temporal demand,
(Aiv) performance,
(Av) effort, and
(Avi) frustration
and leadership confidence among leaders.

H5. There will be a significant positive relationship between reflective capacity and its dimensions
(Ai) self-reflection and
(Aii) insight
and leadership confidence among leaders.

METHOD

Research Design

The present study adopted a quantitative, cross-sectional, correlational research design to examine the relationships between AI-assisted decision-making, cognitive load and its dimensions, reflective capacity and its dimensions, and leadership confidence among leaders. A correlational design was considered appropriate as the study aimed to explore associations among psychological variables without manipulation of any conditions.

Sample

The sample consisted of 60 leaders, selected using non-probability purposive sampling. Participants included individuals holding senior leadership and middle-level managerial positions across various organizational sectors. Both male and female leaders were represented in the sample.

Inclusion Criteria

1. Individuals currently holding leadership or managerial roles
2. Minimum of one year of leadership experience
3. Regular use of AI-based or technology-supported decision-making tools
4. Ability to read and understand English

Exclusion Criteria

1. Individuals not involved in organizational decision-making
2. Leaders with less than one year of leadership experience

Instruments

The following instruments were used for data collection:

Information Schedule

An Information Schedule was used to obtain demographic and professional details of the participants, including age, gender, educational qualification, leadership level, years of leadership experience, organizational sector, and type of AI-based decision-support tools used.

Decision Support System (DSS) Usage Scale

The Decision Support System (DSS) Usage Scale was used to assess AI-assisted decision-making (Power, 2002). The scale consists of 6 items measuring the extent to which individuals use technology-based decision-support systems in leadership decision-making. Responses are rated on a 5-point Likert scale ranging from strongly disagree to strongly agree. Higher scores indicate greater use of AI-assisted decision-support tools. The scale is treated as unidimensional, and a total score is derived by summing all items.

NASA Task Load Index (NASA-TLX)

The NASA Task Load Index was used to measure cognitive load experienced during decision-making tasks (Hart & Staveland, 1988). The scale assesses workload across six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. Participants rate each dimension

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on a 5-point scale, with higher scores indicating greater perceived cognitive load. A composite score was used to represent overall cognitive load.

Self-Reflection and Insight Scale (SRIS)

The Self-Reflection and Insight Scale was used to assess reflective capacity (Grant, Franklin, & Langford, 2002). The scale consists of 20 items measuring two dimensions: self-reflection and insight. Responses are rated on a 6-point Likert scale ranging from strongly disagree to strongly agree. Higher scores indicate greater reflective capacity.

Leadership Self-Efficacy Scale

The Leadership Self-Efficacy Scale was used to measure leadership confidence (Murphy, 1992). The scale consists of 8 items assessing leaders' confidence in their ability to perform leadership roles effectively, manage challenges, and make decisions. Responses are rated on a 5-point Likert scale, with higher scores indicating higher leadership confidence.

Procedure

Participants who met the inclusion criteria were identified and approached. They were briefed about the purpose and nature of the study, and informed consent was obtained prior to participation. Participants were assured of confidentiality and anonymity, and were informed that participation was voluntary and that they could withdraw from the study at any time.

Data were collected using standardized self-report questionnaires administered online. Clear instructions were provided regarding the completion of the questionnaires. No time limit was imposed; however, participants were requested to complete the questionnaires at their convenience. The completed responses were used for further analysis.

RESULTS

The data were analysed using descriptive statistics and Pearson's product–moment correlation to examine the relationships between AI-assisted decision-making, cognitive load and its dimensions, reflective capacity and its dimensions, and leadership confidence. All analyses were interpreted using two-tailed tests of significance.

Table 1

Mean and Standard Deviation of AI-Assisted Decision-Making, Cognitive Load, Reflective Capacity, and Leadership Confidence (N = 60)

Variable	**Mean**	**SD**
AI-assisted decision-making	19.92	5.54
Cognitive load	18.25	4.49
Reflective capacity	73.43	6.83
Leadership confidence	27.13	6.39

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Table 2
Correlation Between AI-Assisted Decision-Making, Cognitive Load, Reflective Capacity, and Leadership Confidence (N = 60)

Variable Pair	r
AI-assisted decision-making and cognitive load	.58**
AI-assisted decision-making and reflective capacity	.67**
AI-assisted decision-making and leadership confidence	.62**
Cognitive load and reflective capacity	.48**
Cognitive load and leadership confidence	.22
Reflective capacity and leadership confidence	.68**

Note. N = 60. Values represent Pearson's correlation coefficients.
$p \leq .01$ (two-tailed).

Interpretation of Results
Table 2 indicates a significant positive relationship between AI-assisted decision-making and overall cognitive load ($r = 0.58$, $p \leq 0.01$). This suggests that leaders who engage more extensively with AI-supported decision-making tools experience higher levels of perceived cognitive demand. Hence, Hypothesis H1 was accepted.
With respect to the dimensions of cognitive load, AI-assisted decision-making showed significant positive relationships with mental demand, temporal demand, effort, and frustration ($p \leq 0.01$). This indicates that increased use of AI in decision-making is associated with greater mental processing requirements, time pressure, effort, and emotional strain. Therefore, Hypotheses H1 (Ai), H1 (Aiii), H1 (Av), and H1 (Avi) were accepted.

However, AI-assisted decision-making did not show a statistically significant relationship with physical demand and perceived performance ($p \geq 0.05$). This suggests that AI-supported decision-making does not significantly influence physical workload or leaders' perceptions of task success. Hence, Hypotheses H1 (Aii) and H1 (Aiv) were rejected.

Table 2 further reveals a significant positive relationship between AI-assisted decision-making and reflective capacity ($r = 0.67$, $p \leq 0.01$). Leaders who reported higher use of AI-based decision tools also demonstrated higher levels of reflective thinking and insight. Thus, Hypothesis H2 was accepted.
Further analysis indicated that AI-assisted decision-making was significantly positively related to both dimensions of reflective capacity, namely self-reflection and insight ($p \leq 0.01$). Hence, Hypotheses H2 (Ai) and H2 (Aii) were accepted.

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The findings also show a significant positive relationship between AI-assisted decision-making and leadership confidence ($r = 0.62$, $p \leq 0.01$). This suggests that leaders who engage more frequently with AI-supported decision processes tend to report greater confidence in their leadership abilities. Therefore, Hypothesis H3 was accepted.

The relationship between cognitive load and leadership confidence was found to be not statistically significant ($r = 0.22$, $p \geq 0.05$). This indicates that although leaders may experience increased cognitive demands during AI-assisted decision-making, such demands do not significantly influence their confidence in leadership roles. Hence, Hypothesis H4 was rejected.

Table 2 also indicates a significant positive relationship between reflective capacity and leadership confidence ($r = 0.68$, $p \leq 0.01$). Leaders with higher levels of reflective capacity were found to report higher leadership confidence. Therefore, Hypothesis H5 was accepted.
Further examination of the dimensions of reflective capacity revealed that both self-reflection and insight were significantly positively related to leadership confidence ($p \leq 0.01$). Hence, Hypotheses H5 (Ai) and H5 (Aii) were accepted.

Summary of Results
Results obtained in the present study have been summarized in the following section. The findings of the study reveal:
Significant relationships between AI-assisted decision-making and:
- Cognitive load
- Reflective capacity
- Leadership confidence

Significant relationships between cognitive load and:
- Reflective capacity

No significant relationship between cognitive load and:
- Leadership confidence

Significant relationships between reflective capacity and:
- Leadership confidence

DISCUSSION
The present study sought to examine the psychological correlates of AI-assisted decision-making among organizational leaders, with specific focus on cognitive load, reflective capacity, and leadership confidence. The findings contribute to an emerging body of research that moves beyond technological efficiency to consider the cognitive and psychological experiences of leaders engaging with AI-supported decision tools.

The results indicate that AI-assisted decision-making is meaningfully associated with leaders' perceived cognitive load. While AI systems are often positioned as mechanisms to reduce mental effort, the findings suggest a more nuanced relationship. This aligns with prior research indicating that advanced decision-support systems may redistribute rather than eliminate cognitive demands (Endsley, 2017). Leaders using AI tools are required not only to process information but also to monitor system outputs, assess reliability, and reconcile algorithmic recommendations with contextual judgment. Such demands may explain why

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cognitive load remains salient even in AI-supported environments, particularly when system transparency or interpretability is limited (Khan et al., 2025).

Reflective capacity emerged as an important psychological dimension in AI-assisted decision contexts. The findings suggest that reflective thinking continues to play a critical role in leadership decision-making despite the presence of intelligent systems. This supports Schön's (1983) conceptualization of reflective practice as central to professional judgment. While concerns have been raised that AI use may encourage cognitive offloading and reduce critical engagement (Gerpott et al., 2023), the present findings indicate that reflective capacity is not inherently diminished by AI use. Instead, reflective engagement may depend on how leaders interact with AI outputs—whether they actively interrogate recommendations or accept them uncritically. This interpretation is consistent with recent research suggesting that human-centric AI systems can support reflection when designed to encourage explanation and comparison (Buçinca et al., 2024).

Leadership confidence was also found to be closely linked with AI-assisted decision-making. Confidence in leadership decisions is fundamental to accountability, authority, and decision ownership. The findings suggest that AI tools can influence leaders' confidence by shaping perceptions of competence and control. This aligns with recent evidence indicating that highly authoritative AI outputs may recalibrate users' confidence, sometimes leading to reduced reliance on personal judgment (Lee et al., 2025). Scoggins (2025) similarly argued that AI-supported decision-making introduces psychological tension related to autonomy and responsibility, which may affect leaders' confidence in their own decision-making abilities. The interrelationships among cognitive load, reflective capacity, and leadership confidence highlight the complexity of AI-assisted leadership decision-making. These findings support contemporary perspectives in human–AI interaction research, which emphasize that AI systems should augment rather than replace human judgment (Parasuraman et al., 2000). Leaders' cognitive and psychological experiences appear to be shaped not only by the presence of AI but also by how responsibility, reflection, and confidence are negotiated within AI-mediated decision processes.

The findings have practical implications for organizations integrating AI into leadership decision-making. Training programs should extend beyond technical competence to include cognitive awareness and reflective engagement with AI tools. Designing AI systems that promote transparency and encourage active reflection may help leaders manage cognitive load while maintaining confidence and accountability. Such approaches may support more effective and psychologically sustainable AI-assisted leadership.

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