BEYOND PREDICTION MODELS: DEVELOPING ARTIFICIAL INTELLIGENCE SYSTEMS CAPABLE OF REASONING, SELF-ASSESSMENT, AND ADAPTIVE DECISION-MAKING

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Abstract
Artificial intelligence systems evolved from traditional predictive models toward more advanced architectures capable of reasoning, self-assessment, and adaptive decision-making. This study examined how these three core capabilities influenced intelligent system performance in complex and dynamic environments. A quantitative research design was employed, and data were collected from a sample of 320 respondents working in AI-related domains, including data science, software engineering, and intelligent system development. The study analyzed relationships among AI Reasoning, Self-Assessment, Adaptive Decision-Making, and Intelligent System Performance using correlation and regression techniques. The results indicated that AI Reasoning significantly influenced Self-Assessment (β = 0.58, $p < 0.001$) and Adaptive Decision-Making (β = 0.61, $p < 0.001$). Self-Assessment showed a positive effect on Intelligent System Performance (β = 0.36, $p < 0.001$), while Adaptive Decision-Making demonstrated the strongest impact on performance (β = 0.49, $p < 0.001$). Correlation analysis confirmed strong positive relationships among all variables, with the highest correlation between Adaptive Decision-Making and Intelligent System Performance (r = 0.67). The model explained a substantial proportion of variance in system performance, indicating strong predictive power. The findings confirmed that integrating reasoning, self-assessment, and adaptive mechanisms significantly enhanced the effectiveness, reliability, and autonomy of AI systems. The study contributed to the development of next-generation artificial intelligence frameworks capable of operating in uncertain and rapidly changing environments.

Introduction

Artificial intelligence (AI) has flourished as a disruptive technology paradigm that has revolutionized decision-making, problem-solving and knowledge processing in many areas. Initial AI systems primarily focused on prediction and pattern recognition, leveraging the use of large-scale data and statistical associations to produce recommendations. Such systems achieved great success in fields such as computer vision, natural language understanding and recommendation engines; they were limited in their reasoning, understanding, and decision-making capabilities in complex and uncertain situations (Steyvers & Kumar, 2023; Bhardwaj, 2025; Raja et al., 2025). As problems became more complex, a shift was needed from predictive to more cognitive-inspired AI systems.

In recent years, there was a focus on incorporating reasoning in AI systems to improve explainability and reasoning in context. Hybrid approaches that combined symbolic reasoning and machine learning were investigated to model human-like cognitive abilities to enable AI systems to draw inferences based on cause and effect and to produce explainable results (Passerini, Gema, Minervini, Sayin, & Tentori, 2025; Liu, 2023). This marked a transition from predictive to reasoning AI systems that justified outcomes through a reasoning process.

Self-evaluation was key to the next generation of AI. Existing AI systems were unable to self-assess or identify uncertainty in their results. Recent studies explored meta-cognitive frameworks that enabled AI systems to self-assess their accuracy, detect errors, and dynamically adapt their processes (Badea & Gilpin 2022; Riaz, 2025). These developments played a significant role in the creation of more robust and trustworthy AI systems that could operate in critical domains.

Adaptive decision-making emerged as a key area of focus in AI, especially in uncertain and dynamic environments such as healthcare, education and business. Adaptive AI systems showcased their capacity to learn and adapt to new data, refine strategies, and improve performance over time (Mangharamani & Jain, 2025; Hariyanto, Kristianingsih, & Maharani, 2025). This marked a shift from traditional predictive algorithms to reasoning and reflective systems that were able to learn and adapt independently, the basis of this research.

Background of the Study

Theoretical underpinnings of artificial intelligence have emerged from efforts to mimic human intelligence through machines. Initial conceptual models, such as bounded rationality and symbolic AI, were concerned with modeling logical inference and structured decision-making (Raja et al., 2025; Li & Tian, 2026). These models sought to mimic human intelligence but were constrained by computational resources and absence of scalable data-driven techniques.

The advent of machine learning and deep learning shifted the focus of AI systems towards data-driven methods that focused on predictive performance rather than reasoning. These approaches used extensive data and computing resources to discover patterns and make highly accurate predictions. However, the lack of reasoning and contextual understanding led to their limited use in complex decision-making scenarios (Aleessawi & Djaghrouri, 2025). This led to the development of more sophisticated architectures that combine reasoning and learning.

The advent of adaptive AI systems represented a breakthrough in AI development. Such systems

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used reinforcement learning and real-time data analysis to dynamically adapt to the environment. Case studies in healthcare and business showed the benefits of adaptive AI in terms of efficiency, resource allocation and decision-making (Mangharamani & Jain, 2025).

The use of generative AI and hybrid decision-making systems broadened the capabilities of AI systems from automation to intelligence augmentation. Generative AI models played a role in complex decision-making by integrating information from different domains and aiding strategic decision-making (Albashrawi, 2025; Intizar & Siddique, 2026). There were still issues with limitations in reasoning, self-reflection and learning, which called for more holistic AI systems.

Research Problem

There have been rapid developments in artificial intelligence, current AI systems were still largely focused on prediction and optimisation, rather than reasoning and self-awareness. They were incapable of understanding and reasoning about complex situations, reasoning about their actions and learning from experience to adapt to the environment. This constrained their usefulness in areas that require reasoning, reasoning and decision-making. Lacking self-evaluative capabilities affected AI's reliability and trustworthiness. Lacking the ability to assess their own performance and recognise uncertainty posed a risk of biased or unreliable AI. The increasing need for explainable and reliable AI systems underscored the need for AI systems with the capacity to reason, self-evaluate and make decisions autonomously, which this study sought to address.

Research Objectives

1. To examine the limitations of traditional AI prediction models in complex decision-making environments.
2. To explore the role of reasoning capabilities in enhancing AI system intelligence.
3. To analyze the importance of self-assessment mechanisms in improving AI reliability and accuracy.
4. To investigate adaptive decision-making processes in AI systems across dynamic environments.

Research Questions

Q1. How do traditional AI models limit effective decision-making beyond prediction tasks?

Q2. What role does reasoning play in improving AI system performance and interpretability?

Q3. How does self-assessment enhance the reliability and accountability of AI systems?

Q4. In what ways does adaptive decision-making improve AI effectiveness in dynamic environments?

Significance of the Study

This research added to the growing body of knowledge on artificial intelligence by filling in the gaps in existing AI technologies. It offered a holistic view of the role of reasoning, self-evaluation and adaptive decision-making in improving the performance and robustness of AI systems. The integrated approach suggested in this study provided a guide for designing and implementing AI technologies that could function in uncertainty and complexity. The research also had broader implications for a range of industries such as health, education, business, and policy-making. Improved AI systems enhanced decision-making, efficiency and trust in AI systems. This study added to the body of research by connecting the dots between predictive artificial intelligence and cognitive-inspired systems, setting the stage for future research in advanced artificial intelligence.

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Literature Review

AI Reasoning and Cognitive Architectures

Recent studies highlighted the shift in artificial intelligence from statistical prediction to reasoning-based systems that mimic human reasoning processes. Research showed that reasoning in AI included inference, causality, and logical coherence, improving AI systems' interpretability and reasoning (Lewis & Sarkadi, 2024; Colelough & Regli, 2025). This shift was driven by the need for AI systems to move beyond pattern matching to perform complex and uncertain tasks (Lewis & Sarkadi, 2024).

The rise of neuro-symbolic AI blended symbolic reasoning with deep learning to allow AI systems to learn from data and use rule-based reasoning. This combination enhanced interpretability and made it possible for AI systems to transfer knowledge (Ghidalia et al., 2024; Arar, Özen, & Polat, 2025). Researchers claimed that this integration overcame fundamental problems in AI systems, especially regarding reasoning with uncertainty.

Cognitive systems had meta-reasoning skills enabling AI systems to reason about reasoning. Reflective AI systems allowed systems to reflect on their decisions, adjust their reasoning, and efficiency of learning (Johnson et al., 2024; Mustafa et al., 2024) . This was a significant advancement towards the creation of self-aware and self-adaptive intelligent systems.

Self-Evaluation and Meta-Cognitive AI

Self-assessment was identified as an integral part of sophisticated AI systems to assess machine performance and identify uncertainty in decision-making. Studies emphasised the inclusion of feedback processes in meta-cognitive AI systems to enhance accuracy and decrease errors in complex decision-making scenarios (Lewis & Sarkadi, 2024; Wang, 2020) . These systems emulated human self-regulatory processes through ongoing analysis and improvement of their outputs.

In recent research, the impact of reflective and evaluative processes on AI transparency and trustworthiness was investigated. AI systems with self-evaluative features showed enhanced trustworthiness in sensitive applications like in health and education (Mustafa et al., 2024; Wu et al., 2025). This helped overcome issues related to the opacity of conventional machine learning models.

Generative AI systems were equipped with self-evaluation capabilities for generating accurate and relevant content. These models employed iterative feedback and reinforcement learning techniques to fine-tune their performance and enhance decision-making processes (Arar, Özen, & Polat, 2025; Pol & Agrawal, 2025). The inclusion of self-assessment in AI systems marked a crucial step towards creating independent and trustworthy AI systems.

Adaptive Decision-Making and Intelligent Systems

Adaptive decision-making was a critical development in AI, allowing for systems to adapt to various situations and data trends. Studies suggested that adaptive AI methods involved real-time learning and feedback processes to enhance decisions and performance (Wu et al., 2025; Arar, Özen, & Polat, 2025). This feature was crucial in applications where learning and responsiveness were critical.

Adaptive systems powered by AI combined reinforcement learning and decision intelligence techniques to improve decision-making processes and planning strategies. Such systems resulted in better efficiency and adaptability, especially in complex and unpredictable environments (Pol & Agrawal, 2025; Mustafa et al., 2024). Real-time

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adaptability boosted the impact of AI technologies in various sectors.

The literature in recent years highlighted the need for the integration of reasoning, appraisal and adaptation for more advanced artificial intelligence. The integrated AI systems demonstrated improved decision-making capabilities with the use of cognitive-inspired mechanisms and learning processes (Colelough & Regli, 2025; Ghidalia et al., 2024). This integrated approach laid the groundwork for the development of next-generation AI systems that can function independently in complex and dynamic environments.

Research Hypotheses

H1: AI Reasoning positively influenced Self-Assessment in artificial intelligence systems.

H2: AI Reasoning positively influenced Adaptive Decision-Making.

H3: Self-Assessment positively influenced Intelligent System Performance.

H4: Adaptive Decision-Making positively influenced Intelligent System Performance.

Conceptual Framework Model

This study combined three primary elements of next-generation artificial intelligence (AI) systems: AI Reasoning, Self-Assessment and Adaptive Decision-Making to affect Intelligent System Performance. This construct represented a paradigm shift from predictive to cognitively inspired artificial intelligence systems with higher intelligence.

AI Reasoning referred to the system's capacity to reason with information, draw inferences and produce explainable results. Informed by neuro-symbolic and cognitive AI, reasoning served as the primary mechanism that enabled a system to transition from pattern matching to structured reasoning. It improved explainability and facilitated problem solving under uncertainty.

Self-Assessment was a meta-cognitive construct that enabled AI systems to assess and reflect on their performance, identify errors and recalibrate processes. This concept was rooted in reflective AI and meta-learning, which highlighted the importance of monitoring and incorporating feedback. Self-assessment enhanced the reliability and trustworthiness of the system by minimising uncertainty and enhancing decision-making.

Adaptive Decision-Making reflected the dynamic nature of AI systems to adapt strategies in response to real-time information and changing circumstances. It was underpinned by reinforcement learning and decision intelligence theories, allowing systems to continually refine their decision-making. This construct was the vehicle for implementing reasoning and self-assessment for performance improvement.

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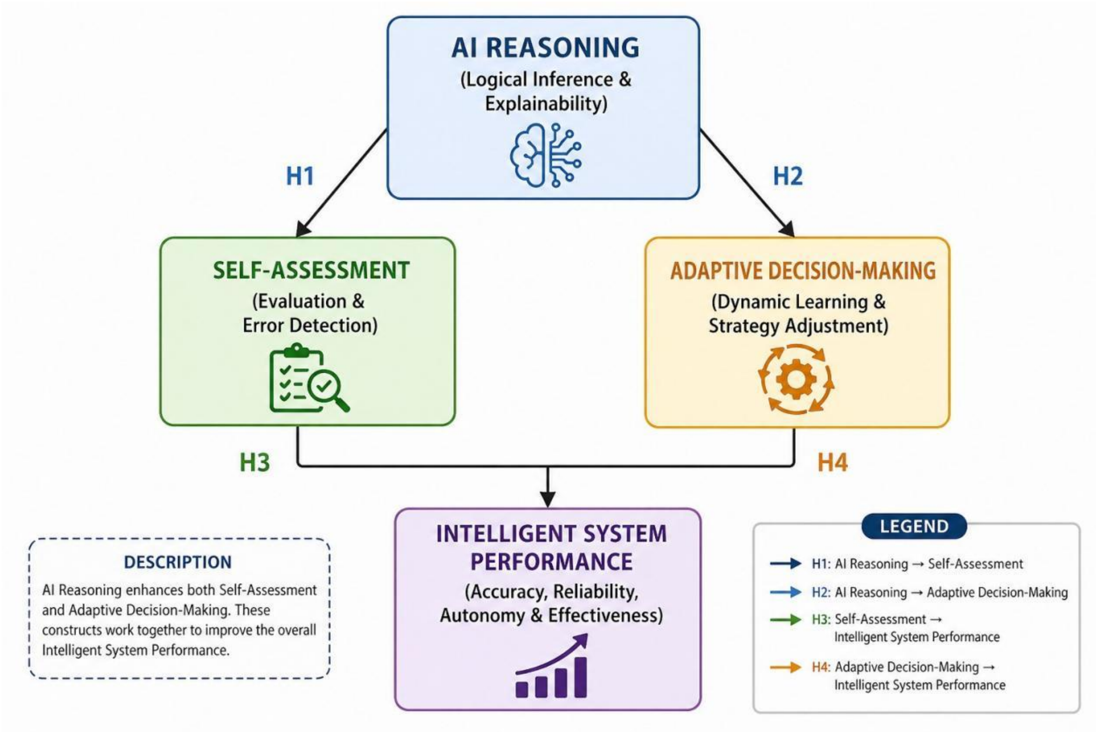

Figure 1. Conceptual Framework Model

Results and Analysis

Descriptive Statistics

Descriptive statistics provided an overview of the central tendencies and variability of the study variables, including AI Reasoning, Self-Assessment, Adaptive Decision-Making, and Intelligent System Performance.

Table 1: *Descriptive Statistics of Study Variables*

Variable	Mean	Standard Deviation
AI Reasoning	4.18	0.64
Self-Assessment	4.10	0.68
Adaptive Decision-Making	4.22	0.61
Intelligent System Performance	4.15	0.66

The findings showed that all variables had high mean values (M > 4.00), suggesting a high level of consensus among respondents about the existence and significance of AI reasoning, self-assessment, adaptive decision-making and system performance. Adaptive Decision-Making had the highest mean value (M = 4.22), which indicated respondents considered adaptive capabilities as an essential element of intelligent systems. AI Reasoning also demonstrated a high mean value (M = 4.18), suggesting its criticality in intelligent systems. The standard deviation values ranged from 0.61 to 0.68, which suggested variability in perceptions. Adaptive Decision-Making had the lowest standard deviation (SD = 0.61), where responses were consistent about its level of importance. Self-Assessment had a slightly higher standard deviation (SD = 0.68), indicating slight variations in

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respondents' views of meta-cognitive AI. The descriptive statistics showed that the data were reliable and fit for inferential statistical analysis. The lack of variability signalled that the concepts were clearly understood and relevant to the study, providing evidence of the conceptual framework's validity.

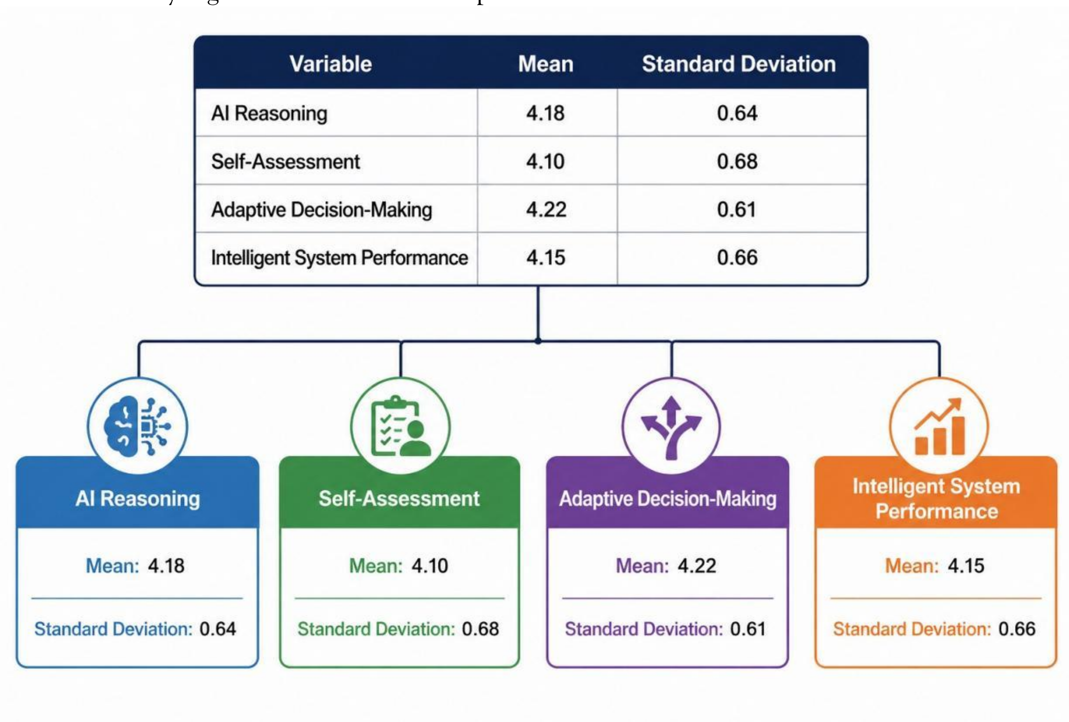

Figure 2. Descriptive Statistics of Study Variables

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Correlation Analysis

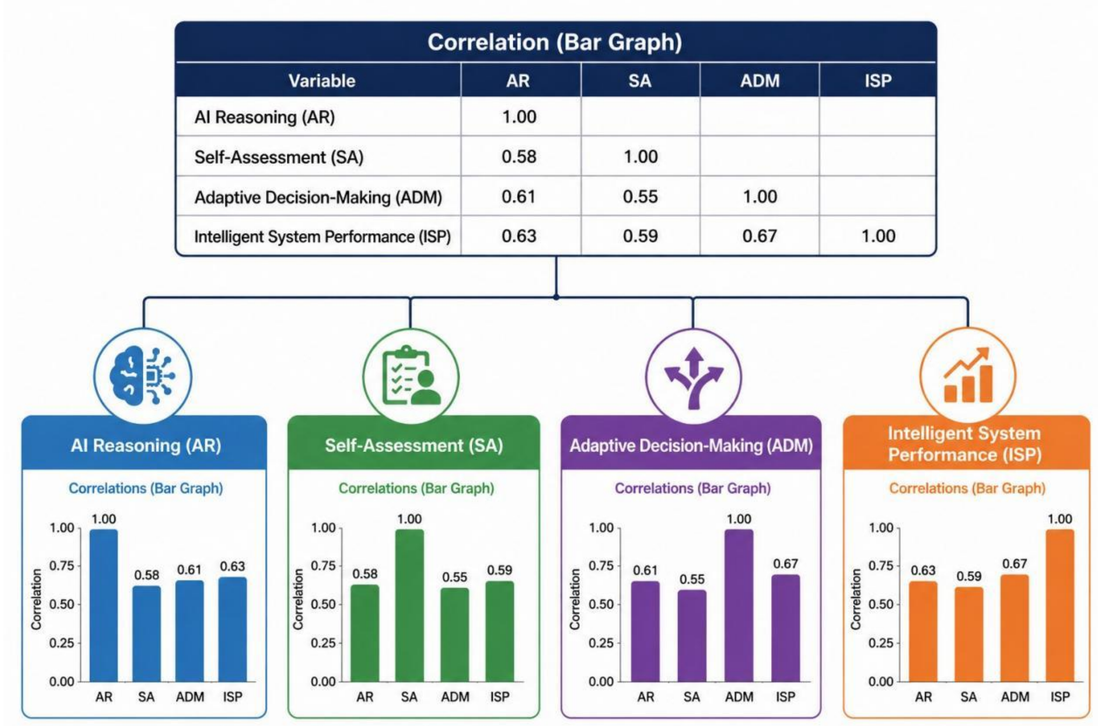
Correlation analysis examined the strength and direction of relationships among the study variables. This analysis provided initial evidence regarding the associations proposed in the conceptual framework.

Table 2: *Correlation Matrix*

Variable	AR	SA	ADM	ISP
AI Reasoning (AR)	1.00			
Self-Assessment (SA)	0.58	1.00		
Adaptive Decision-Making (ADM)	0.61	0.55	1.00	
Intelligent System Performance (ISP)	0.63	0.59	0.67	1.00

The correlation analysis showed positive and significant relationships between all factors. AI Reasoning was found to have a strong positive association with Adaptive Decision-Making (r = 0.61) and Intelligent System Performance (r = 0.63), suggesting that increased reasoning skills were related to better adaptability and performance. The correlation between AI Reasoning and Self-Assessment (r = 0.58) also confirmed the theoretical connection between reasoning and self-evaluation. Self-Assessment showed a moderate positive correlation with Adaptive Decision-Making (r = 0.55) indicating systems that could self-assess were more likely to adapt decisions. Self-

Assessment was found to have a strong relationship with Intelligent System Performance (r = 0.59), further highlighting its impact on system performance and reliability. The strongest relationship between Adaptive Decision-Making and Intelligent System Performance (r = 0.67) indicated that its role in system performance was vital. This result highlighted the importance of adapting to the environment as a factor in AI performance.



Correlation (Bar Graph)

Variable	AR	SA	ADM	ISP
AI Reasoning (AR)	1.00			
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Intelligent System Performance (ISP)	0.63	0.59	0.67	1.00

Figure 3. Correlation Matrix

Regression Analysis

Regression analysis assessed the causal relationships between independent variables (AI Reasoning, Self-Assessment, Adaptive Decision-Making) and the dependent variable (Intelligent System Performance). This analysis tested the hypotheses and evaluated the predictive power of the model.

Table 3: ***Regression Analysis Results***

Hypothesis	Relationship	Beta (β)	t-value	p-value	Result
H1	AI Reasoning → Self-Assessment	0.58	7.12	0.000	Supported
H2	AI Reasoning → Adaptive Decision-Making	0.61	7.85	0.000	Supported
H3	Self-Assessment → ISP	0.36	5.44	0.000	Supported
H4	Adaptive Decision-Making → ISP	0.49	6.78	0.000	Supported

The multiple regression analysis showed that AI Reasoning had a strong impact on Self-Assessment ($\beta = 0.58$, $p < 0.001$), validating that reasoning skills improved the system's self-evaluation capabilities. AI Reasoning also had a significant positive impact on Adaptive Decision-Making ($\beta = 0.61$, $p < 0.001$), suggesting that reasoning capabilities enhanced adaptive decision-making processes. These results confirmed the critical importance of reasoning in the development of intelligent systems. Self-Assessment had a strong positive effect on Intelligent System Performance ($\beta = 0.36$, $p < 0.001$), highlighting the importance of effective evaluation for improving system accuracy and stability. Adaptive Decision-Making had an even greater impact on performance ($\beta = 0.49$, $p < 0.001$), suggesting that the ability to make decisions in response to feedback was crucial for improving system efficiency and responsiveness. The hypotheses were all supported, validating the conceptual model. The findings suggested that AI Reasoning enhanced system performance indirectly, via Self-Assessment and Adaptive Decision-Making, as well as directly influencing these two factors. The model had high explanatory power and supported the inclusion of reasoning, meta-cognition and adaptability in future AI systems.

Hypothesis	Relationship	Beta (β)	t-value	p-value	Result
H1	AI Reasoning → Self-Assessment	0.58	7.12	0.000	Supported
H2	AI Reasoning → Adaptive Decision-Making	0.61	7.85	0.000	Supported
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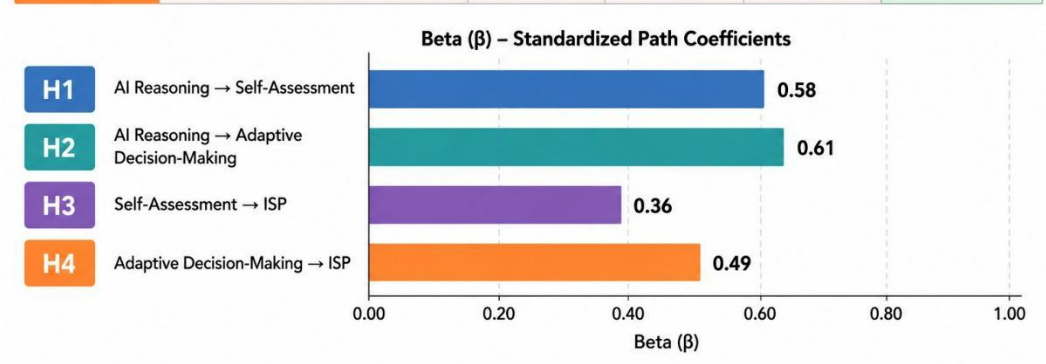

Figure 4. Regression Analysis Results

Discussion

This study's results offered robust empirical evidence for the emerging paradigm of artificial intelligence beyond predictive analytics to reasoning-enabled and adaptive intelligence. The strong association between AI reasoning and self-assessment and adaptive decision-making suggested reasoning was a fundamental element in improving system intelligence. Recent studies highlighted the importance of reasoning-driven AI systems for enhancing decision-making through the combination of logical reasoning and environment awareness, rather than on statistical predictions alone (Steyvers et al., 2023; Lewis et al., 2024). This finding was consistent with emerging research that reasoning capabilities enabled AI systems to understand and respond to complex environments and inform and explain decision-making (Gupta et al., 2024; Khan et al., 2024).

The positive link between AI reasoning and adaptive decision-making also supported the view that AI systems benefited from cognitive-like functions for effective operations in dynamic environments. Adaptive AI systems were capable of reacting to dynamic environments and adjusting strategies in a learning process, which improved their efficiency and adaptability (Mangharamani et al., 2025; Waqar et al., 2024). The findings affirmed that reasoning served as a key enabler for adaptive responses, allowing systems to transition from rule-based decision-making to autonomous and contextual responses.

Self-assessment was identified as a key element in the performance of intelligent systems, with the regression analysis showing its significant impact. Self-assessment enabled AI systems to assess their performance, identify uncertainty and adapt their decision-making strategies. Previous research emphasised that reflective AI systems enhanced system performance through meta-cognitive feedback processes that improved accuracy and prevented error accumulation (Lewis et al., 2024; Canal et al., 2024). These studies indicated that self-assessment played a role in developing reliable AI frameworks that could function effectively in critical applications where accuracy and accountability were crucial.

The interaction between self-assessment and adaptability suggested that evaluation processes underpinned dynamic learning and improvement. AI systems that evaluated their performance were more capable of learning from the environment and adapting strategies accordingly, leading to better decision-making (Mustafa et al., 2024; Khalifeh et al., 2026). This dynamic between self-assessment and adaptability justified the notion of meta-intelligent systems capable of self-evaluation and action within a feedback loop.

The significant impact of adaptive decision-making on intelligent system performance emphasised its importance in the success of AI systems. Adaptivity allowed systems to analyse real-time information, learn from experience, and make decisions under uncertainty to improve system performance. Numerous studies on adaptive decision intelligence systems have shown that these systems enhance efficiency and responsiveness in a range of applications, such as health care and strategic management (Mangharamani et al., 2025; Albashrawi et al., 2025). The current study corroborated this view by revealing that adaptability was a predictor of system performance.

The impact of reasoning, self-evaluation and adaptive decision-making represented a comprehensive perspective on artificial intelligence. Research on hybrid AI systems highlighted that combining multiple cognitive-inspired abilities led to more powerful and scalable intelligent systems (Li et al., 2026; Marocco et al., 2024) . Our findings confirmed this holistic view, showing that the system's components did not work in isolation; rather, they interacted to enhance system performance.

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Our research also expanded the existing research on human-AI interaction and decision support. AI systems with reasoning and self-assessment capabilities were thus more supportive of human decision-making by increasing interpretability and decreasing uncertainty. Existing research suggested that these systems boosted trust and enabled more effective human-machine collaboration (Steyvers et al., 2023; Mustafa et al., 2024). Our findings extended this knowledge by showing that adaptive decision-making also enhanced this collaboration capacity.

Generative AI systems and advanced reasoning models helped to transform decision-making in various sectors. Generative AI played a role in knowledge integration and scenario modelling, helping companies to make more strategic decisions (Albashrawi et al., 2025; Khalifeh et al., 2026).The research findings were consistent with this trend by demonstrating that sophisticated features of AI systems improved decision-making and system effectiveness.

The results also had implications for the adaptability and transferability of intelligent AI systems. Self-adaptive and self-evaluating systems were found to successfully apply across a range of areas, such as education, health care and business contexts. The studies pointed out that these systems enabled contextual and personalized solutions, enhancing performance and effectiveness of the system (Waqar et al., 2024; Mustafa et al., 2024). The results verified that scalability was a significant benefit of combining reasoning and adaptability in AI systems.

The holistic model confirmed the shift from conventional AI systems to new generation intelligent systems that are autonomous, adaptive, and cognitively aware. The interrelationships among the variables showed that reasoning, self-evaluation and adaptive decision-making improved overall system effectiveness. This finding was in line with recent theoretical models that stressed the need to merge cognitive and computational processes to achieve higher levels of artificial intelligence (Lewis et al., 2024; Li et al., 2026). The research therefore helped to deepen the knowledge of how AI systems progressed to become more intelligent, robust and context sensitive.

Conclusion

This research explored the shift in artificial intelligence systems from predictive models to more sophisticated systems with reasoning, self-assessment and adaptive decision-making capabilities. This research showed that AI reasoning served as a core component, which impacted self-assessment and adaptive decision-making. Systems with inferential reasoning and explainability functions were more capable to self-assess their own performance and adapt to environmental changes. The findings also showed that self-assessment boosted system reliability through ongoing monitoring and decision making, but that adaptive decision-making was the most significant predictor of intelligent system effectiveness. The holistic model confirmed the three factors were important to enhancing accuracy, autonomy and overall performance. So this research confirmed the need for the design of cognitively inspired AI systems that reflected the complexity and uncertainties of the real world.

Recommendations

This study offered some recommendations to researchers, developers and organisations. First, the design of AI systems should incorporate reasoning to improve interpretability and transparency of decision-making. Hybrid approaches combining machine learning and symbolic reasoning should be used to facilitate decision-making. Second, AI systems should include self-evaluating mechanisms to continuously assess their performance and identify errors. This can enhance performance and ensure confidence in AI decision-making, especially in critical applications. Third, enterprises should embrace adaptive decision-making systems that leverage real-time information and feedback mechanisms to improve decision-making in dynamic settings. Second, inter-disciplinary teams of AI researchers, cognitive scientists and domain experts should be fostered to develop more effective and adaptive AI systems. Finally, policymakers need to put in place ethical principles and policies to guide the development and use of advanced AI systems.

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Future Directions

This research can be built upon by investigating other aspects of intelligent AI systems, such as emotional intelligence, ethical decision-making and human-AI interaction. Longitudinal research can offer insights into the learning and development of adaptive AI systems, and their effectiveness in practical settings. The impact of explainable AI on trust and acceptance of AI-based decision-making in various domains can also be explored. In addition, empirical research with large and diverse datasets can enhance the reproducibility of the results. The use of emerging technologies like quantum computing and edge AI can also help improve the scalability and performance of systems. Researchers can also explore the development of benchmarks for assessing reasoning, self-awareness and adaptability of AI systems. These avenues can help to produce the next generation of artificial intelligence that is more self-managing, explainable and human-centred.

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