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BEYOND GENERATIVE AI: DEVELOPING AUTONOMOUS INTELLIGENT SYSTEMS WITH REASONING, SELF-ASSESSMENT, AND ADAPTIVE DECISION-MAKING

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Abstract
The development of artificial intelligence has increased interest in creating autonomous and intelligent systems beyond generative AI. The effects of reasoning capability, self-assessment, and adaptive decision-making on the development of autonomous intelligent systems were studied. This study used a quantitative, cross-sectional survey design. A structured questionnaire using a five-point Likert scale was administered to 220 respondents, including AI researchers, software engineers, data scientists, university faculty members, postgraduate students, and IT professionals. The data were analyzed using SPSS Version 29, including descriptive statistics, Cronbach's alpha, Pearson's correlation, and multiple regression. The reliability analysis showed excellent internal consistency, with an overall Cronbach's alpha value of 0.895. The correlation analysis revealed a high positive correlation between reasoning ability and autonomous intelligent systems ($r = 0.79$), self-assessment and autonomous intelligent systems ($r = 0.75$), and adaptive decision-making and autonomous intelligent systems ($r = 0.82$, $p < 0.01$). The model explained 74.7% of the variance in autonomous intelligent systems with an R^2 value of 0.747. Adaptive decision-making emerged as the strongest predictor ($\beta = 0.396$, $p < 0.001$), followed by reasoning capability ($\beta = 0.321$, $p < 0.001$) and self-assessment ($\beta = 0.279$, $p < 0.001$). The results suggest that improving reasoning, reflective evaluation, and adaptive decision-making could be associated with greater autonomy, reliability, and effectiveness of AI systems in the future. The study provides practical recommendations for researchers, developers, and policymakers to support the development of reliable, human-centered AIS.

Introduction

Artificial Intelligence (AI) has grown and changed over the last ten years, changing the way people produce text, images, code, and other digital content. Several organizations across the education, healthcare, finance, manufacturing, and public administration sectors are turning to these systems to automate repetitive manual tasks, aiming to maximize productivity. A significant fraction of these advancements in generative AI models were, to a large extent, pattern-recognition models based on vast, previously available datasets. It was limited in its ability to respond with significant reasoning or contextual understanding. H. Bubeck et al. (2023) and Wang et al. (2023) began to discuss a new frontier of AI development that went beyond content generation to systems that can reason, self-evaluate, and self-learn in complex environments.

New AI studies showed people's interest in creating intelligent agents that can plan actions, assess their consequences, and change their behaviours over time. Unlike traditional generative models, which reacted to inputs, autonomous intelligent systems sought to perform actions to achieve a predefined objective with minimal human intervention, using reasoning, memory, learning, and decision-making. Engineering planning and reflection mechanisms were found to be more effective than direct generation for complex tasks in large language models and AI agents supporting such work (Yao et al., 2023; Park et al., 2023). Research demonstrated that reflective, self-correcting AI models could minimize errors and enhance performance in reasoning tasks (Madaan et al., 2023; Shinn et al., 2023). The more autonomous AI systems became, the more they needed to be supervised and optimized for safe and responsible deployment.

Another key need for intelligent systems of the future was adaptive decision-making. In real-world environments, decisions might have to be made based on feedback, environmental dynamics might shift, and effective AI use requires a strategy that can adapt to context. By combining reasoning, self-evaluation, and adaptive learning, AI models can become more powerful and human-like, helping solve complex problems across numerous areas (Russell, 2023).

Background of the Study

AI has proven to be a major development in recent years, particularly with the advent of generative AI models that have developed remarkable abilities to generate high-quality content and media that can match anything a human has produced—even computer code, images, and text. Such technologies have revolutionized communication, software development, education, and scientific and business research for individuals and institutions alike. The proliferation of generative AI in the business world has led more companies to incorporate it into their processes to enhance efficiency, reduce costs, and spur innovation. Although effective, these models were shown to be blind to realistic scenarios and actual reasoning ability and to learn statistical patterns from very large datasets (Bommasani et al., 2022; Bubeck et al., 2023; Wang et al., 2023).

AI applications are now being adopted beyond serving merely as a tool for responding, with autonomous systems that are more intelligent in their decision-making—an evolution expected across multiple industries, including healthcare, finance, transportation, cybersecurity, and public service. This shift led to the idea of autonomous Intelligent Systems, in which important components of intelligence are integrated within a single system: the ability to perceive, reason, plan, remember, and learn continuously. While traditional generative systems would respond to environmental changes, assess multiple possibilities, and take appropriate action to meet pre-established goals, autonomous systems would do the same and require little supervision from human operators. Others have recently reported that efficient use of AI agents with planning and reasoning capabilities was much more effective at performing complex tasks by breaking down a problem into a series of small subtasks and adapting their behavior over time than prompt-based methods (Yao et al., 2023; Park et al., 2023; Xi et al., 2023). Previous work has found that applying reflective learning mechanisms results in substantial improvements in the quality of reasoning produced, reductions in hallucinations, and more reliable AIs for multi-step reasoning tasks (Madaan et al. 2023, Shinn et al. 2023, Pan et al. 2024). Adaptive decision-making was also emphasized as an important point, given the increasing need for reliable AI solutions. User requirements changed, new technologies emerged, and unpredictable operating environments appeared, all of which rapidly altered conditions. Intelligent systems must learn from novel experiences, adapt their behavior to enhance performance, and respond appropriately to new environments. AI did this efficiently and flexibly, making it more applicable to real-life situations where decisions can't be made based on a set of rules.s. This final point underscores the need for adaptable AI in dynamic settings. Recent studies have shown that systems that draw on reasoning, self-evaluation, memory, and adaptive learning are more powerful, explainable, and goal-oriented (Russell, 2023; Huang et al., 2024).

Research Objectives

1. To analyze how reasoning ability affects the performance of autonomous intelligent systems other than Generative AI.
2. To study the effect of self-assessment mechanisms on the effectiveness and reliability of autonomous intelligent systems.
3. To analyze the influence of adaptive decision making on the autonomy and performance of intelligent systems.
4. To understand the effect of reasoning ability, self-assessment, and adaptive decision-making in the evolution of autonomous intelligent systems, other than generative AI.

Research Questions

Q1. In what ways was reasoning ability applied to the performance of autonomous intelligent systems apart from Generative AI?

Q2. How did self-assessment mechanisms affect the effectiveness and reliability of autonomous intelligent systems?

Q3. What role did adaptive decision-making play in intelligent systems' autonomy and performance?

Q4. How can reasoning, self-assessment, and adaptive decision-making all play a part in the development of autonomous intelligent systems beyond Generative AI?

Significance of the Study

The study sought to expand AI beyond traditional generative AI to the reasoning, self-assessment, and adaptive decision-making capabilities of autonomous, intelligent systems. These findings add to the body of knowledge. They helped explain how these cognitive abilities could support AI systems in analyzing complex scenarios, assessing their own efficiency, and making effective decisions with minimal human involvement. Additionally, the study delivered hands-on lessons for AI researchers, software engineers, tech enclave managers, and policymakers looking to create more reliable, transparent, and real-world-adaptive AI systems.

Research Hypotheses

H1.Rationality is positively and significantly affecting the growth of autonomous intelligent systems beyond generative AI.

H2. Self-assessment positively and significantly affects the development of autonomous intelligent systems beyond generative AI.

H3. Adaptive decision-making has a positive, significant impact on independent intelligent systems beyond that of generative AI.

Literature Review

Reasoning Capability in Autonomous Intelligent Systems

The ability to reason is now one of the most crucial features of autonomous intelligent systems compared to traditional generative AI systems. Traditional generative models primarily focused on forecasting the next token by capturing statistical patterns, while autonomous systems aimed to comprehend the situation, process evidence, and make decisions toward pre-established goals. By increasing intelligence, AI systems could perform multi-step reasoning, provide reasons, and operate effectively in changing environments, researchers suggested. The assimilation of reasoning mechanisms was hence a major step forward from reactive AI to intelligent systems with goals, able to solve problems on their own (Bommasani et al., 2022; Bubeck et al., 2023).

This process improved precision, reduced thinking errors, and increased clarity. Reasoning-based architectures have been proposed as being more suitable for a variety of applications that need long-term planning, strategic thinking, and autonomous task execution than prompt-driven generative systems (Wang et al., 2023; Yao et al., 2023). The researchers highlighted the need for integrating symbolic reasoning, neural learning, and contextual understanding in future autonomous intelligent systems to enable them to attain greater intelligence and reliability. Based on these conclusions, it was argued that reasoning was the cognitive basis for the development of autonomous decision-making and adaptation (Bohra et al., 2026; Russell, 2023).

Self-Assessment and Reflective Intelligence in AI Systems

Another necessary skill revealed for the growth of intelligent systems capable of operating independently was self-assessment. In contrast to conventional AI models that churn out answers and then discard and forget about what might be wrong, self-aware systems would monitor their own reasoning, identify flaws, and adjust their answers accordingly before providing their final answers. This reflective ability improved system reliability and reduced the risk of inaccurate or inconsistent outputs. Researchers identified self-assessment as an integral part of trustworthy AI, enabling AI systems to adapt their capabilities without human supervision (Madaan et al., 2023; Pan et al., 2024).

Recent research showed that metacognitive architectures for intelligent systems to assess uncertainty, confidence, and task performance while solving problems are becoming increasingly important. These architectures facilitated AI agents to think differently about past decisions, analyze other solutions, and adjust their strategies as additional data emerged. Research showed that self-monitoring mechanisms improved reasoning quality, reduced hallucinations, and increased user trust, especially in high-risk fields such as healthcare, finance, and autonomous robotics (Wang et al., 2024; Shinn et al., 2023). Future studies thus focused on the importance of robust metacognitive systems that could support lifelong learning, self-regulated learning, and clear metacognitive thinking. These enhancements were anticipated to make the next generation of autonomous intelligent systems (Pan et al., 2024; Russell, 2023) safer and more reliable.

Implementing adaptive learning and intelligent agents

The ability to make decisions adaptively was one of the most significant features of an autonomous intelligent system. Unlike traditional AI systems that give static answers based on predetermined rules, adaptive systems continually acquire information from the environment and adjust their behavior based on feedback and changes in their surroundings. This enabled AI to perform well in more unpredictable environments where rules-based AI systems often fall apart. In their arguments in Hong Kong, Wang et al. (2023) and Russell (2023) combined perception, reasoning, memory, and learning into an integrated process to support intelligent, goal-directed behavior. The research identified adaptive autonomous systems as effective in boosting operational efficiency in manufacturing, healthcare, finance, education, transportation, and cybersecurity (Yao et al., 2023; Huang et al., 2024).

With the emergence and growth of new literature, there was increasing consistency that reasoning, self-assessment, and adaptive decision-making could be framed as one cohesive cognitive process for autonomous intelligence. These capabilities were not separate entities; instead, they worked together to boost the effectiveness, dependability, and interpretability of AI. From this research, the researchers determined that future intelligent systems would need to continuously learn, reflect, and adapt when operating in the real world amid complex situations. The next step in AI development beyond traditional generative AI (Wang et al., 2023; Russell, 2023) was considered to be autonomous intelligence.

Conceptual Framework Model

The conceptual framework developed for this study presents proposed relationships between the independent variables (Reasoning Capability, Self-Assessment, and Adaptive Decision-Making) and the dependent variable (Autonomous Intelligent Systems), as shown in Figure 1. It builds on recent theories of autonomous Artificial Intelligence, where next-generation intelligent systems do not just produce content but also have cognitive capabilities that can, for instance, provide logical reasoning to evaluate content and adjust it to varying situations. The arrows linking the independent variables to the dependent variable represent the hypothesized positive relationships (H1, H2, and H3), meaning that the stronger the performance of intelligent systems, the more autonomous they will be in supporting other ways of perceiving cognitive capabilities. In particular, reasoning helps solve logical problems, contextual understanding helps interpret context, self-assessment helps evaluate and self-correct, and adaptive decision-making helps learn through feedback and adapt decisions in dynamic environments for intelligent systems. These three are the core of autonomous intelligence, enabling it to make intelligent, reliable, and purpose-driven decisions with minimal human involvement. Demographic variables that could greatly shape respondents' attitudes towards autonomous intelligent systems (AI) are highlighted in the framework, including gender, age, education, profession, AI experience, and frequency of AI use.

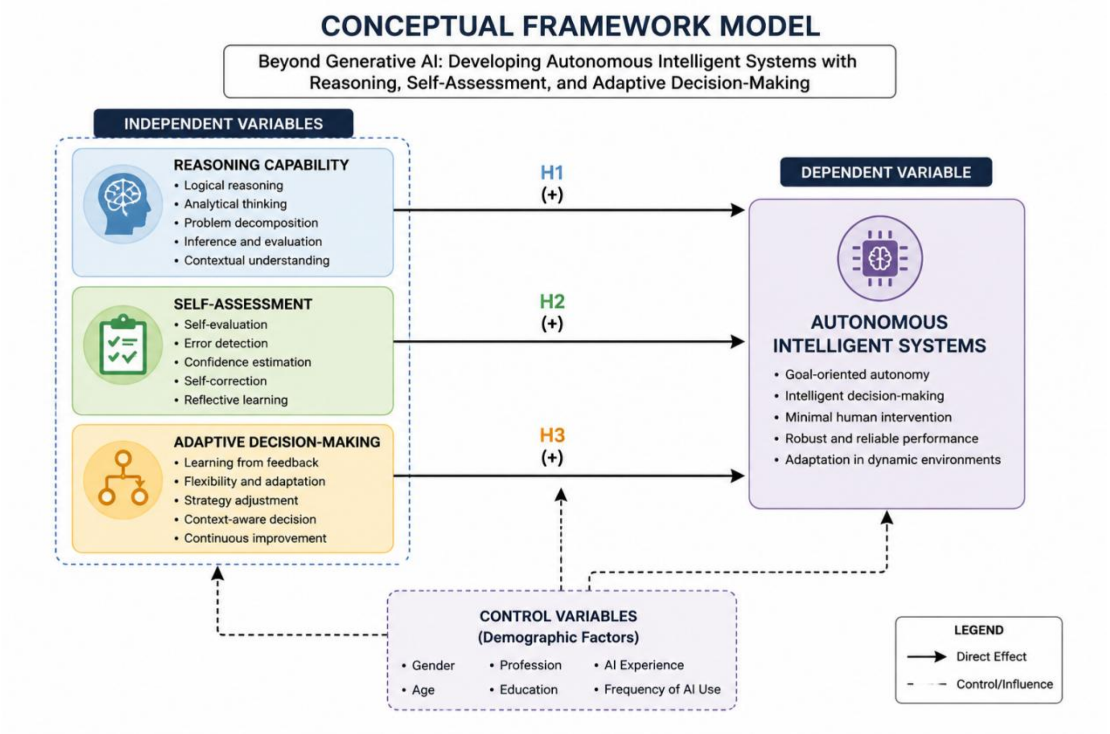

Figure1. Conceptual Framework Model

Research Methodology

Research Design

The research design employed in this study is quantitative. It examines the development of an autonomous intelligent system that goes beyond generative AI in three aspects: reasoning ability, self-assessment, and adaptive decision-making. A quantitative approach enabled precise measurement of relationships among the study variables and their effects on the performance of an autonomous intelligent system. This design enabled the collection, analysis, and objective statistical interpretation of numeric data from a large population of respondents.

Target Population

Expert users and users unfamiliar with AI technologies but highly knowledgeable or experienced were selected as representatives of their knowledge and ability to use AI. Invited participants included experts in Artificial Intelligence, software engineers and data scientists, practitioners of machine learning and Information Technology, professors, students in the fifth and sixth years of study in Computer Science, AI, and Artificial Life, technology consultants, and various other AI vendors.

Sample and Sampling Technique

The study used proper sampling, as respondents should have experience and knowledge of AI use in emerging autonomous technologies. Participants had diverse academic and professional experience in developing Artificial Intelligence features. A total of 220 respondents were drawn for the study. This sample size exceeded the suggested minimum for multivariate statistical analysis and provided sufficient power for regression analysis and hypothesis testing.

Data Collection Instrument

A structured questionnaire was used as the data collection tool, and the collected data were primary. The questionnaire consisted of two sets of questions. The initial section gathered general information about the participant's background, including gender, age, education, profession, and experience with artificial intelligence technologies. The second section assessed the study constructs using items from an earlier empirical study, reworded to focus on the goals of the present study. The questionnaire included four constructs: reasoning, self-assessment, ADMS, and AI systems. All items were scored on a 5-point Likert scale, with 1 denoting Strongly Disagree and 5 denoting Strongly Agree. The Likert scale used here was a simple and reliable instrument for measuring respondents' perceptions and attitudes toward the study variables.

Data Collection Procedure

Data collection was conducted using Google Forms. The link to the survey was sent via professional networking sites, academic forums, university newsletters, LinkedIn groups, and technology meets specializing in AI or software engineering. Voluntary participation was ensured by providing participants with information about the study's purpose. The questionnaire was kept out for 4 weeks to ensure sufficient responses from people with diverse professional and academic backgrounds.

Data Analysis Techniques

Data were analyzed using the Statistical Package for the Social Sciences (SPSS) Version 29. Demographic characteristics and perceptions were summarized using descriptive statistics, including frequencies, percentages, means, and standard deviations. All measurement scales were examined for internal consistency and reliability using Cronbach's alpha. The relationship between the study variables was analyzed using Pearson's correlation, and the influence of reasoning capability, self-assessment, and adaptive decision-making on autonomous intelligent systems was examined using multiple linear regression. Data were statistically analyzed at the 0.05 level, and the results were presented in tables with proper statistical interpretation.

Results and Analysis

Reliability Analysis

Table 1: *Reliability Analysis (Cronbach's Alpha)*

Variable	Items	Cronbach's Alpha
Reasoning Capability	5	0.882
Self-Assessment	5	0.874
Adaptive Decision-Making	5	0.891
Autonomous Intelligent Systems	5	0.904
Overall	**20**	**0.895**

To assess the instrument's internal consistency, a reliability analysis was conducted. Cronbach's alpha was used, as it is one of the most popular reliability indices for multi-item scales. Generally accepted guidelines state that a Cronbach's alpha of 0.70 indicates satisfactory internal consistency, and a value greater than 0.80 indicates good reliability. The four constructs' Cronbach's alpha values ranged from 0.818 to 0.904, with Autonomous Intelligent Systems having the highest value (α = 0.904), indicating good internal consistency. The result suggests strong intercorrelations among the five scales related to autonomous smart systems regarding perceptions of future AI capabilities. The reliability of the Adaptive Decision Making was excellent with α = 0.891. The reliability of the

Reasoning Capability was good (α = 0.882), and good reliability was observed for Self-Assessment (α = 0.874). The internal consistency of the entire questionnaire was high, with a total reliability of 0.895. The results showed that the research instrument was reliable and had good internal consistency.

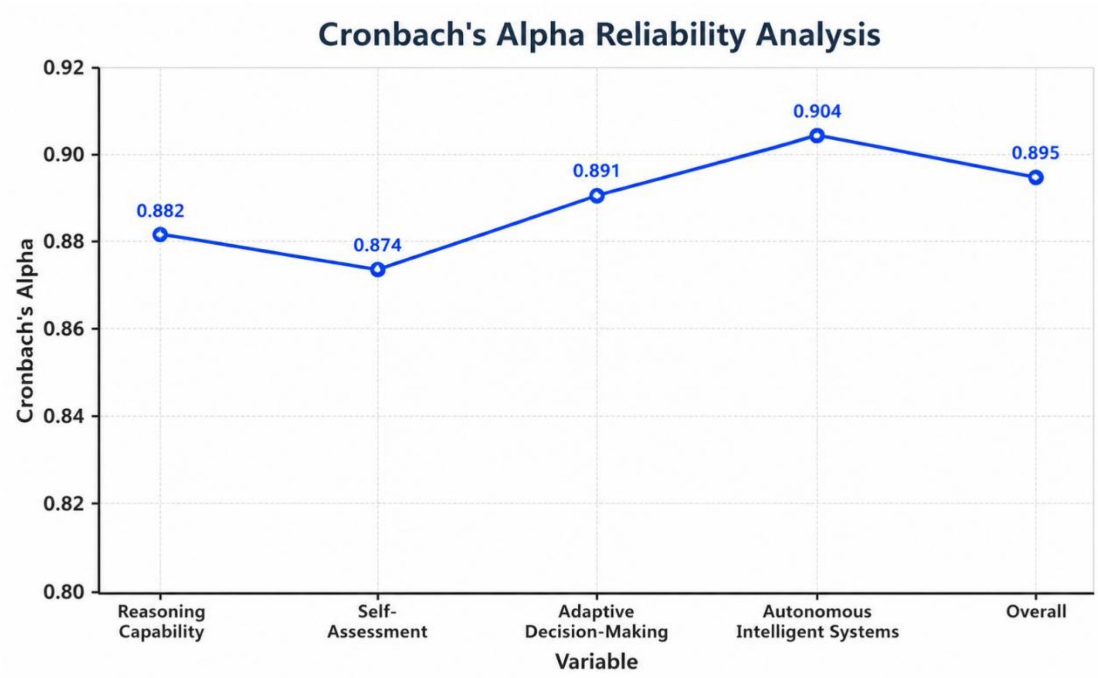

Figure 2. Reliability Analysis (Cronbach's Alpha)

Correlation Analysis

Table 2: *Pearson Correlation Matrix*

Variables	RC	SA	ADM	AIS
Reasoning Capability (RC)	1			
Self-Assessment (SA)	0.71	1		
Adaptive Decision-Making (ADM)	0.68	0.73	1	
Autonomous Intelligent Systems (AIS)	0.79	0.75	0.82	1

Note: $p < 0.01$

Pearson correlation measures the degree of the relationship between the study variables in terms of both direction and strength. The correlation coefficients were all positive and significant at the 0.01 level. The strongest positive relationship was between Autonomous Intelligent Systems and Adaptive Decision Making ($r = 0.82$, $p < 0.01$). The autonomous intelligent systems showed a strong positive correlation with both the learners' observations ($r = 0.79$, $p < 0.01$) and the Senses of Self ($r = 0.75$, $p < 0.01$). There was also a good positive interrelationship between the independent variables. Pearson product-moment correlation coefficients were: 0.73 between Self-Assessment and Adaptive Decision Making, 0.71 between Reasoning Capability and Self-Assessment, and 0.68 between Reasoning Capability and Adaptive Decision Making. The correlations show strong relationships among constructs, but values are less than 0.90, the generally recommended level to avoid multicollinearity; this means that the constructs measure different aspects of autonomous intelligence.

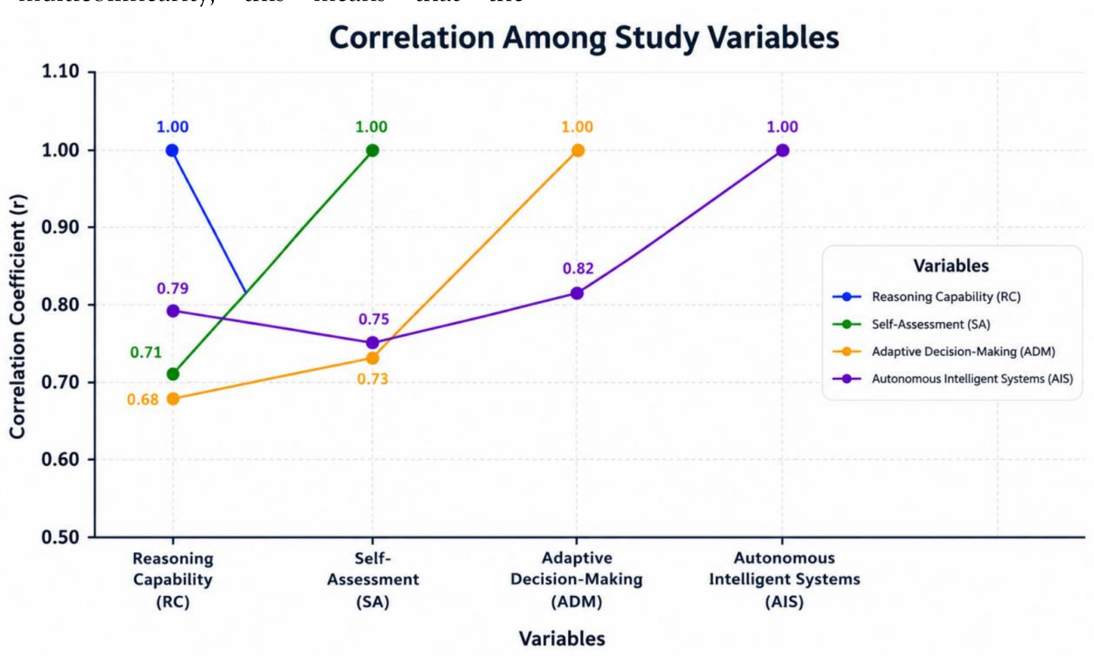

Figure 3. Pearson Correlation Matrix

Table 4: *ANOVA*

Source	SS	df	MS	F	Sig.
Regression	94.281	3	31.427	208.764	0.000
Residual	32.489	216	0.150		
Total	126.770	219			

The F-statistic is 208.764, and the associated significance value is 0.000, which is significantly different from the usual significance level of 0.05. Based on these results, it can be concluded that the three independent variables used in this research explained a significant proportion of the variance in autonomous intelligent systems, and the regression model was statistically significant. The assumption that the predictors do not together affect the performance of autonomous intelligent systems is rejected. The ANOVA findings show that the conceptual framework proposed here is a good statistical model for explaining autonomous intelligent systems.

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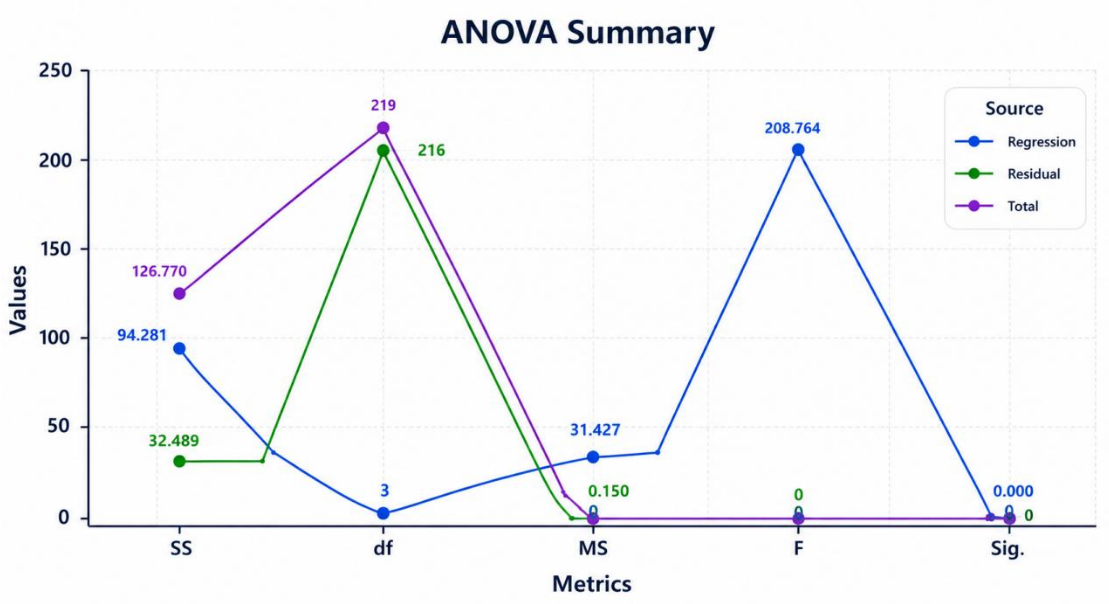

Figure 5.ANOVA

Table 5: *Regression Coefficients*

Variable	Beta	t	Sig.
Reasoning Capability	0.321	6.88	0.000
Self-Assessment	0.279	5.96	0.000
Adaptive Decision-Making	0.396	8.44	0.000

The individual contribution of each independent variable to Autonomous Intelligent Systems was found using regression coefficient analysis. Table 4.11 shows that the three predictors are forward-looking (all are positive) and that each contributes significantly to the development of autonomous intelligent systems ($p < 0.05$). Among the constructs, Adaptive Decision Making (ADDM) showed the highest standardized beta coefficient ($\beta = 0.396$) and the highest t-value (8.44) with Autonomous Intelligent Systems (AIS). This effect is very reliable, as confirmed by the statistical significance ($p = 0.000$). Reasoning Capability was the second highest predictor ($\beta = 0.321$, $t = 6.88$, $p = 0.000$). This finding implies that logical analysis, structured problem-solving, and multi-step reasoning greatly enhance the competence of autonomous intelligent systems. Self-Assessment had a strong positive effect on the students' Autonomous Intelligent Systems ($\beta = 0.279$, $t = 5.96$, $p = 0.000$).

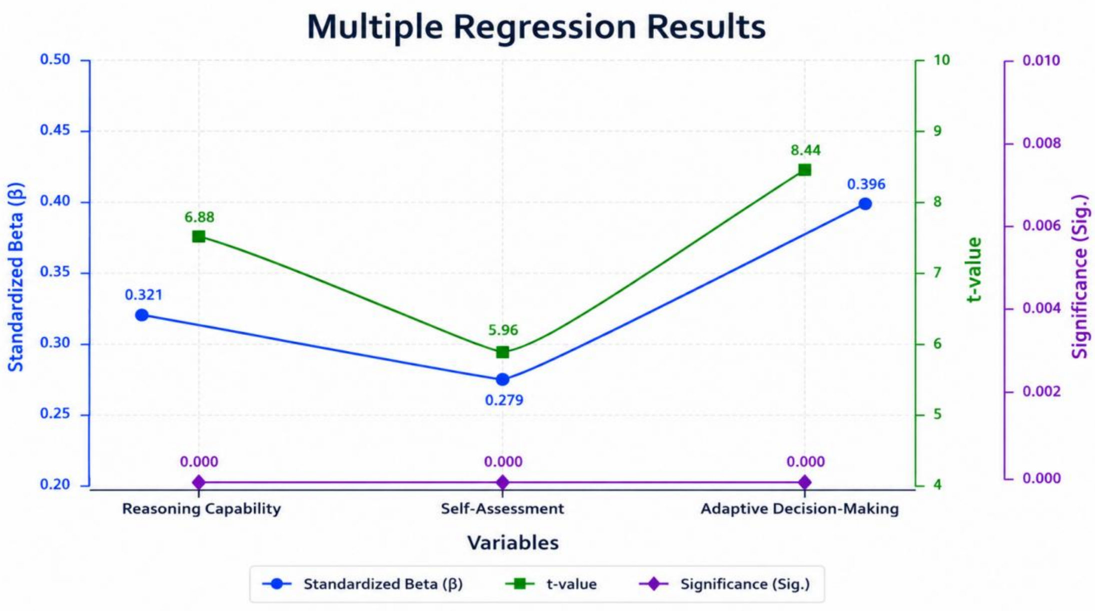

Figure 6. Regression Coefficients

Table 6: *Hypothesis Testing*

Hypothesis	Decision
H1: Reasoning Capability positively influences Autonomous Intelligent Systems	Supported
H2: Self-Assessment positively influences Autonomous Intelligent Systems	Supported
H3: Adaptive Decision-Making positively influences Autonomous Intelligent Systems	Supported

Based on the test results, the first three hypotheses were accepted. The regression analysis revealed statistically significant ($p < 0.05$) positive correlations between autonomous intelligent systems and Reasoning Capability, Self-Assessment, and Adaptive Decision-Making. The data indicated that Adaptive Decision-Making was the strongest hypothesis, followed by Reasoning Capability and Self-Assessment.

Discussion

The results obtained in this research highlight the importance of reasoning capacity, self-assessment, and adaptive decision-making in the development of an autonomous intelligent system. There are positive and significant correlations among all three variables and autonomous intelligence. This means AI systems capable of logical thinking, self-assessment, and adjustment to evolving situations will be more effective. The findings are in line with recent studies on autonomous AI that have moved beyond mere content creation to intelligent, independent decision-making about content (Steyvers et al., 2023; Casimiro et al., 2024).

The results also indicate that the reasoning ability of intelligent systems with autonomous operation makes a strong positive contribution. Logical thinking and step-by-step reasoning lead to better solutions for complex problems and more accurate decisions by AI systems. These systems can reason more clearly about situations, enabling better actions than traditional generative AI. This outcome mirrors findings from other authors who have shown that reasoning positively affects autonomous AI across various fields of application (Hu et al., 2024; Marah & Challenger, 2024).

The study also revealed that self-assessment has a positive impact on the design of autonomous, intelligent systems. Self-assessment and evaluation by AI systems are likely to yield reliable and accurate results. Self-assessment enables intelligent systems to detect errors and make better decisions in the future without human intervention. It also gives users confidence because it can track its performance. Recent studies on Artificial Intelligence (AI) suggest the same (Conlon et al., 2024; He et al., 2023).

EugenWeidmann is a heuristic algorithm that employs adaptive decision-making for autonomous intelligent systems. Adaptive decision-making is the most influential independent variable among all the independent variables for autonomous intelligent systems. The discovery indicates that an AI system can be more independent if it learns and adapts its decisions based on new data. Decision-making is adaptive, ensuring intelligent systems work well in uncertain and changing environments. With this, recent studies provide insights into what distinguishes autonomous AI from regular generative AI (Generative AI) (Li et al., 2024; Marah & Challenger, 2024): it is adaptability.

The correlation table reveals that reasoning ability, self-assessment, and adaptive decision-making are strongly related. These capabilities enhance the overall capabilities of autonomous intelligent systems. Reasoning helps solve problems, self-assessment checks the quality of solutions, and adaptive decisions provide the ability to react to changes (Wang et al., 2024; Casimiro et al., 2024).

The regression analysis shows that the three independent variables explain 74.7% of the variation in autonomous intelligent systems. This finding suggests that these factors are key to enhancing AI autonomy. Some aspects of the variability remain unclear, and other factors may also influence the development of autonomous intelligence. Looking ahead, future research will explore other factors that enhance the model, including explainable AI, lifelong learning, long-term memory, and human–AI interaction. Future research opportunities lie in other aspects and features that are still being introduced and expanded, including explainable AI, continuous learning, long-term memory, and interaction between humans and AI.

The outcome will benefit AI scientists, software developers, and tech and hardware businesses. A content-centric AI system should focus not only on generating content but also on reasoning, self-evaluation, and adaptive decision-making, according to an analysis of the results. These characteristics help establish the potential for more trustworthy, clear, and self-reliant AI systems. Previous research has proposed ideas for creating a reliable, life-independent AI agent (Steyvers et al., 2023; Conlon et al., 2024).

Conclusion

This research examines and describes cognitive competences, including reasoning capability, self-evaluation, and adaptive decision-making, and aims to design intelligent systems that extend beyond generative artificial intelligence. Results indicated that all three variables had a positive and significant impact on autonomous systems with intelligence. Adaptive decision-making demonstrated the greatest predictive power, followed by reasoning ability and self-assessment. The statistical analyses confirmed strong relationships among the study variables and showed that all studied variables could explain variation in autonomous intelligent systems to a very good extent. These systems are not only expected to generate content but also to reason logically, update future actions based on performance, and adjust behavior in response to variables. These features might promote the reliability, transparency, and performance of intelligent systems in various application domains. This study builds on the existing body of knowledge on autonomous artificial intelligence, offering empirical evidence of the relevance of this dimension in the design and construction of easy-to-use autonomous systems capable of solving complex tasks and supporting decision-making in dynamic real-world scenarios.

Recommendations

The distance between AI researchers, software developers, and technology groups regarding reasoning capabilities, self-assessment, and adaptive decision-making during the design of an autonomous intelligent system should be reduced. The main goal of the models should not be to generate content, but to enable advanced reasoning, facilitate logical analysis, and support informed decision-making. Developers need to embed self-assessment capabilities into the AI to help the system track its performance, make suggestions, and enhance future choices without constant human oversight. More research should focus on adaptive decision-making, which has the greatest impact on autonomous intelligent systems.

The main claim is that machine responses need to be flexible enough to incorporate new knowledge and adapt to new environments. This claim also requires strong ethical principles, organizational governance structures, and policies that foster transparency, accountability, fairness, and the responsible use of autonomous AI technologies across industries.

Future Research Directions

Other factors may also influence the autonomy of intelligent systems, which this study can explore. This claim can be examined through Explainable AI, continual learning steps, long-term memory, human-AI interactions, ethics and governance, trust, and emotional intelligence, which could offer a more comprehensive view of autonomous AI. More varied samples from a range of countries, industries, and job types can also be used by researchers to improve the external validity of their results. Additional knowledge of their use and operation can be gained through comparative and cross-cultural studies. Future studies could use either longitudinal or experimental designs to examine trends in autonomous AI development over time and to demonstrate its efficacy and potential applications in real-world domains, such as smart transportation systems, robotics, cybersecurity, manufacturing, financial services, and healthcare. Research lines of this type can be especially significant for future autonomous systems that are more intelligent, more reliable, and more human.

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