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Optimizing Digital Market Decision-Making Through Artificial Intelligence Platforms:

Governing Mediating Powers of Cognitive Engagement

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ABSTRACT

As artificial intelligence rapidly advances, addressing the interplay of technical, ethical, and risk factors in optimizing digital market decision-making through AI platforms has become increasingly prominent. However, the impact of these factors on market performance, particularly in investment value, remains underexplored. The study, based on 412 validated responses from service industry professionals gathered through a carefully designed questionnaire, aims to predict the relationship among these factors and their influence on market performance. It also explores how cognitive engagement mediates the relationship between AI platforms and financial metrics. Key findings:(1) the interplay of technical, ethical, and risk factors optimizes market decision-making and guides AI investments; (2) cognitive engagement, especially in the services sector, is essential to maximize the impact of AI platforms on market performance. The study provides valuable insights into AI's role in shaping market dynamics within the services sector and relevant governance recommendations for policymakers.

KEYWORDS

Artificial Intelligence Platform, Decision-Making, Cognitive Engagement, Services Sector, Investment Value

INTRODUCTION

AI is a branch of research that aims to develop machines or systems that can do tasks that typically require human intelligence (Guingrich & Graziano, 2024; Martini et al., 2024; Qadri et al., 2024; Waly, 2024). AI has emerged as a prominent subject of discussion in modern boardrooms and social gatherings (Eroğlu & Karatepe Kaya, 2022; Möslein, 2018). It encompasses the ability of a system to effectively interpret external input, acquire knowledge from such data, and utilize that knowledge to accomplish predetermined goals and tasks using adaptable modifications (Mikalef & Gupta, 2021; Nemati et al., 2002; Triguero et al., 2024). Nevertheless, the field of AI continues to present numerous unresolved issues, such as its application to breast cancer, product making and innovation, IoT security, language translation problems, online human algorithm interaction, and health issue diagnosis (Alwahedi et al., 2024; Shin, 2024; Shin et al., 2024a).

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Gaining a comprehensive understanding of AI necessitates the adoption of a more refined methodology (Kee et al., 2024). Four discrete academic and professional scientific groups have historically outlined the concept of "artificial intelligence:" individuals focused on "rational action," "human action," "rational thinking," and "human thinking" (McAfee & Brynjolfsson, 2017a; Tataj & Muhamet, 2021).

According to McAfee and Brynjolfsson (2017a), AI is categorized into two main types: narrow, or weak, AI; and strong AI, also known as artificial general intelligence (AGI). This classification is supported by Fjelland (2020) and Gobble (2019). Most practical advancements in AI stem from narrow AI (Wahl et al., 2018), which operates within limited frameworks to mimic human intelligence. Examples include AI personal assistants, partially autonomous vehicles, International Business Machines Corporation (IBM)'s Watson, Google search, and image recognition software (Ghorpade, 2020; Mich, 2020; Škavić, 2019).

In contrast, AGI refers to AI systems with human-level intelligence (Kumpulainen & Terziyan, 2022; Landgrebe & Smith, 2019), though progress toward AGI has been limited (Baum, 2017; Summerfield, 2022). Advances in narrow AI have significantly impacted various business management and service domains, leading to substantial transformations (Dwivedi et al., 2021; Fu et al., 2023; Gazi, 2024) and enabling the exploration of new applications. Davenport and Ronanki (2018) highlighted ML, deep learning, signal processing, and natural language processing, natural language understanding, and natural language generation as crucial AI technologies. Notable applications include speech recognition, image recognition, and computer vision (Majumder, 1988; Marcus et al., 2022; Michie et al., 2017; Najam et al., 2022). The increasing use of AI technologies, such as generative AI tools, in organizations underscores the importance of understanding surrounding issues such as technical competency, ethical considerations, and associated risks (Bankins et al., 2024; Rane et al., 2024).

This research aims to examine the impact of effective AI systems on market performance through investment value and terminal value, focusing on the potential advantages to the services sector through AI implementation. A quantitative approach was used to identify key elements of a proficient AI platform and its influence on value generation aligned with enhancing shareholder wealth (Norling, 2024). The study identified three pillars of such a platform: effective AI: technical competency, ethical considerations, and risk management (Dabbagh et al., 2024; Habbal et al., 2024). Additionally, a comprehensive survey of healthcare professionals was conducted (Duggal & Tripathi, 2024). (SEM) results indicate that efficient AI is fundamental and highly significant (Dahri et al., 2024; Zhang et al., 2024), correlating with ethical AI and its core attributes—technological proficiency, ethical deliberations, and risk mitigation (Beil et al., 2019; Diaz-Asper et al., 2024; Jedlickova, 2024). These insights guide the ethically conscious development of AI systems (Dwivedi et al., 2021; Gupta et al., 2024; Stahl, 2021).

Quantitative analysis supports these findings, demonstrating that responsible AI components facilitate the creation of a digital healthcare environment that meets stringent privacy regulations (Kumar et al., 2023) and offers strategies to mitigate data security concerns. The research is grounded in the technological acceptance model and resource-based view, supported by recent literature (Gupta, 2024; Ooi et al., 2023), and aligns these theories with stakeholder theory within the services sector (Morgan et al., 2023; Wang et al., 2022).

This study successfully addresses knowledge gaps and presents systematic methodologies for developing ethical AI systems that align with stakeholder expectations under the technology acceptance model and resource-based view theoretical approaches. The present study is divided into five main parts: an introduction, a review of the literature, a presentation of the development of the research model and hypothesis, a statement of the results with a discussion, and a conclusion with a discussion of implications.

THEORETICAL BACKGROUND

Market Performance

AI solutions enhance targeting and optimize advertising spending, leading to improved performance even in advanced campaigns (Haleem et al., 2022; Theodoridis & Gkikas, 2019). In marketing, AI effectively forecasts client behavior and enhances consumer experiences by integrating customer data (Campbell et al., 2020). Utilizing big data, AI drives market performance (Phay, 2019). Breakthroughs in AI provide organizations with advanced methods to achieve these outcomes, thereby improving market performance (Gupta & Tomar, 2021; Yaiprasert & Hidayanto, 2023). Under the technology acceptance model, effective AI use optimizes market decision-making, enhances return on investment, and boosts market performance (Desta & Amantie, 2024; Hassan, 2021; Yaiprasert & Hidayanto, 2023).

Effective AI

Effective AI is linked with various factors in diverse contexts by social scientists (Di Vaio et al., 2022). AI's degree of effectiveness in any industry depends on technical aspects, ethical considerations, as well as risk-related aspects (Deng et al., 2022; Rana et al., 2022).

High-quality AI platforms depend on data quality and processing, particularly data cleaning and normalization, to achieve desired outcomes (Gudivada et al., 2017; Zha et al., 2023). Feature engineering, which integrates domain knowledge and creativity, is essential for predicting model performance and is a key technical aspect of AI (Janiesch et al., 2021). Provost and Fawcett (2013) state that effective AI combines appropriate algorithms, data features, and resources, enabling accurate model performance forecasting. Additional technical aspects include model testing, training, evaluation, deployment, and hardware integration (Vishnukumar et al., 2017).

Beyond technical factors, ethical issues are critical when AI systems generate performance-based reports. Various AI systems address fairness and transparency using methods like exploratory cues, interpretable tools, and revealing algorithms (Shin et al., 2024b). However, AI can inherit biases from training data, leading to unjust outcomes, especially for underprivileged communities (Bostrom & Yudkowsky, 2018; Romele, 2022). Mitigating bias requires careful data selection, preprocessing, and continuous monitoring to ensure fairness (Chen et al., 2023). Additionally, providing justifications for AI decisions enhances accountability and allows for scrutiny of harmful outcomes (Danry, 2023; Díaz-Rodríguez et al., 2023). Protecting user privacy is crucial to preventing unauthorized access or misuse through data anonymization, encryption, and access controls within an ethical AI framework (Xu et al., 2014; Khan & Mer, 2023). Effective AI also involves risk identification, data governance, transparency, explainability, bias detection, and ethical guidelines for stakeholders across industries (Díaz-Rodríguez et al., 2023). Thus, this study addresses effective AI through technical, risk mitigation, and ethical considerations within the service industry.

Technical Aspects

The association of the concept of AI with "intelligence" inadequately addresses the inherent definitional issues, as noted by Bakker and Korsten (2021), Russell (2019), and Russell and Norvig (2020). While AI encompasses a broad spectrum of possibilities, including machines that emulate human behavior and those with autonomous minds capable of benevolent actions and compassionate thoughts, the definition of AI remains ambiguous. Greenfield (2017) and Qing et al. (2024) highlight that architects of AI systems, such as those designed to win the game of Go, aim for "superhuman proficiency in challenging domains," surpassing human intelligence. To mitigate the ambiguity of the term "AI," Broussard (2019) and Brynjolfsson and McAfee (2017b) advocated for the term "knowledge engineering" and the designation of systems as "knowledge-based systems." However, this approach fails to specify the definitions of "knowledge" and "knowledge-based," leaving the issue unsettled.

Azizi (2020) posits that developing effective AI systems aims to minimize user skepticism and enhance cognitive engagement with AI-integrated technology. Studies by Kakatkar et al. (2020) and Schmidt et al. (2020) have extensively examined the significance of customer perspectives and the drivers behind the broad acceptance of contemporary technologies in marketing strategies. Despite the potential benefits of socially effective AI technologies in facilitating cognitive engagement, the relationship between "cognitive engagement" and the formation of a client's self-esteem remains the subject of ongoing inquiry (Stewart & Segars, 2002). Future research should explore this relationship further to understand how AI can effectively contribute to psychological processes and enhance customer self-esteem.

Dahl (2018) conducted industrial research analyzing several qualitative studies to enhance understanding and predict the prospective impacts of AI on marketing and business. Dahl (2018) addresses a conceptual framework comprising three dimensions of AI: task categorization (distinguishing numerical from non-numerical data analysis such as that of text, voice, images, or facial expressions), level of intelligence (differentiating task automation from context awareness), and AI integration within robotic entities (ranging from virtual to real). Additionally, Johnson et al. (2003) and Khalifa et al. (2019) divide AI applications into three categories: analytical AI (cognitive intelligence), human-inspired AI (cognitive and emotional intelligence), and humanized AI (cognitive, emotional, and social intelligence). The potential of AI to enhance consumer focus and interaction is linked to its cognitive capabilities, such as concentration and repetitive categorization, presenting both opportunities and challenges. The development of AI systems with human-like or emotional intelligence raises ethical concerns (Barrett et al., 2019).

Operating large data models in AI solutions requires extensive datasets known as "big data." Analyzing these vast datasets demands specialized "big data" skills, including ML, data extraction, purification, statistical analysis, and programming paradigms like MapReduce (Bag et al., 2021; Duan et al., 2019). Despite available courses, there remains a significant shortage of big data specialists. Y. Wang et al. (2018) project that the USA will need 140,000 to 190,000 professionals with expertise in big data. Technical IT competencies such as programming, database administration, and system analysis can be formalized through processes and documentation (Zuboff, 2015), and similar proficiency in big data analytics is expected to yield comparable benefits. As big data technology is still emerging, organizations with skilled big data professionals gain a competitive advantage. However, this advantage may quickly diminish as big data skills become more widespread within and across organizations, turning into a common corporate resource (Y. Wang et al., 2018).

In contrast, management abilities are highly distinctive to individual firms and are cultivated over a gradual process by individuals inside the same organization. Organizations have the option to provide training to their existing workforce or recruit new individuals to enhance their technical competencies. The development of these skills is enhanced by strong interpersonal relationships among employees within the same or other departments of an organization (McClure, 2018).

The aforementioned abilities are deeply embedded in organizational culture and serve as benchmarks for evaluating managers' daily decisions and behaviors (Duan et al., 2019). However, managers often lack explicit knowledge, leading to uneven enterprise allocation (Wimmer et al., 2016). Without senior executives' ability to recognize the importance of big data insights, the data becomes ineffective. Therefore, managers must thoroughly understand how and where to implement technical teams' results. This can only be achieved by skilled big data administrators who grasp the current landscape and anticipate the needs of various departments, clients, and collaborators. Furthermore, fostering mutual trust and strong working relationships between big data managers and other functional managers promotes the development of exceptional big data talent, creating an advantage that is difficult for competitors to replicate (Al Azzam et al., 2023).

Ethical Consideration

The moral and ethical implications of AI have been debated since 1962 (Samuel, 1962). As AI rapidly advances and permeates the personal, economic, and societal domains, ethical discourse has intensified (Coeckelbergh, 2020; Alazzam,F. et al., 2023). This surge in AI research has prompted discussions on key ethical principles. Mikalef and Gupta (2021) note a growing willingness to engage in these debates, while Smids et al. (2020) examine various ethical AI concepts from the commercial, public, and academic sectors. Van Oorschot et al. (2018) found that discussions typically focus on transparency, justice and fairness, non-maleficence, responsibility, and privacy. Jobin et al. (2019) highlight that openness can both facilitate and hinder other ethical principles.

AI is a multifaceted phenomenon that reduces inefficiencies, enhances system reliability, and introduces innovative solutions to longstanding problems (Bankins, 2021). Its applications support diverse marketing strategies and actions (Puntoni et al., 2021). Advances in computational power, data accessibility, contextual understanding, and emotional detection have fostered interactive and beneficial customer relationships (Chen et al., 2017). Recent studies have raised ethical concerns related to extensive consumer data collection in AI platforms, AI's emotional intelligence, and the rise of AI-powered sales and consumption (Brisimi et al., 2018). The dominance of AI-driven online shopping platforms and uneven business presence on these platforms can impact companies both negatively and positively (Lui & Lamba, 2018). Additionally, AI-based applications may exhibit discriminatory tendencies by targeting specific consumer groups, leading to unfair practices at the individual level (Gursoy et al., 2019). The concentration of market share through AI-enabled e-commerce platforms results in unequal representation, affecting firms differently (Lui & Lamba, 2018).

Unjust treatment associated with AI in marketing can exacerbate societal and economic inequalities, raising ethical concerns at individual, business, and societal levels. However, AI ethics in marketing has largely relied on anecdotal evidence and focused on specific applications, often centering on principles like explainability or privacy (Porra et al., 2020). Concerns about AI hazards emphasize justice, fairness, non-maleficence, and privacy, with non-maleficence gaining prominence to prevent AI-induced harm. Trust also emerges as a crucial facet of AI governance. Ethical discussions focus on establishing frameworks to ensure AI's positive societal impact (Bankins, 2021). Shakhatreh et al. (2023) distilled five ethical principles: beneficence, non-maleficence, autonomy, equality, and explainability. Beneficence promotes well-being and societal welfare (Formosa et al., 2021), while non-maleficence safeguards against AI's negative consequences.

Risk Mitigation

Multiple studies emphasize prioritizing privacy, security, and safety measures while mitigating risks and harms from both intentional and unintentional AI misuse (Jobin et al., 2019). Autonomy-based AI concerns pertain to individuals' inherent freedom to make unrestricted decisions and control AI technology use in their personal affairs without external influence. Equality in AI ensures just and impartial access to AI technology and its benefits, regardless of race, gender, religion, or other personal attributes. Explainability requires AI systems to interpret their decisions and actions in a manner understandable to humans, facilitating assessment and improvement in case of errors or adverse outcomes.

Cognitive Engagement

Relational governance models facilitate stakeholder cooperation through decision coordination, education, and discourse (Barello et al., 2016). Shared development environments enhance communication within AI-based cross-functional teams. Technical and business knowledge are crucial for developing AI competencies, making employee training essential (Ashraf & Himel, 2023). Training imparts AI skills and equips workers whose roles may be automated or enhanced by AI, mitigating unforeseen consequences (;Faleh Alazzam, 2023). Transparent management of AI to augment employee capabilities, rather than displace them, can alleviate workforce concerns. However, the management and regulation of ML models and AI platforms are often given less attention than data governance (Ashraf & Himel, 2023; Chen et al., 2017; Kumar et al., 2021).

Cognitive engagement, defined as stakeholders' knowledge and interpretation of services and their implications (Barello et al., 2016), is vital for learning and experiential growth (Jena et al., 2021). Enhancing cognitive engagement with personalized care tools is a primary AI objective in the services sector (Bourne, 2019; Shakhatreh & Jadallah, 2023). AI solutions aim to boost stakeholder satisfaction, improve decision-making, and foster productive interactions within service systems (Alami et al., 2020). Additionally, customer perspectives and drivers behind technology acceptance are crucial for developing effective marketing strategies (Kakatkar et al., 2020; Schmidt et al., 2020). Despite the benefits, the relationship between cognitive engagement and client self-esteem remains underexplored, highlighting the need for further research (Stewart & Segars, 2002).

Two decision-making processes linked to cognitive capacities in older adults are strategy implementation and information assimilation. Mumali (2022) found that age-related differences in strategy selection were due to declines in reasoning and fluid intelligence, leading older individuals to adopt simpler approaches like the take-the-best heuristic (Guo et al., 2023; Naeem et al., 2023). Suseno et al. (2022) discovered that older adults often use non-compensatory decision-making techniques, reflecting a lack of comparative analysis or familiarity with available options. These strategies require fewer cognitive resources, leading to challenges when people are faced with multiple choices owing to diminished cognitive processing and working memory (John & Cole, 1986). Rasool et al. (2020) found that supplementary stimuli can amplify age-related differences in information-seeking behaviors, as decision-making demands additional knowledge and cognitive resources. Consequently, older adults exhibit lower decision-making quality and higher cognitive demands in complex tasks, often resorting to low-effort judgments owing to difficulties in information retrieval and analysis.

According to Acemoglu and Restrepo (2020), AI capabilities significantly impact decision-making processes and business outcomes by improving the efficacy and quality of decisions, thus enhancing organizational performance. The speed of decision-making is crucial for improving organizational performance. Neiroukh et al. (2024) found that the pace of decision-making mediates the relationship between AI capabilities and organizational effectiveness. Intellectually engaging with ethical AI technology offers benefits, including enhanced perception of value. Bandura (1986) and Cusumano et al. (2019) proposed that cognitive engagement with specific scenarios and the service environment increases perceived value, linking cognitive engagement to instrumental and experiential values, as well as delight and satisfaction (Eggers & Lee, 1997). Consumers' judgments of their consumption experiences are crucial for generating both instrumental and terminal values.

Organizations should prioritize developing consumer relationships to enhance the value of their service offerings. Vaio et al. (2023) found that examining service items through a cognitive lens aids in understanding value creation. The benefits of these advancements depend on how much patients value cognitive engagement with ethical AI devices and technology. Ethical AI systems significantly impact the decision-making process in care, emphasizing both ultimate and instrumental service values (Sullivan & Wamba, 2024). AI-enhanced work practices integrate human and algorithmic intelligence, either competing to inform decisions or collaborating to leverage strengths for more effective job division (Mikalef & Gupta, 2021). Research shows that consumers actively participate in producing media that blends algorithmic and human intelligence, driven by intellectual and emotional investment (Alboqami, 2023; Haque Mukit et al., 2021; Joshi & Rahman, 2019). Kim and Park (2013) explored how consumers regulate their emotional attachment when high-frequency trading algorithms take over decision-making from human traders.

Return on Investment

The increasing utilization of AI in business operations has attracted significant scholarly attention, aiming to assess its long-term positive or negative implications for organizations. However, few studies have comprehensively evaluated AI's tangible impacts using both qualitative and quantitative methodologies. For example, Jain (2019) conducted an online survey with fifty business decision-makers and employees in Indian organizations, revealing that AI significantly enhances enterprises' economic well-being. Similarly, Chetthamrongchai and Jermsittiparsert (2020) found that AI implementation in Thai pharmaceutical firms improves business performance and optimizes market decision-making. Data for these studies were collected primarily through structured questionnaires and interviews with corporate executives and experts. Fragapane et al. (2022) demonstrated that AI-assisted social media marketing can boost client acquisition and profitability. Additionally, Aouadni & Rebai (2017) highlighted AI's achievements in multinational enterprises across various sectors. For instance, autonomous trucks reduced delivery times and increased prediction accuracy for Domino's Pizza from 75% to 95%, while Australian mining companies achieved cost reductions, enhanced worker safety, and achieved a 20% productivity gain through advanced drilling technologies. Despite these advancements, scholarly investigations have yet to quantify the precise economic benefits firms derive from AI implementation.

Empirical evidence suggests that AI yields a favorable return on investment despite short-term challenges. Corporations like Amazon, Apple, and Facebook have successfully automated their commercial operations, enhancing market perception (Basri, 2020). Domino's Pizza has used AI to expedite deliveries and improve delivery time accuracy (Dash et al., 2019), underscoring AI's significant advantages for businesses, though exact economic benefits remain to be fully quantified. Similarly, Barclay leverages AI to detect fraud and enhance customer interactions through chatbots. Joyce et al. (2021) found that banks could cut operational expenses by up to 22% with AI implementation. These results may motivate investors to set ambitious AI targets and consider investing in AI-adopting companies. Given AI’s impact on costs, risks, and revenues, investors will scrutinize it closely. While some stakeholders may favor the adoption of AI, others may be less enthusiastic. Prior research indicates that introducing new IT can yield both positive and negative effects on a firm’s market valuation (Chatterjee et al., 2002).

DEVELOPMENT OF RESEARCH HYPOTHESIS AND MODEL

Research Model

On the basis of an extensive review of literature and sessions with experts in the field of AI, the following research model was developed. The effective AI system has three main aspects. The first is the technical aspect, which consists of two further aspects: targeted data and algorithms, which are developed to utilize the data for business purposes effectively.

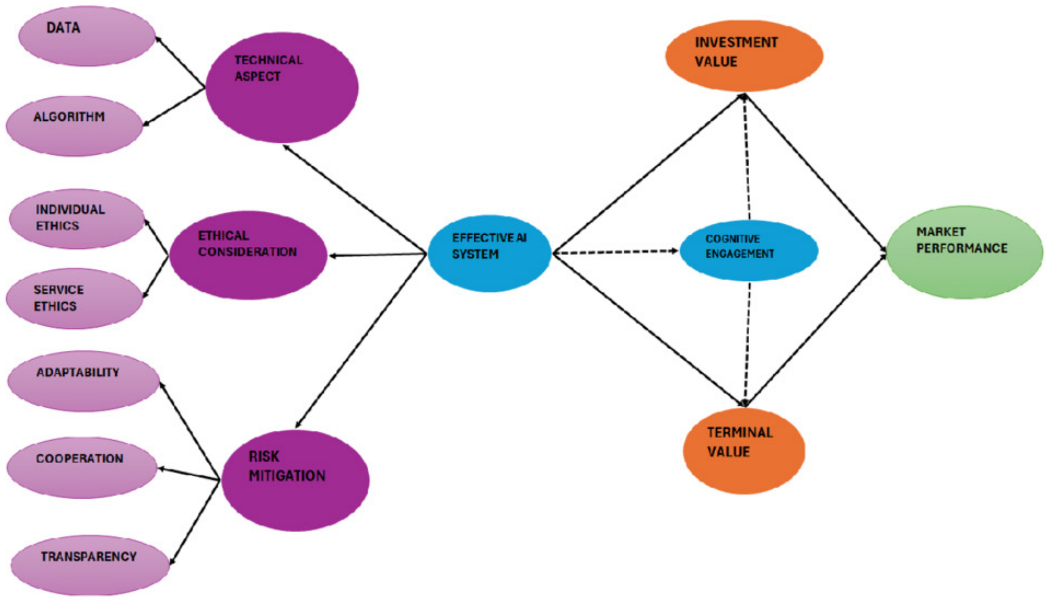
The second major aspect is the ethical consideration of AI-based systems. These include individual ethics, i.e., individual privacy concerns addressed by developers and businesses, in conjunction with service ethics, which mainly include the practical implementation of policies and procedures, including legal and organizational policies to mitigate social discrimination, fraudulent transactions, and generation of false information, in line with effective corporate governance.

The third major aspect of an effective AI system is adaptability, meaning the ability to make intelligent and timely judgments through the analysis of vast quantities of data. Adaptible AI platforms can enhance their accuracy and reliability by assimilating knowledge from their interactions with the environment, enabling organizations to make more informed decisions.

In this respect, the second aspect of risk mitigation is the cooperation between the AI platform and its users, which relies upon machine behavior research. It is considered a key aspect of risk mitigation within the organization (Fox & James, 2020). AI tansparency is the user’s ability to gain insight into the internal mechanisms of an AI model and comprehend the processes by which it arrives at its findings. Gaining a comprehensive understanding of the functioning of an AI platform, specifically its decision-making processes and data management, is vital for all stakeholders.

Figure 1 presents the research model for this study.

Figure 1. Research model



Source: Author's own

It is suggested that an effective AI system directly impacts the overall value addition created by investment in AI, as the capital expenditure on the development of such a platform is considerable in terms of money, time, and human resources. Previous research indicates that the implementation of an effective AI system tends to impact the terminal value directly, as the terminal value refers to the valuation of an asset, business, or project that extends beyond the projected timeframe in which future cash flows may be reliably calculated. These aspects tend to have a positive impact on the overall market value of the business (Chen et al., 2017).

In addition, present research postulates that cognitive engagement refers to the exchange of dialogue between personnel and clients using everyday language and tends to mediate the relationship between effective AI systems, investment value, and terminal value, as AI platforms integrate ML and emotional intelligence in real time. The objective of this initiative is to streamline consumer encounters, data collection, and communication processes (Chen et al., 2017). As a result of these processes, the overall business processes tend to improve, result in the overall efficiency of the business, which tends to lead to an improvement in the market performance of the business (Ravichandran & Lertwongsatien, 2005).

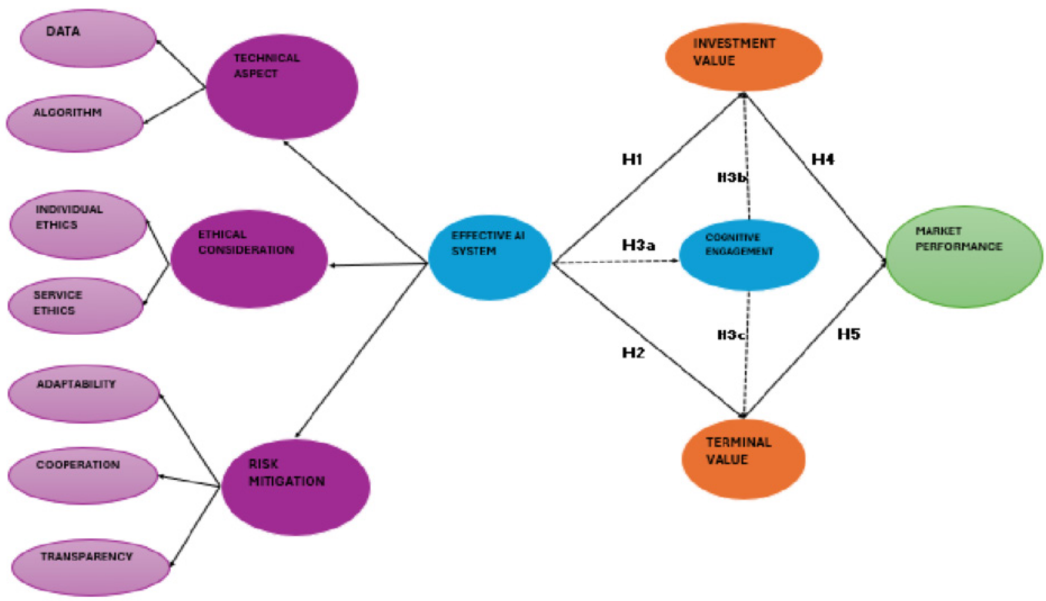
Research Hypothesis

Our hypotheses are as follows:

H1: Effective AI in services-based businesses has a positive influence on perceived investment value.
H2: Effective AI in services-based businesses has a positive influence on perceived terminal value.
H3: Cognitive engagement with effective AI mediates the relationships between effective AI investment value and effective AI terminal value.
H4: Perceived investment positively influences market performance.
H5: Perceived terminal value positively influences market performance.

The conceptual framework of the study is presented in Figure 2.

Figure 2. Conceptual framework



METHODOLOGY

Database

The data for the present research was collected via a questionnaire developed after an extensive review of existing literature and in-depth consultation with AI users and business professionals working in the services industry using AI-based decision tools.

Initially, we contacted these professionals using personal and professional networks (LinkedIn, Facebook, Whatsapp). After gaining their consent, we shared the questionnaire with them using various electronic means, including Google Forms and email. The total number of questionnaires sent was 600, but only 412 completed questionnaires were validated and included in the results. Because of privacy concerns, the names of organizations and respondents' personal details were not recorded.

Measurement

Researchers utilized SEM using IBM SPSS Amos software. The reason for the choice of technique was based upon the major advantages of SEM over other similar techniques, which mainly include explicit measurement error evaluation, along with estimation of latent (unobserved) variables via observable variables, and model testing, in which a structure can be imposed and its data fit evaluated, as held by Byrne et al. (2011). Moreover, SEM, which is built on the general linear model, allows researchers to investigate numerous regression equations at the same time. We investigate a network of relationships between independent variables and dependent factors using SEM (Lowry and Gaskin, 2014). SEM software makes it easier to validate classic models while also exploring complicated linkages and frameworks like confirmatory factor analysis and time series analysis. SEM improves the ability to visualize relationships, resulting in a better understanding of the issue at hand (Hair et al., 2011).

RESULTS

The majority of the respondents were male, working at operations and lower management levels in services organizations. Given the nature of their jobs and their responsibilities, it was expected that the respondents would have at least an undergraduate or postgraduate degree in the relevant field, but to our surprise, more than one third of the respondents did not possess such an academic background. Still, they were hired on the basis of professional courses in AI engineering. A significant majority, 81%, of the respondents had less than 10 years of relevant experience. Indicating that the majority of the sample population consisted of young professionals, the details of the demographic profile of the respondents are provided in Table 1.

Table 1. Demographics profile

Gender	Percentage	Frequency
Male	60%	248
Female	40%	164
Position in Organization		
Director	8%	32
Manager	20%	82
Executive	49%	200
Trainee	21%	86
Education		
Masters	41%	167
Professional certification	36%	150
Undergraduate Degree	23%	95
Experience		
More than 20 years	6%	26
10 to 15 years	13%	55
5 to 10 years	32%	132
1 to 5 years	28%	116
Less than 1 year	20%	82

Ensuring the reliability of data for the research model is critical, as it allows for the constructs with lower levels of factor loadings, ensuring the accuracy of analysis results in the SEM analysis (Danks et al., 2020). As per the first step, the composite, convergent, and discriminant validities were assessed. The outer loadings of the constructs were held to be significant, as their values of Cronbach's alpha and that of composite reliability (CR) were greater than 0.7, which is a threshold in social sciences research. Along with this, the convergent validity of the construct was determined by the average variance extracted (AVE) values, which were greater than the recommended value of 0.5 (Hair et al., 2011). The details of the analysis (Hair et al., 2011) are provided in Table 2.

Table 2. Reliability and validity results

	Outer Loadings	t- value	VIF	CR	AVE
Data				0.782	0.5544
Data-1	0.792	24.036	1.427		
Data-2	0.777	24.087	1.328		
Data-3	0.706	14.237	1.276		
Data-4	0.706	11.469	1.305		
Algorithm				0.803	0.5995
Algo-1	0.804	24.995	1.492		
Algo-2	0.795	28.302	1.455		
Algo-3	0.730	25.632	1.347		
Algo-4	0.757	27.664	1.431		
Individual Ethics				0.821	0.5918
InETH-1	0.800	27.638	1.281		
InETH-2	0.748	21.956	1.214		
Service-ethics				0.773	0.5665
SerETH-1	0.785	26.489	1.401		
SerETH-2	0.760	22.310	1.368		
SerETH-3	0.717	16.585	1.292		
SerETH-4	0.754	23.324	1.195		
Adaptability				0.791	0.5709
ADPT-1	0.743	18.672	1.220		
ADPT-2	0.803	29.790	1.394		
ADPT-3	0.722	20.743	1.152		
Cooperation				0.807	0.7436
CopR-1	0.843	32.049	1.201		
CopR-2	0.885	48.713	1.307		
Transparency				0.801	0.5863
Transp-1	0.738	22.188	1.607		
Transp-2	0.766	22.145	1.251		
Transp-3	0.815	29.867	1.281		
Market Performance				0.792	0.6831
MrPer-1	0.740	17.968	1.486		
MrPer-2	0.796	25.581	1.540		
MrPer-3	0.731	18.833	1.302		
MrPer-4	0.749	19.266	1.341		
Cognitive Engagement				0.841	0.6952
CogEng-1	0.742	17.719	1.397		
CogEng-2	0.767	19.136	1.512		

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Table 2. Continued

	Outer Loadings	t- value	VIF	CR	AVE
CogEng-3	0.765	21.246	1.369		
CogEng-4	0.812	27.453	1.546		
Investment value				0.803	0.6479
InstVL-1	0.713	14.983	1.320		
InstVL-2	0.764	17.831	1.484		
InstVL-3	0.763	20.566	1.342		
InstVL-4	0.804	26.407	1.498		
Terminal value				0.79	0.5775
TerVaL-1	0.696	16.233	1.395		
TerVaL-2	0.851	32.243	1.437		
TerVaL-3	0.754	17.727	1.433		
TerVaL-4	0.730	15.918	1.292		

One of the main issues related to research based on primary data is the presence of biases. According to Podsakoff et al. (2003) and MacKenzie et al. (2011), procedural bias has the potential to alter both the reliability and validity of items, as well as the covariance of constructs. Factors that may contribute to method bias include a lack of cognitive or verbal sophistication, unfamiliarity with the concept, ambiguous or complex questions, reliance on retrospective recall, and auditory presentations conducted via telephone surveys or face-to-face interviews. Technique bias can be addressed in two distinct ways. The initial phase, after data collection, entails using statistical approaches to address methodological bias. The next step is to develop a research plan that acknowledges and reduces the influence of methodological bias. We ensured the anonymity of participants to prevent any potential methodological bias. Surveys collected the data, randomly assigning the randomization instrument to each participant. We then used Harman's single factor test to evaluate a solution that contained a single unrotated factor. Podsakoff et al. (2003) and Podsakoff et al. (2012) proposed a 50% criterion for explained variation, but the test produced just 28.32%. The data was immune to methodological bias. The details of the results can be seen in Table 3.

Table 3. Discriminant validity results

	Data	Algo	InETH	SerETH	ADPT	CopR	Transp	MrPer	CogEng	InstVL	TerVaL
Data	0.762										
Algo	0.582	0.778									
InETH	0.439	0.531	0.87								
SerETH	0.285	0.319	0.167	0.751							
ADPT	0.192	0.118	0.207	0.016	0.681						
CopR	0.189	0.088	0.187	0.002	0.893	0.776					
Transp	0.751	0.805	0.667	0.474	0.611	0.518	0.799				
MrPer	0.883	0.697	0.781	0.282	0.245	0.214	0.893	0.653			

continued on following page

Table 3. Continued

	Data	Algo	InETH	SerETH	ADPT	CopR	Transp	MrPer	CogEng	InstVL	TerVaL
CogEng	0.157	0.116	0.182	0.027	0.977	0.605	0.56	0.22	0.76		
InstVL	0.56	0.935	0.473	0.755	0.079	0.066	0.826	0.652	0.07	0.61	
TerVaL	0.624	0.598	0.534	0.226	0.206	0.157	0.769	0.726	0.2	0.55	0.77

Note. Diagonal elements are the square root of AVE.

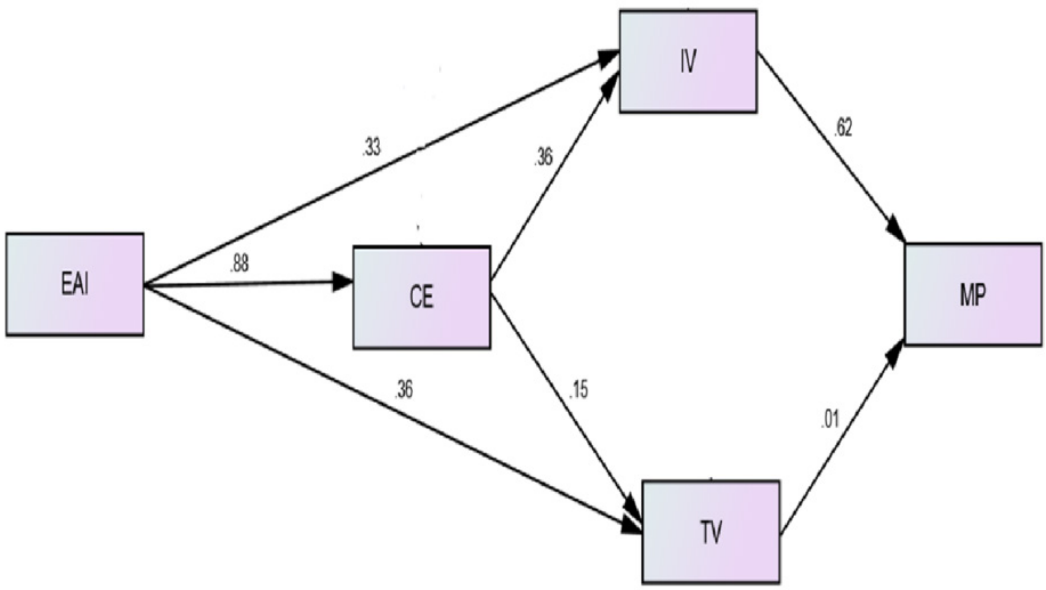
InETH-3, CopR-3, CopR-4, and Transp-4, were removed from the scale, as their overall factor loadings was less than the threshold mentioned above. The discriminant validity of the components was also demonstrated (see Table 3). To begin with, Fornell and Larcker (1981) discovered that the square root of AVE was higher than the highest correlation of any other construct. Second, Hair et al. (2017) found that the outer loadings of each construct were greater than the cross-loadings with other constructs.

To further verify the validity of our data and research model, we opted for non-parametric bootstrapping, given that the bootstrapping involves taking the sample from our existing population sample to verify the model further. For this purpose, researchers chose 500 re-samples, as suggested by Becker (2018). This procedure also allowed us to ensure that our results and research data meet the basic underlying assumptions of appropriate distribution and also allowed results to be more statistically accurate. Table 4 presents the path coefficient after bootstrapping, and the bootstrapping conceptual model is shown in Figure 3.

Table 4. Path coefficient after bootstrapping

Path	Estimate
CE <--- EAI	0.883
IV <--- EAI	0.325
TV <--- EAI	0.363
IV <--- CE	0.359
TV <--- CE	0.155
MP <--- IV	0.619
MP <--- TV	0.009

Figure 3. Bootstrapping conceptual model



As shown in Table 5, H1, which stated that effective AI in services-based businesses has a positive influence on perceived investment value, is accepted on the basis of the p-value, which was held to be significant. H2, which stated that effective AI in services-based businesses has a positive influence on perceived terminal value, was also accepted. At the same time, H3, which concerned the mediating role of cognitive engagement between AI investment value and terminal value, only two of the paths were held to be significant, indicating that cognitive engagement does not mediate the relationship between effective AI and terminal value. In comparison, H4 was accepted, confirming that an effective AI system indeed has a positive impact on market performance. H5, stating that perceived terminal value positively influences market performance, was rejected. One of the possible reasons for the rejection of H3-c is that "cognitive engagement" refers to the exchange of dialogue between personnel and clients using everyday language, and it may take a while for a beneficial relationship to translate into terminal value, as "terminal value" refers to the financial impact of the project in the long term. At the same time, H4 was rejected, as, once again, perceived investment value does not immediately have a positive impact on the market performance of the company, as its impacts can be determined only in the long term, as held by Setiawan and Rosa (2023).

Table 5. Hypothesis results(Paths, estimate, SE, CR, P-values, decision)

Hypothesis	Path	Estimate	SE	CR	Critical value (P-value)	Decision
H1	IV <--- EAI	0.25	0.06	4.194	***	Accept
H2	TV <--- EAI	0.271	0.067	4.061	***	Accept
H3-a	EAI <--- CE <---IV	0.906	0.023	38.617	***	Accept
H3-b	EAI<-- CE<---TV	0.269	0.058	4.631	***	Accept
H3-c	TV <--- CE	0.113	0.065	1.731	0.083	Reject

continued on following page

Table 5. Continued

Hypothesis	Path	Estimate	SE	CR	Critical value (P-value)	Decision
H4	MP <--- IV	0.82	0.054	15.33	***	Reject
H5	MP <--- TV	0.012	0.055	0.215	0.829	Reject

CONCLUSION

This research underscores the critical importance of integrating social and ethical considerations in AI technology development, highlighting the limitations inherent in typical AI projects. Utilizing a comprehensive survey methodology, insights were gathered from diverse industry professionals, AI specialists, and clients. The study identified key variables contributing to AI efficacy, categorized into three primary dimensions: technological proficiency, ethical deliberations, and risk management. It revealed that factors such as privacy infringement, adaptability, error resolution time, and collaborative efforts are pivotal in evaluating AI effectiveness in service-oriented contexts. Our analysis demonstrates that technological advancements significantly impact users' cognitive engagement, providing valuable insights for service providers aiming to develop and deploy efficient AI systems. The study also illustrates how AI contributes to the growth and market performance of service companies by optimizing market decision-making processes and enhancing overall business outcomes. According to Wang et al. (2021), current research is beginning to explore the challenges in developing efficient AI systems. Our findings address existing gaps by presenting a structured framework for ethical AI development and implementation, aligned with stakeholder expectations. The empirical study validated the hierarchical model, establishing it as a reflective-formative framework. Furthermore, the structural model analysis confirmed the significance of the investigated pathways, leading to a robust evaluation framework that clarifies the concepts of efficient AI.

The quality of AI, services provided, and delivery methods within organizations significantly affect both investment and terminal values. Quantitative analysis provides empirical evidence of a positive correlation between the value attributed to effective AI and responsible investment, indicating a strong cognitive connection between these factors. Our analysis determined that investment value influences market performance, despite a significant correlation between terminal value and market performance. The results suggest that service sector companies can enhance their market presence and launch innovative solutions by implementing efficient AI technologies. This study explored how AI is transforming the service industry, focusing on ethical issues, practical guidelines, and strategies to improve market outcomes and build stakeholder trust. Key aspects such as privacy and adaptability were emphasized, demonstrating how effective AI use leads to improved market performance and more intelligent engagement strategies. While recognizing certain limitations, the research proposes future study areas, including cultural analysis, emerging technologies, and long-term investigations, to further understand AI's effects.

IMPLICATIONS OF THE STUDY

On the basis of the findings of this study, a comprehensive understanding of cognitive engagement perspectives provides valuable insights for automating, refining, and customizing service marketing efforts. The fair and safe use of AI tools can enhance stakeholder engagement, thereby influencing the market performance of service providers. Our study offers managers valuable insights into developing value propositions by uncovering previously unexamined outcomes related to the psychological processes of cognitive engagement. Service providers can better address consumer demands by emphasizing solutions through marketing strategies reinforced by socially impactful AI technologies.

The study indicates that service providers must consider the implications of medical modernization and ethical factors in developing service goods and AI-enabled technologies. It offers valuable insights for service practitioners and policymakers on AI implementation, including developing guidelines, standard operating procedures, data privacy regulations, technical training programs, data theft risk mitigation, recovery response mechanisms, and implementation of transparency audits. These recommendations aim to benefit various stakeholders involved in AI deployment. Policymakers in the service sector should adopt a strategic perspective beyond limited delivery paradigms, while service managers can leverage insights from Almquist et al. (2016) to understand AI's advantages and its role in value generation. Additionally, the techniques proposed in this study can facilitate the assessment of service pathways and the development of value propositions using AI-powered service robotics technologies. Implementing cognitive engagement strategies with AI-enabled technologies can foster positive attitudes and trust among stakeholders.

LIMITATIONS AND FUTURE RESEARCH AVENUES

Although this study has certain limitations, it paves the way for future research opportunities. A promising direction involves expanding the framework to include cultural factors and employing cross-sectional samples to evaluate the robustness of the observed connections. Additionally, this research enhances the understanding of critical elements necessary for the successful implementation of AI in diverse sectors such as services and manufacturing by examining various psychological and sociological factors that influence AI platform effectiveness. However, environmental factors not addressed in this study may also play a role in AI advancement, warranting further investigation into the fundamental principles that drive effective AI.

Furthermore, the study suggests that the relationship between AI capabilities and organizational outcomes may be moderated by the nature of tasks and the extent of AI technology utilization. For example, users might select different tools and platforms according to their specific needs, and the rewards and values they experience can vary depending on task-related and rational factors. Future research should explore individual habits and task characteristics to assess their impact on AI effectiveness. Psychological theories indicate that cognitive engagement depends on the service brand and can fluctuate over time. Therefore, conducting longitudinal studies to examine brand values associated with AI-enabled technology is recommended, as such studies would provide deeper insights into AI's long-term effects and contributions.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

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