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In the Era of Emerging Technologies: Discovering the Impact of Artificial Intelligence Capabilities on Timely Decision-Making and Business Performance

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Abstract **- In the contemporary environment of rapidly advancing technologies, this study investigates the influence of artificial intelligence (AI) capabilities on business performance, focused on the era of emerging technologies. Furthermore, this study is to examine how the combination of artificial intelligence capability; the timely decisions influence overall business performance, and to provide insights into how these factors interact and contribute to enhancing organizational success in the context of modern AI-driven decision-making processes. The research employs a quantitative approach to analyze data collected from 184 upper echelons from diverse firms. The study revealed that businesses leveraging higher artificial intelligence capability often achieved improved timely decisions. However, the optimal balance between timely decision-making varied across contexts, influencing overall business performance outcomes. Understanding this interplay is crucial for organizations seeking to enhance their operational effectiveness and strategic outcomes. The general perspective of this study offers valuable insights for organizations aiming to strategically enhance operational efficiency and overall effectiveness in an AI-driven environment.**

Keywords **- Artificial Intelligence Capability, Timely Decision-Making, Business Performance.**

I. INTRODUCTION

In a dynamic business environment, organizations constantly strive for improvements to maintain a competitive edge. An essential development influencing operations is the integration of Artificial Intelligence (AI) [1]. This study delves into the relationship between AI capabilities, timely decision-making, and their combined impact on business performance.

The emergence of AI marks a transformative moment in business, with McKinsey projecting a significant economic impact of $3.5 trillion to $5.8 trillion by 2030 [2]. AI empowers businesses to analyze vast amounts of data efficiently, revealing insights that were once elusive. However, challenges persist, such as translating predictive insights into actionable strategies [3]. The intricate link between AI and human aspects opens up new avenues for collaboration [4].

The interplay between AI capability, timely decision-making, and business performance is complex [5]. AI enhances decision-making attributes, enabling quick and accurate decisions, and ultimately impacting business outcomes. The Resource-Based View (RBV) emphasizes the role of organizational resources in competitive advantage, illustrating how AI capabilities act as mediators [6], [7].

This study aims to shed light on the interaction between AI capabilities, timely decision-making, and their collective influence on business performance. Theoretical enrichment involves understanding how AI integration transforms decision dynamics, whereas managerial insights guide organizations in optimizing AI tools to enhance business outcomes. Bridging theoretical frameworks with practical implementation, this study contributes to navigating the complexities of AI integration in the modern business era.

II. LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1. Theoretical Framework

Applying Resource-Based View (RBV) theory, this study examines the intricate relationship between AI capabilities and firm performance. The RBV serves as a managerial framework for identifying the strategic resources crucial for competitive advantage [6], [8]. Emphasizing the role of resources in enhancing performance, the RBV framework is appropriate for understanding the impact of AI capabilities on organizational success [9]. As a resource, AI influences organizational performance by expediting decision-making and improving efficiency [7]. This study utilizes the RBV to develop a conceptual model, highlighting how various factors mediate the influence of AI utilization on organizational performance.

2.2. Artificial Intelligence (AI)

Within the business context, AI involves advanced computational techniques that enable machines to simulate human-like cognitive functions [10]. AI empowers systems to analyze data, identify patterns, and make autonomous decisions [11]. AI in business encompasses algorithm development for sensing, comprehending, acting, learning, enhancing operational efficiency, and strategic insights [12].

AI capabilities include a spectrum of technologies, such as natural language processing and predictive analytics, which transform raw data into actionable insights [13]. This digital counterpart to human problem solving equips businesses with tools for innovation, personalization, and navigating dynamic market dynamics.

2.3. Artificial Intelligence Capabilities

AI involves creating algorithms for processing information, learning, and decision-making, encompassing machine learning, natural language processing, and computer vision [14]. In the business context, AI capabilities integrate these technologies to enhance operations, automate tasks, analyze data for insights, and improve customer interactions [15]. AI-driven decision-making assists in refining strategies, optimizing logistics, and predicting market trends [16]. The term "Artificial Intelligence Capability" denotes an organization's effective integration and utilization of AI technologies to achieve strategic goals and enhance business performance across sectors [15], [17].

2.4. The Impact of AI Capability on Business Performance:

AI capabilities have emerged as pivotal in transforming diverse business sectors, driving operational efficiency, and fostering competitiveness [18]. Across industries, the healthcare sector benefits from AI's ability to detect diseases from medical scans and to revolutionize diagnostics through image recognition software [19]. In retail, AI analyzes consumer behavior, enabling personalized shopping experiences with tailored product recommendations that enhance customer loyalty and boost sales [20]. The manufacturing sector leverages AI for predictive maintenance and minimizes downtime and costs by predicting the equipment maintenance needs [21]. Real-time defect detection through AI-enabled quality control ensures a high standard production. In the financial industry, AI analyzes vast datasets for data-driven investment decisions and market trend predictions, and AI-powered chatbots enhance customer support [22]. These examples underscore AI's transformative impact of AI across sectors: improving efficiency, fostering innovation, and enhancing customer engagement. For instance, AI's ability of AI to process customer data can optimize inventory management by predicting demand patterns and reducing costs [23]. While AI's potential of AI in business is substantial, its effective implementation and management are crucial for realizing its benefits [24]. AI capability is a driving force behind enhanced decision making, operational optimization, and innovation across diverse business sectors. Its adaptability to various contexts makes it a critical tool for achieving and sustaining competitiveness in modern business environments [25]. Therefore, we propose the following hypothesis:

H1. Business AI capability has a positive impact on business performance.

2.5. The Impact of AI Capability on Timely Decision-Making

Timely decision making denotes the speed at which businesses analyze information and reach conclusions, influencing their responsiveness and competitive advantage. In a fast-paced business environment, swift and efficient decision making is crucial for capitalizing on opportunities and promptly responding to market changes [26]. Agility enhances organizational effectiveness, adaptability, and overall performance, emphasizing the integral role of timely decision-making in business success. AI technologies have revolutionized timely decision making by introducing unprecedented levels of automation and effectiveness. Notably, machine learning algorithms rapidly analyze vast datasets to reveal intricate patterns and trends that are imperceptible to human observation. This capability empowers decision makers with accelerated insights, steering strategic choices, and operational adjustments [27]. The convergence of AI and real-time data processing further enhances decision-making speed, providing immediate feedback on market dynamics, customer behavior, and other critical factors [12]. This real-time adaptability symbolizes modern business competitiveness, allowing organizations to dynamically adjust their strategies in response to changing conditions. The integration of AI technologies into decision-making processes has redefined timely decision-making. Machine learning algorithms and real-time insights driven by AI-powered systems collectively enable organizations to navigate the complexities of contemporary business environments with remarkable speed and efficacy [28]. Therefore, we propose the following hypothesis:

H2. Business AI capability has a positive impact on timely decision-making.

2.6. The Mediating Role of Timely Decision-Making

In dynamic markets, the demand for rapid strategic decisions significantly influences business performance, thereby impacting responsiveness and competitive positioning [29]. Academic investigations emphasize the pivotal role of timely decision making in organizational quickness and competitive advantage. Swift strategic decisions, as highlighted by recent studies [30], enable manipulation of emerging opportunities and enhance a company's market position. Eisenhardt [26] stressed the importance of quick strategic responses in turbulent environments, proactively managing uncertainties. In the context of digital transformation, Bharadwaj et al. [31] emphasized how rapid strategic decisions contribute to technological adaptation and improved performance. Finkelstein and Hambrick's concept of "efficiency as a competitive advantage" [32] further supports the idea that the pace of strategic decisions directly affects business success. In conclusion, the literature suggests that strategic timely decision making significantly influences business performance through adoption, innovation, and competitive positioning. Therefore, we hypothesize as follows:

H3. Timely decision-making has a positive impact on business performance.

The interplay between business AI capability, timely decision-making, and business performance is complex and crucial in modern business environments [33]. AI capability, marked by advanced analytics and automation, enables organizations to extract actionable insights from large datasets [27]. Although enhanced analytical processes aid decision-making, the effectiveness of these insights relies on the speed of their execution, highlighting the role of timely decision-making [30]. The interconnectedness between business AI capability, timely decision making, and business performance is multidimensional. Organizations with strong AI capabilities can generate valuable insights; however, these insights must be enacted promptly to yield competitive advantages [9]. Empirical research demonstrates the positive impact of AI-enhanced timely decision making on business performance [13]. As illustrated in Figure 1, the mediating role of timely decision-making acts as a conduit through which AI's potential is realized, ultimately shaping business outcomes. This mediation reveals the synergy between business AI capabilities and business performance. While AI capabilities provide insights, timely decision making transforms these insights into strategic actions, bolstering organizational responsiveness and competitive positioning. This interaction underscores the fundamental importance of timely and informed decision-making in translating AI investments into tangible business success [34]. Therefore, we hypothesize as follows:

H4. Business AI capability and business performance are mediate timely decision-making.
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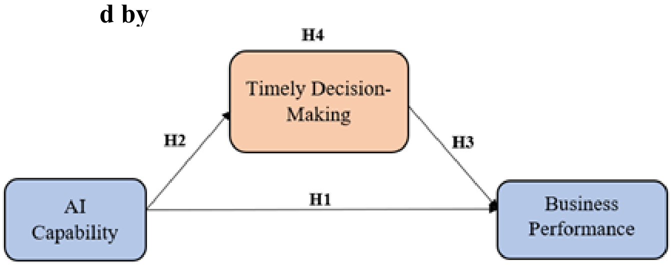

Figure 1: Research Model.

III. RESEARCH DESIGN AND METHOD

3.1. Research Setting and Sampling

To investigate the AI-related aspects, we conducted a survey targeting CEOs and senior management members across various companies. Prior to the official survey, we pilot-tested it with CEOs and senior managers to ensure its validity, incorporating feedback to refine some questions. The survey was distributed to 600 companies, with our target audience being CEOs and senior management members. Contact information was sourced from industry directories in the USA, focusing on organizations along the East Coast (Washington DC and the State of New York) and West Coast (California).

Before the survey invitations, we encountered 56 bounced emails, of which 360 companies did not respond. Ultimately, 211 responses were received, resulting in an overall response rate of 35.1%. To maintain consistency, companies with fewer than 50 employees and those with more than 500 employees were excluded from the analysis [35]. This decision aimed to focus on companies likely to utilize AI technology while also ensuring that the selected companies were not too small or too large for the scope of the study. After eliminating incomplete responses, the valid sample consisted of 184 responses. It is important to note that the relatively low response rate aligns with the common trend of lower participation from CEOs and upper-level management owing to their busy schedules and responsibilities within the organization [36].

3.2. Variable Measurement

In our study, we used an online survey with a five-point Likert scale to collect subjective measures, specifically investigating the influence of AI capabilities on organizational performance. For the independent variable, we employed the AI capability scale developed by Mikalef and Gupta [15]. This scale, derived from existing academic research, practitioner reports, and expert interviews, categorizes resources into tangible and human. Intangible resources, such as, have also been identified as crucial for building AI capability. To measure the dependent variable, organizational performance, we adapted four items from Chen et al. [37]. Respondents were asked to rate their organization's performance relative to their current status. Finally, timely decision making was assessed using three items adapted from Talaulicar et al. [38].

IV. DATA ANALYSIS AND RESULTS

To assess the hypothesized relationships and establish model validity and reliability, we employed partial least squares-based structural equation modeling (PLS-SEM) analysis using SmartPLS 4 software. Our analytical framework followed a two-step process [39], incorporating measurement model estimation and structural model evaluation. The analysis involved confirmatory composite analysis (CCA) within the PLS-SEM framework, following Hair et al.'s [40] recommendations.

4.1. Measurement Models Estimation

In the initial phase, we rigorously examined the reliability, convergent validity, and discriminant validity. Composite reliability (CR) and Cronbach's alpha values were scrutinized at the construct level with a threshold of 0.70 [41]. Construct-to-item loadings exceeding 0.70 were confirmed for convergent validity (Table I). Average Variance Extracted (AVE) values above 0.50 validated convergent validity, while indicator loadings surpassed cross-loadings for discriminant validity [42]. Heterotrait–monotrait ratio (HTMT) analysis was also conducted [43]. This comprehensive assessment ensured the validity and reliability of our measurement models, thus forming the foundation for subsequent analysis.

TABLE I:
Validity and Reliability of Latent Constructs.

Constructs	***a***	***CR***	***AVE***
Tangible resources (TR)	0.92	0.95	0.71
Human resources (HR)	0.89	0.91	0.68
Intangible resources (IR)	0.90	0.92	0.85
Artificial Inelegance (AI) Capability	0.95	0.96	0.61
Timely decision-making (TDM)	0.82	0.85	0.73
Business Performance (BP)	0.91	0.93	0.8

Note: Cronbach's alpha [α], composite reliability [CR], average variance extracted [AVE].

4.2. Structural Model Evaluation

The results of the structural model analysis, presented in Figure 2 and reported in Table II, provide insights into the relationships between the variables in the research model. A bootstrapping procedure with 5,000 resamples in SmartPLS 4.0 assessed the significance level with t-statistics.

The analysis reveals that AI capability significantly impacts business performance ($\beta = 0.513$, $p < 0.001$) and timely decision making ($\beta = 0.799$, $p < 0.001$); thus, H1 and H2 were supported. In addition, timely decision-making speed positively influences business performance ($\beta = 0.405$, $p < 0.001$); therefore, H3 is supported. Finally, H4 proposes the mediation of timely decision-making in the positive relationship between AI capability and business performance. Following the guidelines of Preacher and Hayes [44], the bootstrapping process revealed statistically significant results, supporting this hypothesis ($\beta = 0.323$, $p = 0.001$). The results highlight the crucial role of AI capability in influencing timely decision-making and business performance.

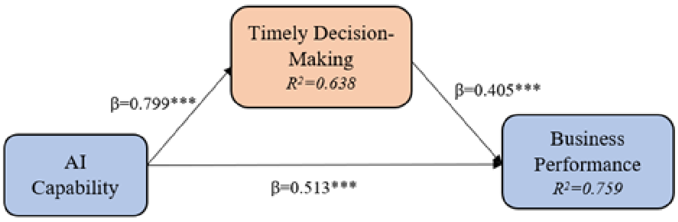

Figure 2: Structural Model Results.

The determination coefficients (R^2) demonstrate the model's effectiveness, explaining 63.8% of the variance in timely decision making and 75.9% in business performance. The effect size (f^2) values, indicating the contribution of exogenous constructs to R^2, range from moderate to high, reinforcing the substantial influence of AI capabilities.

TABLE II:
Structural Model Hypothesis Testing Results.

Paths	***O***	***SD***	***T***	***P-Values***	***CIs***		***Decision***
					2.50 %	**97.50 %**	
H1: AI capability → business performance	0.51	0.06	8.029	0.000***	0.388	0.64	Supported
H2: AI capability → timely decision-making	0.8	0.04	22.76	0.000***	0.725	0.863	Supported
H3: Timely decision-making → performance	0.41	0.07	5.459	0.000***	0.251	0.542	Supported
H4: AI capability → TDM → performance	0.32	0.06	5.339	0.000***	0.202	0.44	Supported

Note: Sample estimate (O), standard deviation (SD), T-statistics (T), ***p-value at the 0.001 level, artificial intelligence (AI), timely decision-making (TDM).

V. DISCUSSION AND IMPLICATIONS

The study's findings contribute significantly to RBV theory, aligning with the theory's emphasis on strategic resources and their role in securing a competitive advantage [6]. AI capabilities are recognized as strategic resources that positively influence timely decision-making and, consequently, business performance, highlighting the evolving nature of organizational resources in the contemporary business environment [29].

Moreover, the study enriches the understanding of timely decision making, emphasizing its pivotal role as a mediator in the relationship between AI capability and business performance. The impact of AI extends beyond its technical functionalities, emphasizing the importance of how AI contributes to efficient and prompt decision-making. This aligns with the broader literature on decision making in organizations, where timeliness is recognized as a key determinant of organizational effectiveness [33], [45].

In terms of practical implications, this study underscores the strategic integration of AI capabilities into organizational operations. This aligns with the literature that emphasizes the strategic role of technology in organizations [14]. Organizations are urged to invest in AI technologies that align with specific business objectives and operational needs. This strategic integration is crucial for ensuring that AI capabilities are not only present, but also effectively contribute to decision-making processes and, subsequently, business performance. Furthermore, this study highlights the importance of training and skill development for employees to fully harness AI capabilities. This resonates with the literature that emphasizes the human aspects of technology adoption and implementation. The effective utilization of AI tools and the interpretation of insights generated by AI systems require a skilled and knowledgeable workforce, aligning with the broader discourse on the role of human capital in organizational success [4], [11].

The emphasis on fostering an agile decision-making culture within organizations aligns with the literature advocating organizational agility in dynamic environments [46], [47]. Organizations are encouraged not only to possess advanced AI capabilities but also to create an environment that values and facilitates timely decision making. This cultural shift is crucial for realizing the full potential of AI capabilities in achieving business objectives and maintaining competitiveness [9].

This study acknowledges certain limitations, such as a relatively low response rate and a specific focus on companies within certain regions and industries. This limitation aligns with the broader challenges in survey research, where response rates can be influenced by various factors, including the busy schedules of top management. Future research could address this limitation by exploring a more diverse sample encompassing a broader range of industries and global regions to enhance the generalizability of the findings.

CONCLUSION

This study illuminates the pivotal role of AI capabilities in shaping timely decision making and influencing business performance. Grounded in RBV theory, the findings underscore the transformative impact of AI, emphasizing its strategic significance as a catalyst for agile decision-making and organizational success in the era of emerging technologies.

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