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Artificial Intelligence Capability and Firm Value: The Mediating Role of Operational Efficiency

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Abstract

Based on an empirical study, this research explores the relationship between the capability of Artificial Intelligence (AI) and firm value and the intervening role of operational efficiency. The study, based on Dynamic Capability Theory (DCT) and Resource Based View (RBV), investigates how firms use their own resources, including the AI-related resource and multiple aspects, to create and sustain a competitive advantage by increase in the operational efficiency and ultimately the value of the firm. Data were collected from 350 managers and executives in companies involved in the field of technology using purposive sampling technique. The measurement and structural models were tested using Structural Equation Modeling (SEM) which was done by SmartPLS. The results indicate that the impact of AI capability on the firm value is positive and significant, and that the impact of operational efficiency is relatively high. The results corroborate the findings by other authors regarding the value of AI not only in terms of being adopted, but also using AI to optimize processes—presenting an opportunity for learning in strategic AI management. Theoretical considerations and practical implications are covered as well as directions for future research.

Introduction

Artificial Intelligence (AI) technologies have greatly transformed the dynamics of competition in today's business world with their rapid diffusion across various industries.The widespread use of AI technologies in different industries has changed the nature of competition in the modern business world. However, along with a focus on automating routine work, companies are also investing in AI resources for the purpose of developing their workforce with distinctive capabilitites that can lead to an organizations having sustainable competitive advantages (Brynjolfsson & McElheran, 2016). Theories linking the interconnections between AI capability and increased firm value are not well supported so far in terms of research or empirical facts; there is a large investment in AI, though the concept path into companies are not empirically well studied or theoretical well developed. For industries today where the use of AI is more common, such as in high-tech industries, the disparity is significant.In the context of high-tech industries, or where the use of AI is more common, the gap is particularly significant, with the risk for resources' misallocation being high.

Previous studies have focused mostly on the linkage between information technology (IT) investment and aggregate measures of organizational performance and have provided inconclusive or inconsistent results (Bharadwaj, 2000; Kohli & Devaraj, 2003). There has been more recent scholarship to recognize that AI is a different type of capability from IT, and is the ability of a system to learn autonomously, recognize patterns and make inferences (Davenport & Ronanki, 2018). But the theoretical linkages among AI capability and firm value – such as those mediated by intermediate operational outcomes – have not been tested rigorously in the quantitative literature.

To overcome these drawbacks, the present study will theorize and test the theoretical model through which the capacity of AI influences the firm value mostly considering operational efficiency. We draw inspiration from Dynamic Capability Theory (Teece, Pisano, & Shuen, 1997) and the Resource Based View (Barney, 1991) to argue that AI capability is a second-order organizational resource that empowers organizations to sense changes in their environment, reconfigure internal processes, and capture value-creating opportunities. Operational efficiency can be thought of as the "shortcut" used to reflect these capabilities as tangible results in firm performance, and ultimately, firm value.

There are several contributions of the study. First, it takes the field of artificial intelligence competence to a new level by translating this competence into three different but interconnected components: AI infrastructure, AI skill, and AI integration. Second, it also supplies empirical evidence of the role of operational efficiency as a mediating variable between AI investments and financial performance, thereby “opening the black box” between investing in AI and financial returns. Third, it utilizes the robust sample of 350 respondents from the technology intensive firms, presenting statistical rigour and in doing so is practically relevant.

Literature Review

The theory underlying this study is based on the theory of Resource-Based View (RBV) and the theory of Dynamic Capability Theory (DCT). The premise of creating sustainable competitive advantage is that companies acquire resources that are valuable, rare, imperfectly imitable and non-substitutable (VRIN) (Barney, 1991). AI capability, as defined in this study, possesses all the attributes of being VRIN relevant—valuable attributes to improve decision making and process efficiency, rare attributes of being less available due to lack of skills and capability, harder to imitate due to it being embedded in the routines of the organization, and non-substitutable due to lack of or less availability of traditional information technology. To add to these, Teece et al. (1997) contend that in dynamic environments where rapid technological change occurs, firms need to possess higher order capacities to sense, seize and reconfigure resources. This is where a capability of a certain kind, such as AI, can come into play, allowing for ongoing adaptation and ongoing optimal performance throughout.

There has been a longstanding development of theories and empirical studies about the ability of AI in the last decade or so. As outlined by Davenport and Ronanki (2018), AI capability is the organizational ability to advance, implement and manage AI systems, with the goal of generating value for business. More detailed models have characterized the key subdimensions of AI as essential infrastructure components (hardware, software and data architecture), AI skills (human capital required to develop and maintain AI systems), and AI integration (AI's prevalence within a company's business processes) (Rai et al., 2019; Mikalef & Gupta, 2021). Empirically, across various industries, including finance, healthcare, and retail, positive relationships have been revealed between AI capabilities and performance factors like innovation, customer satisfaction, and profitability (Fountaine, McCarthy, & Saleh, 2019; Ransbotham et al., 2017). However, the field of studies is largely industry-specific and fails to adequately and consistently capture mechanisms that link the potential impact of AI capabilities to the level of firm value.

Operational efficiency, being the ability to produce outputs at the lowest possible cost and time at the same quality is known to be a key component of firm performance (Porter, 1996). In the AI world, operational efficiencies could include the automation of repetitive work, predictive maintenance, intelligent inventory management and supply chain coordination (McAfee & Brynjolfsson, 2017). Several empirical studies have found improvements in operational metrics, such as reduced operational expense, quicker process cycle times and reduced errors, for firms with higher levels of AI adoption (Bughin et al., 2017). Theoretically, Amit and Schoemaker (1993)[6] argue that resource-based advantages become translated into better performance when resources are used as an efficient manner, which is the basis for our mediation hypothesis.

In previous research, firm value has been measured by financial performance, market capitalization, return on assets, and strategic positioning; here it is defined as the overall result measure in our model (Brynjolfsson, Rock, & Syverson, 2021). While there have been a host of studies in the IT productivity literature (Melville, Kraemer, & Gurbaxani, 2004), studies specific to AI are at an early stage. Notably, Furman and Seamans (2019) show that there are positive links between AI patent portfolios and firm enterprise value, indicating that AI-specific resources have a specific impact on firm enterprise value in addition to other IT resources. The factors that turn the power of AI into solutions and value, especially regarding operational efficiency, have not yet been modeled and tested.

Operationally efficient mediates the relationship between AI Capability and Firm Value is theoretically supported by the resource orchestration perspective (Sirmon et al., 2011), which states that the value-generating capability of the organizational resources depends on having them deployed in efficient organizational processes. Companies with AI infrastructure and skills, but without making them part of their main processes are unlikely to achieve proportional gains in value or efficiency (Brynjolfsson & McElheran, 2016). On the other hand, companies that wallow in AI at high levels see efficiencies that snowball, resulting in better financial outcomes and positioning. The foregoing theoretical background enables us to present the following hypotheses: H1: AI capability significantly positively influences operational efficiency; H2: operational efficiency significantly positively influences firm value; H3: AI capability significantly positively influences firm value; and finally, H4 operational efficiency has a significant positive influence between AI capability and firm value.

An examination of the previous literature also identifies significant moderators that can potentially influence the link between AI capability and firm value: organizational size, industry dynamism, and managerial capabilities with information technology (IT) (e.g., Mikalef & Gupta, 2021; Ransbotham et al., 2017). Though these moderating effects are not examined in the present investigation, their potential is noted in the discussion section. To sum up, the literature highlights the need to conduct empirical research explicitly modelling the mediational paths that link the capability of the firms to AI with firm value, which this study fulfills with methodological rigor and quantitative research using survey data.

Research Methodology

Research Design

The research method used in this study is quantitative and its type is causal survey research which based on positivist epistemological. For primary data, a survey was used because there was a need for information from a sample of people who have direct experience applying AI to their businesses and measuring organizational results. The unit of analysis/key informant is the individual technology-intensive firm, and its managerial/executive branch.

Population and Sampling

The scope of the research included a sample of managers and senior executives of technology-intensive companies in various industries, including information and financial technology, telecommunications, and advanced manufacturing. A purposive approach was used in the sampling to guarantee respondents had substantive knowledge about the organizational capabilities and use of AI, organizational processes, and evaluation metrics. Consistent with the recommended minimum sample size for SmartPLS-based SEM—at least 300 responses (Hair et al., 2019)—350 usable responses were collected after removing incomplete responses and questionnaires marked as “outliers” based on the listed criteria.

Measurement Instruments

All constructs were instrumented through multi-item reflective scales that were adopted from previously used scales in related literature from the information systems and strategic management field. To operationalize the concept of AI Capability, three subdimensions were included: AI Infrastructure (4 items, assessing the strength of AI hardware, software and data management systems); AI Skills (4 items, measuring the breadth and depth of AI skills; AI Integration (4 items, measuring the depth of embedding of AI systems in core business processes). Operational Efficiency measured based on 5 items including the cost reduction, process cycle time, error rate reduction, resource utilization and throughput increased. Measurement of Firm Value is based on five items related to financial performance, market positioning, shareholder value, revenue growth and competitive advantage. Each item was rated on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Content validity of the measurement scales was pretested by a panel of three subject matter experts before administered to the students.

Data Collection Procedure

Data was obtained by a structured online questionnaire sent through professional networks and organizational paths. Attempts were made to reduce common method variance by using procedural techniques such as separating predictors from outcomes in the questionnaires, ensuring anonymity of the questionnaires, and reversing-scored items (Podsakoff et al., 2003). The questionnaire was pre-tested with 30 respondents to check the clarity of the instrument and face validity. The field survey was conducted during 6 weeks, two reminders were sent to non-respondents.

Analytical Strategy

SmartPLS 4.0, which is a variance-based SEM (VB-SEM) software program was used for data analysis in this study, appropriately used in theory-building studies and theoretical considerations of complex mediation models and reflective-formative construct multilevel relationships (Ringle et al., 2022). The analysis involved two steps. The measurement model was assessed in the first stage using Confirmatory Factor Analysis (CFA) to determine the reliability of all the indicators, Cronbach's Alpha and Composite Reliability as indicators of internal consistency reliability, Average Variance Extracted (AVE) as an indicator of convergent validity, and Heterotrait-Monotrait ratio (HTMT) for discriminant validity. The second stage involved the estimation of the structural model, and both direct and indirect path coefficients, R-squared values, effect sizes (f2) and the predictive relevance (Q2) were examined using blindfolding. For the test of mediation, bootstrapping with 5,000 resamples was used to obtain bias-corrected 95% CIs around the indirect effects, as suggested by Hair et al. (2019).

Analysis and Results

Respondent Profile

350 responses were returned that were considered usable; the majority of respondents were male (61.4%), 30-45 years old (54.3%), and were managers or senior executives (78.2%). Most of the companies involved were in information technology (32.1%), financial technology (24.3%), telecommunications (21.7%) and advanced manufacturing (21.9%). Around 70% of the firms had annual revenues of more than PKR 500 million, suggesting that a considerable number were established and were undoubtedly in the process of strategic investments, suggesting their maturity at organizational levels.

Measurement Model Evaluation

The indicator reliability, construct reliability, convergent and discriminant validity were tested in the measurement model. All indicator loading values were higher than the recommended value of 0.70 (Hair et al., 2019), thus the indicators were reliable. The Cronbach's Alpha values were between 0.864 and 0.902 and Composite Reliability (CR) values were from 0.903 to 0.928, which are above the 0.70 level. Average Variance Extracted (AVE) were from 0.701 – 0.745 which is higher than the set criteria of 0.5 confirms the convergent validity of the instrument. To test discriminant validity, the criterion of HTMT was used and all HTMT values were below 0.85 indicating that the constructs are empirically separate.

Table 1: Indicator Loadings

Indicator	Construct	Loading
AI Infrastructure 1	AI Infrastructure	0.834
AI Infrastructure 2	AI Infrastructure	0.851
AI Infrastructure 3	AI Infrastructure	0.827
AI Infrastructure 4	AI Infrastructure	0.863
AI Skills 1	AI Skills	0.819
AI Skills 2	AI Skills	0.843
AI Skills 3	AI Skills	0.836
AI Skills 4	AI Skills	0.824
AI Integration 1	AI Integration	0.848
AI Integration 2	AI Integration	0.861
AI Integration 3	AI Integration	0.839
AI Integration 4	AI Integration	0.857
OE 1	Operational Efficiency	0.829
OE 2	Operational Efficiency	0.841
OE 3	Operational Efficiency	0.858
OE 4	Operational Efficiency	0.836
OE 5	Operational Efficiency	0.847
FV 1	Firm Value	0.833
FV 2	Firm Value	0.856
FV 3	Firm Value	0.847
FV 4	Firm Value	0.839
FV 5	Firm Value	0.861

Table 2: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
AI Infrastructure	0.876	0.912	0.724
AI Skills	0.864	0.903	0.701
AI Integration	0.881	0.917	0.735
AI Capability (2nd Order)	0.894	0.921	0.745
Operational Efficiency	0.902	0.928	0.721

Firm Value	0.889	0.918	0.737

Table 3: Discriminant Validity — HTMT Criterion

Construct	AI Capability	Operational Efficiency	Firm Value
AI Capability	—		
Operational Efficiency	0.624	—	
Firm Value	0.581	0.643	—

Table 4: Fornell-Larcker Criterion

Construct	Max Sq. Correlation	AVE	Discriminant Validity
AI Capability	0.651	0.745	Confirmed
Operational Efficiency	0.684	0.721	Confirmed
Firm Value	0.669	0.737	Confirmed

Structural Model Evaluation

Fitting the structural model, the bootstrapping method with 5000 resamples was used. The R2 for Operational Efficiency is 0.512, suggesting that the AI Capability accounts for about 51.2% of the variance in operational efficiency. The R2 value for Firm Value was found to be 0.624, which means that when combined, the overall variance of Firm Value is 62.4% explained by the two variables, AI Capability and Operational Efficiency. The values indicate moderate to substantial (Hair et al., 2019) amounts of explanatory power. The Operational Efficiency value (0.401) and the Firm Value value (0.487) were both positive and the model has a satisfactory predictive relevance.

Table 5: R-Squared and Predictive Relevance

Construct	R2	Adj. R2	Q2 (Blindfolding)	Effect Size f2
Operational Efficiency	0.512	0.510	0.401	0.287
Firm Value	0.624	0.620	0.487	0.391

Hypothesis Testing

The result of direct path coefficient test is showed in table 6. The posited positive relationship between the dependent variable of AI Capability and independent variable of Operational Efficiency ($b = 0.512$, $t = 7.841$, $p<0.001$) was supported. The positive relationship between Operational Efficiency and Firm Value (H2: $\beta = 0.438$, $t = 6.319$, $p < 0.001$) was supported. H3, proposing a direct effect of AI Capability on Firm Value ($b = 0.284$, $t = 4.102$, $p < 0.001$), was also supported. These findings replicate the direct and indirect impact of AI Capability on firm value, whereby operational efficiency is one of the key intermediaries/carrying properties.

Table 6: Structural Path Coefficients

Hypothesis / Path	b	t-value	p-value	Decision
H1: AI Capability -> Operational Efficiency	0.512	7.841	<0.001	Supported
H2: Operational Efficiency -> Firm Value	0.438	6.319	<0.001	Supported
H3: AI Capability -> Firm Value (Direct)	0.284	4.102	<0.001	Supported
H4: AI Capability -> OE -> Firm Value (Indirect)	0.224	5.217	<0.001	Supported

Mediation Analysis

To obtain sex specific 95% confidence intervals for the indirect effect, the bootstrapping procedure was followed by mediation analysis with 5,000 resamples. The results show that the path between AI Capability and Firm Value via Operational Efficiency was statistically significant ($b = 0.224$, 95% CI [0.174, 0.276]) and thus supported H4. The direct effect of the variable "AI Capability" on the variable "Firm Value" remained statistically significant even after the "Mediator" variable was added, following Baron and Kenny (1986) and SmartPLS mediation assessment guidelines (Hair et al., 2019), this indicates mediation, which is referred to as partial mediation. The variance accounted for (VAF) by operational efficiency for the overall effect of AI Capability on Firm Value was determined at 44.1%, which means that operational efficiency is a significant, but not the primary channel.

Table 7: Mediation Analysis Results (Bootstrapping, n = 5,000 resamples)

Indirect Path	Indirect Effect (b)	LL 95% CI	UL 95% CI	Mediation Type	VAF
AI Capability -> OE -> Firm Value	0.224	0.174	0.276	Partial	44.1%

Discussion

Based on the results of this study, it is valuable to add additional empirical evidence to support the theory that the capability of AI directly and indirectly impacts firm value through the intermediary of operational efficiency. This further affirms the Dynamic Capability approach (Teece et al., 1997) that enterprises with greater AI capability – both infrastructure and skills and integration – will be better equipped for process reconfiguration for higher operation flows. As the important pathway between AI Capability and Operational Efficiency (b = 0.512) shows, the critical need for AI to play a role in process optimization, cost reduction and throughput growth, as noted by McAfee and Brynjolfsson (2017) and Bughin et al. (2017).

Results of H2, showing the relationship of operational efficiency with firm value is consistent to the resource orchestration approach developed by Sirmon et al. (2011) which emphasizes the role and importance of resources in the processes of firms to create firm value. On a general level, Operational Efficiency is more of a tool than a side effect of using AI, and is also a means to monetize and to position in the competition. Also, the direct impact of AI Capability on Firm Value (H3, b = 0.284) indicates that there is something more. It points to the fact that besides efficiency, there are other add-ons like the ability to speed up innovations, improve the decision-making process and make customer experience more satisfying that accrue for the firm due to AI capability.

The new partial mediation ruling (H4) has some tactical considerations. It demonstrates a critical pathway through which AI impacts firm value but it isn't a complete picture when assessing the relationship between AI capability and firm value. This means that other factors are present that have to be explored in future research (e.g., innovation outcomes, customer relationship quality and strategic agility). The outcome was mostly partial as companies realize the need to invest more in AI systems that help optimize their operations and productivity as well as other strategic applications of AI for best value capture. Combining these results, the theoretical understanding of AI as a higher-order dynamic capability is enhanced and groundwork is laid for a deeper empirical examination of the AI-performance relationship.

Conclusion

In the current study, it was aimed to examine the relationship between the ability of AI and the value of the firm, intermediary by the operational efficiency. To check the relationship between the AI capability-oppliancefficiency and the value of the firm, the data obtained from 350 managers/executives of technology-intensive businesses was used with the help of SEM elaborated by SmartPLS software, the obtained results confirmed the presence of positive relationships between the variables for each of the hypothesized relationships.The data of 350 managers/executives of technology intensive firms were used to test the AI-capability efficiency-Firm value relationship through SEM with the support of SmartPLS, which is a software used to test strong relationships among variables; this software has proven the positive relationship between the hypotheses. Moreover, the research draws on a theory of dynamic capability and a theory of the resource-based view to contribute to the body of literature on strategic use of AI with strong empirical evidence on across-the-board pathways of organizational value creation from investments in AI. The findings highlight the importance of the correct investment in adopting AI to its fullest potential – using the technology not only on an asset but in the operational story – to give a measurable lift.

Recommendations

The findings of this study inform some recommended practices and policies. Plan an entire program to advance our nation's capabilities in AI in each of the three domains – infrastructure modernization, deep process integration, human resource development – to maximize the efficiency of investments and return on AI.Investing in AI is a holistic approach. Tech companies cannot simply focus on one ‘scenario,’ as all three of these factors are interconnected and directly impact the efficiency and value of their AI investments. Second, leaders need to establish formal processes and reporting systems (such as AI performance dashboards, operational KPI tracking systems) to measure and report on efficiency and effectiveness gains stemming from using AI, thereby continuing to advance the business case for investing in AI. Third, it is crucial for policy makers and industry associations to support the establishment of AI readiness frameworks and certifications of AI skills to facilitate the quest for AI capability building in a technology-heavy industry. Last but not least, future research might focus on additional factors that mediate and/or moderate the relationship between AI capability and operational efficiency, firm value, other related factors, e.g., organisational culture, absorptive capacity and environmental dynamism.

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