Framework for Measuring the Impact of a Firm's Artificial Intelligence Capability on Creativity within the Organizational and Performance of the Firm

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DOI: https://doi.org/10.30212/JITI.202503.005

Submitted: Dec. 09, 2024 Accepted: Mar. 09, 2025

ABSTRACT

Artificial Intelligence (AI) may benefit businesses in the future. This study (1) identifies AI-specific resources, (2) develops a framework for measuring AI capabilities in enterprises, and (3) examines how AI capabilities affect organizational creativity and productivity. Recent research on organizational artificial intelligence, coupled with a firm's resource-based approach, strengthens this foundation. The findings confirm the theoretical framework and instrument, showing that AI capability boosts organizational performance and innovation. Our solution organizes the AI development resources of a company. These questions center on artificial intelligence (AI), knowledge, and intangible assets, although many structures and technologies leverage various digital capabilities. We evaluate artificial intelligence and its business applications literature by applying new methods and altering old ones. This empirical study proved the reliability, validity, and generalizability of the AI capacity concept as well as its main components and properties. The IS community can analyze and communicate how a company uses AI to achieve its business goals. We demonstrate how artificial intelligence affects organizational performance. Researchers have also focused on business productivity and innovation. An extensive study reveals that the adoption and utilization of AI in enterprises significantly impacts critical results. To the best of our knowledge, no empirical research has linked theoretical AI concepts to key business KPIs. According to our research, AI proficiency boosts organizational performance and creativity. This study emphasizes the importance of integrating AI throughout a firm because data and technology alone cannot produce meaningful business benefits.

Keywords: Artificial Intelligence , Technology, Resource Based Theory, Risk Propensity, Organizational Change, Interdepartmental Coordination

1. Introduction

Although not new, artificial intelligence (AI) has recently received considerable attention.

According to, artificial intelligence has the potential to disrupt numerous organizations around the world, expecting firms using AI technology to reap additional economic benefits such as increased income, lower costs, and higher operational efficiency. According to a recent MIT Sloan Management Review survey), over 85% of organizations see AI as a way to gain a competitive edge, while more than 80% see AI as a strategic opportunity. More organizations are investing in AI technologies to gain a competitive advantage [1]. Despite growing interest in AI, many companies still struggle to reap their benefits. According to, companies may devote resources (time, energy, and capital) to AI adoption without knowing whether they will reap rewards. The incorporation of AI into organizational processes introduces additional challenges and difficulties. Developing exact and relevant models requires the integration of cross-domain information, including data source identification, amalgamation, and purification [2]. To fully realize the benefits of AI, businesses must understand how these technologies can provide value and overcome associated challenges. However, modern AI research prioritizes the technical aspects of AI adoption by addressing organizational barriers to its implementation. Some studies have identified research gaps and examined the important factors in the use of AI technologies [3].

Artificial intelligence (AI) has become a main technological goal for organizations in recent years owing to the availability of vast amounts of data and the growth of complex procedures and infrastructure. According to a recent Gartner survey, the number of organizations that use AI has steadily increased, tripling in the last year and increasing by 270% over previous years [4]. Despite the excitement surrounding the potential economic benefits of AI, organizations face various challenges that impede their capacity to improve their performance with AI solutions [5]. In the MIT Sloan Management Review's 2019 survey of global CEOs, 70% of the companies asserted that AI had minimal to no influence on their financial performance. Brynjolfsson et al. Lucia-Palacios, Bordonaba-Juste [6] emphasize that we are currently facing a productivity quandary, regardless of the possibilities of AI technology. According to the authors, delays in implementation and reorganization are the key causes of unsatisfactory AI performance. To obtain the most out of their AI investments, organizations must invest in complementary resources. Identifying and implementing additional resources is crucial for achieving the performance benefits of AI. It is time to examine how organizations build their AI competencies [7].

Businesses can improve their competitiveness by building distinct, difficult-to-duplicate talents through the integration and application of many complementary firm-level resources, as suggested by IS literature [8]. This study explores AI technology as an important but insufficient component of the growth of AI capabilities, drawing on previous research in this area. This suggests that AI techniques are unlikely to provide major competitive advantages on their own, because of their marketability and potential for replication. Furthermore, these systems cannot generate unique AI features solely from the data that supports them. According to preliminary research from companies that have employed AI, organizations require a unique combination of organizational, human, and physical resources to establish an AI capability that enhances their competitive advantage [9]. Despite the rise in popular news articles, largely written by technology consultants and vendors, emphasizing critical issues that organizations must consider while developing AI capabilities, there is a scarcity of theoretically grounded information on the implementation process.

We propose the concept of AI competency by combining previous literature on IT capabilities with current research on AI in the workplace. A large body of research in information systems aims to understand the causes and consequences of diverse IT capabilities, such as social media capabilities [10], social commerce capabilities [11], and business analytics capabilities [12]. Organizations must, like with any new technology, cultivate a specialized set of resources in order to efficiently optimize their investments and reap economic benefits. Based on the findings of these and other recent studies on AI in business contexts, we divided various resource types into three categories: tangible, human skills, and intangible. This study not only assesses these resources, but also proposes a survey approach for assessing an organization's AI capacity. We consulted management information systems (MIS) literature and followed their suggestions for scale development [7]. Rather than focusing on the overarching notion of artificial intelligence (AI), the following definition strives to capture the approaches used to attain the goals described in the previous definitions. The current study reveals a variety of approaches to achieve this goal, with a focus on scenarios incorporating deep learning and machine learning applications. Among several domains of AI, machine learning has recently emerged as the most popular approach. This section will look at the literature's definitions of common AI technology categories, compare and contrast their essential traits, and outline their strengths in practical applications.

We performed a detailed survey of 98 senior technology managers familiar with AI initiatives in their organizations to assess the psychometric properties of each measure. Following validation of the measures by an expert panel, we used this information to guide our analysis. To determine the nomological validity of the AI skill scale, we linked it to innovation and organizational success. The Resource-Based Theory (RBT) is one of the most frequently used theoretical frameworks to explain differences in performance among companies in the same market [13].

2. Literature Review

2.1 The Resource-Based Theory (RBT)

RBT, which is based on strategic management literature, states that companies compete based on their resources [14]. These resources may be important, unique, difficult to replicate, or irreplaceable and can help improve performance. Thus, the framework separates and interconnects the resource selection and capacity development components of the RBT. Peteraf [15] and Verona [16] defined resources as a corporation's marketable and non-specific assets, while capabilities are non-transferable firm-specific competencies that facilitate the integration, deployment, and utilization of resources within the business. Competence is the capacity to make the best use of existing resources to boost productivity and income. Embracing this approach implies the unstated assumption that an organization's capabilities depend on and stem from its available resources. As a result, a company's capability strength is proportional to the resources it uses to create it [17]. Resource-Based Theory (RBT) is an important theoretical framework for understanding how investments in information technology (IT) add value and help organizations improve their performance [18]. This theoretical perspective is relevant to our study's setting, as selecting appropriate AI resources for organizations is critical for maximizing investment returns. As previous RBT research has shown, maximizing investment requires more than just technology.

This includes both human and organizational resources. RBT provides consistent reasoning for the relationship between organizational resources and corporate success, as demonstrated by these and other empirical findings from earlier research [19, 20]. Several MIS studies have used Resource-Based Theory (RBT) to examine the potential influence of information technology and more resources on performance gains. Pugliese and Minichilli [21] assert that RBT enables researchers to formulate testable hypotheses, which they can subsequently assess to gain an understanding of the importance of different IT resources and their influence on organizational performance. Wade and Hulland [22] argue that the Resource-Based Theory (RBT) provides a solid framework for determining the strategic value of resources in an information system. RBT's widespread application beyond marketing, supply chain management, and operations management demonstrates its importance in understanding organizational phenomena [23-26] among others. With over 30 years of empirical validation, RBT has emerged as an ideal framework for developing theoretical arguments and conducting experiments to evaluate the impact of organizational resources on business performance. Resource complementarity and the development of unique hard-to-copy skills have long been linked to competitive success.

2.2 Role of Artificial intelligence in Business

Scholars have proposed several definitions of artificial intelligence to distinguish it from traditional information technology. To grasp the concept of AI, one must first independently define AI and “artificial intelligence” and “intelligence.” The cognitive processes that comprise "intelligence" include learning, thinking, and comprehension [27]. In contrast, anything that does not exist naturally but is made by humans is considered "artificial" [28]. These two ideas form the cornerstone of artificial intelligence, which is defined as the ability of robots to perform tasks commonly associated with human intelligence (). Research suggests that artificial intelligence (AI) entails programming a machine to mimic human thought and behavior. This indicates that it can execute activities that normally require human intelligence. According to), these activities include understanding, cognition, and problem-solving [29]. Artificial intelligence (AI) can mimic human performance by acting as an intelligent agent that evaluates and responds to environmental stimuli based on a predetermined understanding of the input [30].

AI aims to create machines capable of learning and interpreting data in a manner similar to human cognition. Cognitive technology is a common aspect of this type of capability. Computers equipped with cognitive technologies can mimic human cognition and behavior. Some researchers argue that AI does not require explicit programming to execute intelligent activities [31]. According to Pacelli, Bevilacqua [32], AI should be capable of detecting, interpreting, learning, planning, understanding, and autonomous action. This necessitates accurate data interpretation, learning, and the adaptive application of that learning to complete specified activities and achieve specific goals.

The goal is to accomplish this without following specific criteria or conventions[33]. Furthermore, can be defined in two ways. Zarkadakis [34] argued that AI can address jobs that humans may find excessively time-consuming or impractical. The second set of qualities defines AI as a system capable of learning, interpreting, and inferring in the same way as humans.

There are two perspectives on artificial intelligence: one perceives it as a tool that is incapable of fully reproducing human capabilities, and the other says that AI can completely replicate human behavior [35]. There is a clear divide in viewpoints, with some sources classifying artificial intelligence as a scientific subject [36], while others define it as a system or computer's practical competence. The breadth and depth of artificial intelligence are defined differently, and the essential assumptions and differences between the two are clear. Artificial intelligence (AI) is a practical field that enables computers to recognize, evaluate, infer, and learn from data. Companies and society use it to achieve specific goals [36].

The rapid increase in the use of big data and advances in computer capacity have contributed significantly to the recent rise in interest in machine learning [37]. Machine learning aims to train computers to study data, make predictions, and detect patterns that can inform their decisions [38]. Machine learning, which includes algorithms capable of analyzing data, drawing conclusions, and applying obtained information, is a critical component of this process [39]. This inductive technique uses statistical approaches to generate decision rules from collected data [38]. There are four categories of machine learning algorithms: supervised, semi-supervised, unsupervised, and reinforcement learning [40]. In supervised learning, the goal value is a part of the training data. The system then identifies patterns in the training data and creates its own rules using the labeled data [41]. However, the training set for the unsupervised learning technique lacks a goal value. To address this issue, the system must assess the structure and statistical properties of the training data [42]. Automatic clustering, anomaly detection, and association mining, among other applications, widely use unsupervised learning to uncover previously unknown patterns in the datasets.

According to Miklosik and Evans [41], historical data do not support reinforcement learning. Instead, it promotes data acquisition through interactions with the real world. A human agent provides a goal to the system and then compensates for it based on how effectively it achieves that goal. This goal-achieving process involves determining the best course of action [43]. Typically, we divide machine learning into two categories: "shallow" and "deep." All four training types were useful for machine learning, whether deep or shallow. The most common type of architecture is shallow, which uses predetermined features to represent the data [44].

2.3 Domains of Expertise in AI

Earlier definitions of AI focused on its broad goals and the approaches used to attain them. However, today's understanding of AI capabilities stresses an organization's ability to deploy AI applications to improve operations [45]. Kobbacy and Vadera [46] demonstrated the growing literature on the potential of artificial intelligence (AI) technology and approaches to help businesses achieve their objectives. The establishment of an AI competency elucidated the realization of this value and structuring strategies that organizations might employ to optimize their AI investments [47].

While there are not many research studies examining AI through the lens of organizational capacity, the literature on the subject is expanding. Although there are slight differences, all definitions consider the goals that a firm hopes to achieve through AI investments; some go into greater detail regarding the expected outcomes of deploying AI capabilities [48].Dahlin [11] define AI capabilities as "the ability of organizations to utilize data, methods, processes, and personnel in a manner that generates new opportunities for automation, decision-making, collaboration, etc., unattainable through conventional means."

This concept encompasses not only the requisite knowledge and tools for AI development and implementation but also the personnel and systems engaged in the process. Alternative definitions include the additional resources needed to capitalize on AI technology, as mentioned in [49]. All definitions () agree that AI capability refers to a company's use of AI-specific resources to create value. Both technical and non-technical resources, such as human talent [50] and training data [47], are AI specific. As a result, AI is now more widely defined by the concept of AI capability, which includes both the technical and organizational resources required to fully realize AI's strategic potential emphasized the importance of data quality in AI training. Using detailed data is critical for accurate forecasts [51]. According to the "garbage-in, garbage-out" paradigm of artificial intelligence, insights gained by an AI system using poor training data will be of little value in a practical commercial scenario[52]. Difficulties in data quality commonly include missing information, incorrect entries, and unnecessary features. However, these quality flaws are difficult to identify. Data scientists and domain specialists must work closely to identify data-quality issues [47].

Another important aspect of quality is the use of data that is objective and that complies with dependable and ethical guidelines. Multiple potential entry points for bias existed in the data used, including the generation, collection, and processing stages. () offer detailed guidelines for identifying bias, minimizing its impacts, and correcting it to avoid negative consequences. Bias is not only visible during data collection; it also occurs during annotation, which gives meaning to the data (). Empirical research has show that data features are complex and critical to the growth of AI applications.

The concept of automating tasks previously conducted exclusively by humans, such as assembly line robotics, is not new and has been around for a long time. We define AI-driven automation in this manner, yet the significant transformations they have ushered in are not new. Advances in artificial intelligence have enabled robots to learn and improve their skills, indicating potential future performance [53]. Thus, AI can automate more complex cognitive processes such as learning and problem solving. [46] refers to this type of automation as an intelligent automation. Intelligent automation has made it possible to automate thought-to-be-too complex services and cognitive processes. The industry uses artificial intelligence to automate construction and industrial tasks, including planning, budgeting, inventory management, and restocking. AI, through the provision of digital and robotic services, has the potential to influence the user experience in service environments. Chatbots, which are software systems meant to emulate human conversational skills, are an excellent example [54-57].

Chatbots facilitate customer access to services through speech or text interfaces. Credit card insurance carriers use chatbots to market products, manage claims, address commonly asked questions, and ensure consumer coverage. Chatbots are gradually replacing human workers. AI can automate previously manual company processes and provide new or improved products and services that optimize customer operations. Conversational intelligent agents such as Apple's Alexa and Amazon's Siri exemplify this strategy. In response to verbal commands, these agents may automate tasks such as messaging, calling, and playing music. Furthermore, by integrating these agents with platforms like Raspberry Pi and Arduino, we can use voice commands to control smart home gadgets [57]. This technology allows for the automation of common household tasks, such as controlling the lights and television. Another example is the usage of facial recognition technology on cell phones, which enables automated user authentication. It is crucial to prioritize the development of new organizational resources and the AI-specific technology that will support projects. These additional organizational resources are critical for developing unique AI skills that are difficult to replicate [58].

A company's AI competency is defined by its capacity to successfully identify, coordinate, and deploy AI-specific resources. To optimize the value of your AI efforts, one must acquire the complementary resources identified by [1]. According to the Ransbotham, Kiron [59], insufficient leadership to advocate for AI is a significant barrier to value creation, despite finding that more than one-third of managers in the examined firms lack understanding of AI technologies and their functionalities. Several studies based on real-world scenarios have highlighted the importance of these additional resources. Martini, Bellisario [60] emphasize the importance of fostering interdepartmental communication and forming cross-functional teams consisting of individuals with diverse perspectives and competencies. Collaboration with analytics specialists, as well as business and operational personnel, allows companies to ensure that AI initiatives serve overall corporate goals rather than just specific business concerns. Furthermore, it will ensure that the produced AI applications are more tailored to practical needs. The development of AI-specific knowledge is a substantial hurdle, as emphasized by multiple studies [61-64], because engaging with AI demands an altogether new skill set for both technical and management workers. Several scholarly journals have already published our analysis of the research.

An individual with "technical AI skills" may manage the infrastructure supporting AI projects, create, test, and deploy AI algorithms, and ensure that AI applications accomplish their goals. Algorithm developers must use advanced AI research to create reproducible approaches based on mathematical formulas that work in both software and hardware. According to reports, the bulk of technical tasks in AI require extensive knowledge in mathematics, algebra, logic, Bayesian algorithms, statistics, and probability. A strong understanding of programming, logic, data structures, language processing, and cognitive learning theory is required for basic technical competence in artificial intelligence [65, 66]. According to a recent article in the MIT Sloan Management Review, in the age of artificial intelligence, the three main professions that will assume technology characteristics are trainers, explainers, and sustainers [67] . Training artificial intelligence systems requires assigning them tasks such as teaching customer service chatbots to understand complicated human language. Explainers link technology and business management by educating non-technical audiences on the use of AI technologies. Finally, the maintainers bear the responsibility of ensuring the smooth operation of AI systems and promptly addressing any unexpected consequences [68, 69].

Each of these three roles entails a set of increasingly important responsibilities that modern businesses cannot ignore. Although there may be a scarcity of people with these abilities right now, many believe that as online training programs and institutions grow, they will become commodities for organizations [70]. People frequently criticize managers for their poor grasp of the appropriate uses and implementation of AI technology in the workplace [71]. According to poll in the MIT Sloan Management Review revealed that senior management's insufficient support for AI efforts significantly hinders AI implementation. To maximize AI investments, executives must properly understand the concept and be willing to make major adjustments. Managers must also be familiar with the many applications of AI in order to properly oversee the transition to AI-enabled tasks [72]. David and R. formed a stunning realization. Carpanzano and Knüttel [73] claims that one-third of managers have an incorrect grasp of the complexities of AI. Managers must be familiar with the various types of artificial intelligence and its possible uses in a variety of corporate functions. Another important consideration is managers' ability to prepare for AI implementation [73]. Given the tremendous internal organizational factors that oppose change and the potential for AI to succeed it, this issue becomes increasingly important.

In uncertain and unpredictable markets, competitors view intangible assets as the most important of the three types of organizational resources outlined in the Resource-Based Theory (RBT) [13]. Organizations view intangible resources as far more elusive and difficult to detect than the other two resource categories [13]. Each organization's resources differ due to the diversity and uniqueness of these assets. Intangible resources are different and difficult to imitate because they stem from a unique combination of an organization's history, current state, and future possibilities in terms of persons, procedures, and external variables. Empirical information systems research and early studies on artificial intelligence show that intangible resources are critical for commercializing innovative inventions[74]. We identified three resources within the AI framework: risk propensity, organizational change competence, and interdepartmental coordination.

Organizations view the ability of multiple departments to collaborate and achieve a shared goal as critical for the success of cross-disciplinary projects [75]. Organizations have long recognized the importance of interdepartmental collaboration in fostering innovative thinking and novel ideas. Interdepartmental coordination is characterized as "a state of high degrees of shared values, mutual goal commitments, and collaborative behaviors" [76]. According to this viewpoint, long-term departmental relationships are more important than temporary agreements. According to recent research, firms cannot fully exploit AI unless they foster a collaborative environment in which people unite around common goals and share resources [77].

Barney and Hesterly [78] argue that teams of people with different academic backgrounds and professional skills produce more successful AI. As a result, businesses may ensure that AI programs address all organizational concerns rather than just operational ones. Furthermore, organizations should form interdisciplinary teams to better understand the possible operational difficulties raised by emerging AI applications and to select the most effective deployment techniques. This will improve the overall effectiveness of existing AI systems. Organizations can improve interdepartmental cooperation to increase their agility and flexibility while deploying AI applications. This is because a shared language and comprehension among employees allows departments to quickly develop new AI applications or alter existing ones as needed. A several studies have stressed how important it is for people from different departments to work together. It says that functional silos make it harder to create end-to-end solutions and make it harder for companies to get value from their AI investments [21, 49, 61].

3. Research Design

By employing a deductive approach that included literature studies, analysis of practitioner reports, and many unstructured interviews with subject-matter experts, we successfully identified the aforementioned resources. We additionally categorized the identified chemicals into three distinct groups using Grant's methodology. Tangible resources include data, technology, and physical assets, whereas human resources encompass technical and business abilities. The most valuable intangible resources for cultivating AI expertise are propensity to take risks, ability to implement organizational change, and interdepartmental collaboration. Given the available literature on the topic, we formulated the conceptual framework provided in figure 1 below.

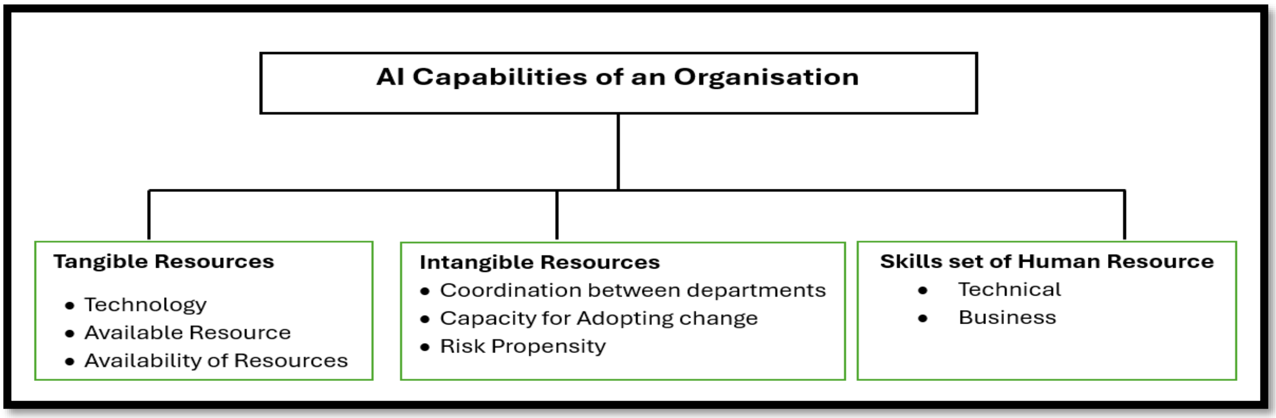

Figure 1. Conceptual framework

Source: Present Reaserch

Supplementary relevant views for practice include the RBT and the identification of important resources in competence development. This allows managers and practitioners to create exact benchmark standards and assess their readiness in each area. This suggests that a tailored initiative to address any identified problems can be implemented. The resource-based theory literature defines tangible resources as assets available for purchase or sale in the marketplace [13]. Financial assets like debt and equity, along with physical assets like buildings or machinery, represent tangible resources. The possibility that these resources will give enterprises a competitive edge is low, given that most organizations can obtain the same tangible resources from the market. Tangible resources, while necessary, are insufficient to promote competency growth. Based upon the review of existing literature following research framework is proposed.

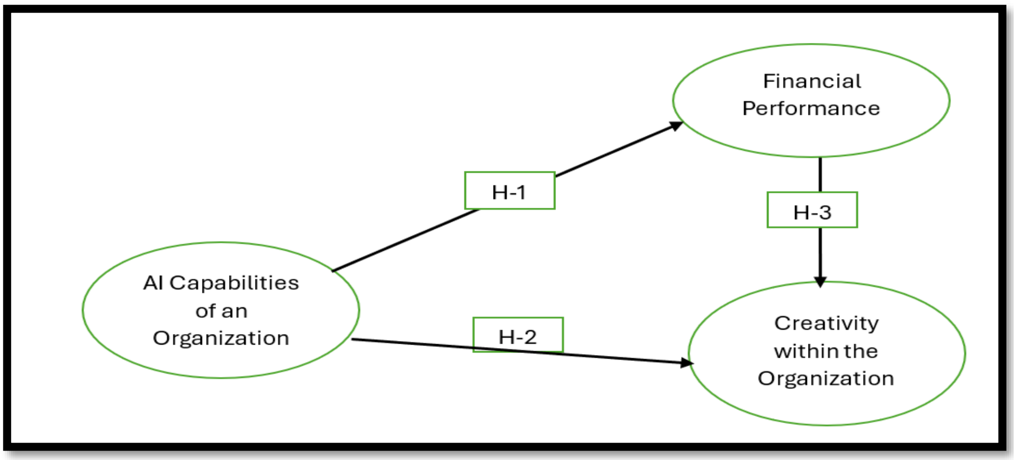

Figure 2. Research Framework

Source: Present Reaserch

4. Results and Discussion

4.1 Data Collection

We followed suggestions MacKenzie, Podsakoff [79] to ensure the validity and reliability of the survey instrument we created. After designing the measurement model, we gathered data to assess the scale's discriminant, convergent, and nomological validity, as well as its psychometric characteristics. The goal of assembling an expert panel was to determine the most appropriate questions for each first-order construction in order to assess the content validity of the indicators during the adoption and modification processes. After we explained each component to the panel, we instructed them to arrange the elements in the correct constructions. We also asked them to identify missing information or improved questions.

A manager at a company headquartered in the United Arab Emirates reviewed the updated survey instrument to ensure that it met convergent, discriminant, and nomological survey validity standards. The selected respondents contacted only senior-level technology management professionals via email. We received 98 responses after sending an initial invitation and three reminders, each one week apart. The responses came from a variety of businesses, including manufacturing, banking, and technology.

4.2 Results and Discussion

Table 1. Demographic details of respondents

Items	Number of respondents	% of sample
Experience of respondents		
Less than one year	20	20%
1 to 3 years	15	15%
4 to 7 years	37	38%
More than 7 years	26	27%
Organization size w.r.t employees		
Micro (less than 10 employees)	9	8%
Small (less than 50 employees)	24	25%
Medium (more than 50 but less than 250 employees)	38	39%
Large (more than 250 employees)	27	28%
Job position of respondent		
Chief Information/Technology/Digital Officer	25	26%
IT Director	18	18%
Head of IT Department	14	14%
Chief Executive Officer	10	10%
IT Project Manager	18	18%
Business Analyst	13	13%

To reduce the danger of informant bias, we confirmed that there was no significant difference in early and late responses. We divided the responses into two categories: those who provided input during the first two weeks of data collection and those who supplied feedback in the last two weeks. We use Mann-Whitney U-tests to analyse all study questions and the constructs they represent. Because we discovered no statistically significant differences between the items and constructs, we conclude that our sample is free of late-response bias. We identified non-responding enterprises based on their age, size category, or industry. We also addressed frequent technique bias, as recommended by Chang et al., due to the perceptual nature of the data originating from a single source at a specific moment. The email invitation notified participants that we would solely use their data for research purposes and handle it with total confidentiality. Furthermore, we emphasized the confidentiality of the entire process. We have not accounted for one hundred twenty-nine individuals. Subsequent to data collection, we examined the study variables employing principal component factor analysis and Harman's one-factor tests. The study revealed that none of the constructs explained the majority of the variation. We subsequently assessed the items' validity concerning the formative constructs, utilizing Edwards' adequacy coefficient (R2a). We aggregated the squared correlations of the construct indicators and then divided them by the total number of indicators to obtain the result. To ensure precision, we followed the protocols outlined by MacKenzie, Podsakoff [79] and Schmiedel, Brocker [80].

Table 2. Validation of the formative constructs.

Construct	Measure	Weight	Significance	VIF	R^2a
Technology	Tec-1	0.21	P<0.001	1.995	0.61
	Tec-2	0.31	n/s	2.451	
	Tec-3	0.121	P<0.001	1.819	
	Tec-4	0.119	n/s	2.31	
	Tec-5	0.59	P<0.001	2.031	
	Tec-6	0.23	P<0.01	2.001	
Available resources	AvRes-1	0.079	n/s	2.312	0.7
	AvRes-2	0.189	P<0.001	2.891	
	AvRes-3	0.153	P<0.5	3.213	
	AvRes-4	0.61	P<0.001	2.984	
	AvRes-5	0.144	n/s	1.987	
	AvRes-6	0.324	n/s	3.112	
Availability of Basic resources	AvBres-1	0.621	P<0.5	2.992	0.8
	AvBres-2	0.196	n/s	3.023	
	AvBres-3	0.231	P<0.001	2.316	
Tangible resources	Technology	0.269	P<0.001	1.694	0.79
	Available resour	0.513	P<0.001	1.561	
	Availability of re	0.503	P<0.001	1.364	
Skill set of Human resource	Technical skills	0.394	P<0.001	2.315	0.79
	Business Skills	0.361	P<0.001	2.103	
Intangible Resources	Coordination be	0.419	P<0.001	1.964	0.78
	Capacity for adc	0.299	P<0.001	1.564	
	Risk propensity	0.361	P<0.001	1.894	
AI capabilities of the organisation	Skill set of Huma	0.213	P<0.001	2.31	0.77
	Intangible Resou	0.231	P<0.001	2.063	

All R^2 values were above 0.50, indicating that the formative construct accounts for most item variance. Similar methods and dimensions were used to explore higher-order structures. Weight transfer between lower-order dimensions and higher-order constructs was always positive and substantial. All adequacy coefficients exceeded 0.50. Finally, we examined formative construct indicator for multicollinearity. Multicollinearity helps reflectively modelled indicators but hinders formative assessments. We typically select multicollinearity criteria below 10, [81]. Since all VIF values for the first, second, and third-order constructions were below 3.3, multicollinearity was not found.

We assessed the item- and construct-level validity and reliability of the reflective constructs using a variety of techniques. Our focus was on first-order reflective latent construct reliability, as well as convergent and discriminant validity. We assessed the reliability of both the items and the construct. Confirmation was based on construct-level composite reliability (CR) values greater than 0.70 and Cronbach's alpha (CA) values. In order to assess the reliability of the indications, we looked for construct-to-item loadings higher than 0.70. We looked at AVE values greater than 0.50 to determine convergent validity. The minimum score of 0.58 exceeds this level.

Verified discriminant validity was assessed in two ways. We first examined whether each indicator's outer loading exceeded its cross-loadings with other constructions [82]. Following Henseler et al.'s recommendation, we derived the Heterotrait-Monotrait ratio (HTMT), a more accurate discriminant validity metric [82]. Calculating the average correlations of indicators inside a concept and comparing them to constructs that measure other model characteristics yields the HTMT

[83]. We found sufficient discriminant validity with all values below 0.85.

Table 3. Results pertaining to HMTM ratio

	Tangible resources	**Skill set of Human resource**	**Intangible Resources**	**AI capabilities of the organisation**	**Risk propensity**
Tangible resources					
Skill set of Human resource	0.612				
Intangible Resources	0.399	0.701			
AI capabilities of the organisation	0.402	0.511	0.702		
Risk propensity	0.433	0.533	0.601	0.706	

All items were credible indicators of the corresponding constructs, and the results in Table 4 demonstrate the effectiveness of first-order reflective measures. To our knowledge, there are no established approaches for assessing the discriminant validity of formative constructs. Nonetheless, [81, 83] have all proposed formative constructs. They highlight the importance of evaluating loadings, weights, and significance levels, as well as investigating multicollinearity. By ensuring that the VIF stayed below 3.3 at all levels, we assessed multicollinearity (Table 2).

Table 4. Assessment of convergent, reliability, and discriminant validity of constructs.

	Technology	**Available resources**	**Availability of Basic resources**	**Tangible resources**	**Skill set of Human resource**	**Intangible Resources**	**AI capabilities of the organisation**	**Risk propensity**
Technology	n/a							
Available resources	0.69	n/a						
Availability of Basic resources	0.596	0.693	n/a					
Tangible resources	0.712	0.599	0.701	n/a				
Skill set of Human resource	0.496	0.596	0.712	0.694	**0.798**			
Intangible Resources	0.567	0.594	0.369	0.493	601	**0.961**		
AI capabilities of the organisation	0.323	0.496	0.401	0.421	0.596	0.655	**0.813**	
Risk propensity	0.298	0.531	0.396	0.394	0.513	0.591	0.751	**0.896**
Mean	4.99	5.36	5.01	4.36	4.89	4.69	5.02	5.01
SD	1.59	1.79	1.7	1.5	1.59	1.83	175	1.8
AVE	n/a	n/a	n/a	0.801	0.801	0.796	0.694	0.741
Cronbach's Alpha	n/a	n/a	n/a	0.896	0.899	0.944	0.721	0.967
Composite reliability	n/a	n/a	n/a	0.966	0.913	0.896	0.696	0.892

The loadings have a significant impact. The investigation revealed that five indicators had no significant findings. All first, second, and third-order loadings were statistically significant at the 0.001 level. Formative construct indicators, like reflective constructs, should favour their own constructs over others [83]. The results of the cross-loading and correlation show that all formative and reflective constructs fit both criteria. After determining that the formative and reflective items are psychometrically sound, we can test nomological validity by comparing AI skill to various indicators of corporate performance.

4.3 Confirmatory Composite Analysis

The confirmatory composite analysis provides the essential aspect of understanding the adequacy of a saturated measurement model. In conclusion, a confirmatory composite analysis facilitates the detection of model misspecifications and evaluates the feasibility of the proposed formative construct. The technique evaluates the composite model's adequacy by comparing the actual correlation matrix with the matrix proposed by the model. The procedures defined by [83] can accomplish this. By analyzing the SRMR, d_{ULS}, and $d_{G,}$ whicg respectively denotes standard root mean squares and unweighted least squares, enables the assessment of the saturated model fit quality [84].

We can use the indicators' data to determine if the concealed variables are real or imagined. We used Smart PLS latent variable scores and ADANCO 2.2.0 Professional for Windows to calculate these results. The SRMR measures the average difference between actual and projected correlations to determine absolute model fit. The SRMR score was 0.037, below the 0.080 threshold [83]. Table5 shows that all discrepancy measures, including d_{ULS} and d_G, fell below the reference distribution's 95% quantile. The results confirm the composite structure measurement framework's reliability.

Table 5. Results of the confirmatory composite analysis

Discrepancy	Overall Saturated model fit evaluation		
	Value	**HI95**	**Conclusion**
SRMR	0.04	0.062	Supported
d_{ULS}	0.253	0.604	Supported
d_G	0.061	0.249	Supported

4.4 Measurement Model

To assess the construct's nomological validity, we developed two performance indicators that reflect the expected impact of AI capabilities at the organizational level. We then incorporated organisational creativity (ORC) and organisational performance (ORP) into the previously established AI capacity scale constructs. We used the firm's size classification and industry as control variables. We assessed organisational creativity using measures from Scheibe and Gupta [85], and operationalised organisational performance using items provided by Lee and Choi [86]. Numerous findings on the adoption and implementation of AI technology across organizational boundaries support both constructs, as proven by prior empirical studies. A re-evaluation of the tests revealed that the integration of outcome factors did not affect the psychometric properties of the scale.

Table 6. Inter-correlations of the latent variables for first-order constructs

	Technology	Available resources	Availability of Basic resources	Tangible resources	Skill set of Human resource	Intangible Resources	AI capabilities of the organisation	Risk propensity
Technology	n/a							
Available resources	0.622	n/a						
Availability of Basic resources	0.599	0.681	n/a					
Tangible resources	0.722	0.559	0.711	n/a				
Skill set of Human resource	0.502	0.588	0.724	0.689	**0.798**			
Intangible Resources	0.577	0.598	0.401	0.493	0.601	**0.961**		
AI capabilities of the organisation	0.346	0.501	0.421	0.421	0.596	0.665	**0.813**	
Risk propensity	0.301	0.542	0.402	0.384	0.522	0.601	0.792	**0.896**
Mean	4.99	5.36	5.01	4.36	4.89	4.69	5.02	5.01
SD	1.59	1.79	1.7	1.5	1.59	1.83	175	1.8
AVE	n/a	n/a	n/a	0.806	0.811	0.799	0.693	0.752
Cronbach's Alpha	n/a	n/a	n/a	0.898	0.901	0.946	0.728	0.988
Composite reliability	n/a	n/a	n/a	0.963	0.919	0.899	0.696	0.897

4.4 Structural Model

After assessing the scale's psychometric features, we explored the AI competency construct's nomological validity by looking at its correlation with organizational innovation and performance. Prior empirical studies define creativity as an organization's ability to produce novel, constructive ideas or products within a complex organizational structure. According to the literature on AI's benefits, automation of routine tasks can free up human resources to work on jobs that require creativity and innovation, while people can take on jobs that don't require much in the way of originality, complexity, or the ability to deal with new or unexpected situations.

Furthermore, AI technology can improve human skills in a variety of ways, including enhancing cognitive abilities, replicating human talents to raise physical capacities, and facilitating communication with customers and employees to free up humans for more difficult duties [87]. According to a previous study, organizational performance is defined as an organization's ability to achieve its objectives. We expect AI to impact a wide range of organisational processes, including the achievement of significant business goals [88]. According to a recent study, AI has the ability to help organizations reach a variety of goals. These include improving products in every way, facilitating manager decisions, improving internal procedures, and increasing marketing and sales efficiency. Previous research on the relationship between IT and business value supports interfirm comparisons as a valid measure of organizational success [14] . As a result, we believe that comparative organizational performance indicators are acceptable for assessing the impacts of AI capabilities. We used Smart PLS 3.0 to conduct a PLS-SEM analysis to look into the relationship between the two variables.

Figure 3 illustrates the variance (R2) and standardized path coefficients (β) for the terminating variables, demonstrating the structural model of the PLS analysis. We analyze R2 values, path coefficient magnitudes, and predictor variable effect sizes to assess the accuracy of the structural model. We conducted a bootstrap analysis using 500 resamples to determine the statistical significance of the estimates (t-values).

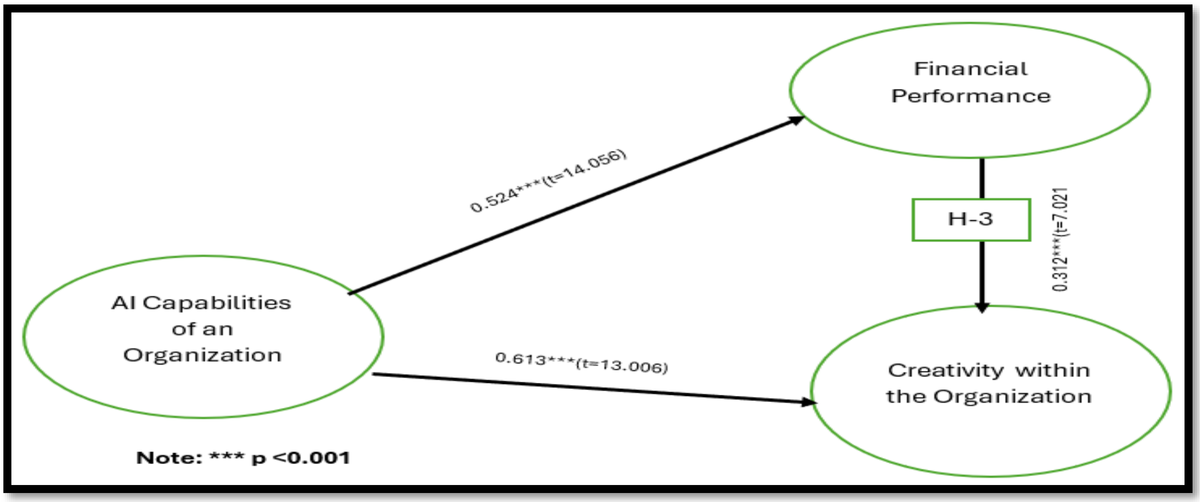

Figure 3. Results of structural model

Source: Present Reaserch

The study found that AI Capabilities of an organisation had a significant impact on financial performance ($\beta = 0.524$, $t = 14.056$, $p < 0.001$) and creativity ($\beta = 0.613$, $t = 13.006$, $p < 0.001$). Our study found a significant relationship between creativity within the organisation and performance ($\beta = 0.312$, $t = 7.021$; $p < 0.001$). By assessing model fit in these scenarios, we can establish whether we have neglected a significant influence on the model [83]. The model's SRMR was 0.036, d_{ULS} was 0.237, and d_G was 0.051, indicating a satisfactory fit. The nomenclature model's findings show that

AI skills have a strong positive correlation with creativity within the organisation and performance, whereas creativity within the organisation improves performance significantly.

Despite growing interest in AI's commercial potential, reports and empirical research from early adopters show that many companies do not get economic rewards from their AI investments. The vast studies highlighting the potential benefits of incorporating AI into key organizational processes make this finding quite surprising. Brynjolfsson, Rock [89] effectively highlight this gap between ambitions and realities by claiming that the media and vendors have dominated AI discourse, resulting in inflated expectations. The widespread promotion of AI as a solution for all organizational challenges leads to unrealistic expectations about the technology's potential. Consultants in business and technology, who lack the theoretical framework to synthesize data, have published various papers on the financial benefits of AI for businesses

5. Conclusion and Implications

We created a rigorous technique as an inventory for organizations' AI-specific development resources, inspired by [89]. Other constructs and instruments used a variety of digital capabilities, but the questions to assess the major dimensions are exclusive to AI technology, knowledge, and intangible assets. We applied novel methodologies while changing established ones, taking into account AI literature and important components relevant to business applications. This empirical investigation showed the AI capacity construct's generalizability, validity, and reliability, as well as its fundamental dimensions and elements. This method fits IS community requirements for assessing and communicating an organization's AI capabilities to achieve business goals. Third, we showed how AI affects organizational performance measurements. The impact on company efficiency and innovation was carefully examined. AI adoption and implementation in organizations affects critical outcomes, according to extensive studies. We are unaware of any empirical study linking a theoretically grounded AI idea to important business KPIs. Our research shows that AI proficiency improves business performance and innovation. This study emphasizes the significance of a full AI application within a corporation, as focusing only on data and technology would not yield substantial commercial results.

The findings imply that AI can influence important outcomes to help firms increase and maintain competitive performance. The findings suggest that AI talents could improve creative processes and boost organizations' knowledge bases and innovation outputs, highlighting AI's strategic potential. AI technology may help organizations execute ambidextrous strategy, according to these associations. Innovating and performing better are linked to an organization's AI competencies. These studies support IT-enabled organizational capabilities, which assert that organizations can add and grow new capabilities through strategic IT use. To conclude, our study extends RBT's theoretical framework to AI, adding to IS research. It does this by outlining the AI resources firms need to reap its benefits. Wade and Hulland [90] recommend Resource-Based Theory (RBT) for the Information Systems (IS) community in three ways: 1) It defines firm-level resources; 2) it helps researchers distinguish between cross-functional and non-technical resources; and 3) it allows systematic analysis of the correlation between firm-level resources and capabilities and substantial performance. We increased the RBT's explanation capacity and relevance to the fast-emerging field of artificial intelligence by exploiting these qualities.

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