Understanding & Measuring AI Capability: An Empirical Study on its Influence on Organizational Performance and Creativity

فهم وقياس قدرات الذكاء الاصطناعي: دراسة تجريبية حول تأثيرها على الأداء التنظيمي والإبداع

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المستخلص:

تسعى هذه الورقة البحثية إلى إستكشاف تأثير قدرات الذكاء الاصطناعي على الأداء التنظيمي والإبداع في الشركات المصرية باستخدام إطار نظرية الموارد .(RBT) تصنف نظرية الموارد الموارد إلى موارد ملموسة وغير ملموسة وبشرية. باستخدام نهج استنتاجي، تعتمد الدراسة على بيانات نوعية تم جمعها من خلال استبيان، مما أدى إلى الحصول على ١٥٠ استجابة صالحة. تشير النتائج إلى أن الموارد الملموسة والبشرية لها تأثير إيجابي على الأداء التنظيمي والإبداع، بينما الموارد غير الملموسة لها تأثير سلبي. تؤكد هذه النتائج الفرضية التي تنص على أن قدرات الذكاء الاصطناعي تعزز بشكل كبير كل من الإبداع والأداء التنظيمي، مما يوفر رؤى حاسمة للشركات التي تهدف إلى الاستفادة من الذكاء الاصطناعي لتحقيق ميزة تنافسية في مصر.

الكلمات المفتاحية: الذكاء الاصطناعي - قدرات الذكاء الاصطناعي - الإبداع - الأداء - نظرية الموارد.

Abstract

This Paper explores the influence of AI capabilities on organizational performance and creativity of the Egyptian firms, using the Resource-Based Theory (RBT) framework. RBT categorizes resources into tangible, intangible, and human resources. Employing a deductive approach, the study utilizes qualitative data gathered through a survey, resulting in 150 valid responses. Findings indicate that tangible and human resources positively impact organizational performance and creativity, whereas intangible resources have a negative effect. These results confirm the hypothesis that AI capabilities significantly enhance both organizational creativity and performance, providing critical insights for firms aiming to leverage AI for competitive advantage in Egypt

Keywords: Artificial Intelligent- AI Capabilities - Creativity- Performance- Resource-Based theory.

Introduction

Over the past few years, the availability of big data, along with advanced techniques and infrastructure, has made artificial intelligence (AI) a top technological priority for many organizations. Although AI was established in academia in the 1950s, it wasn't until the big data revolution and the post-digital era that it started to attract the attention it deserved (Fountaine et al., 2019; Haenlein and Kaplan, 2019). Artificial Intelligence (AI) is defined by Russell and Norvig (2016) as "systems that mimic cognitive functions generally associated with human attributes such as learning, speech, and problem-solving," highlighting AI's goal to replicate human cognitive functions. Similarly, Kaplan and Haenlein (2019) describe AI as "a system's ability to correctly interpret external data, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation," emphasizing AI's capacity to process and learn from data for achieving objectives.

Dwivedi et al. (2019) focused on AI's growing role in automating tasks previously performed by humans, highlighting its practical applications in various fields. Knowles (2006) defined AI as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages," underscoring AI's technical advancements and its ability to execute complex tasks.

Building on these varied definitions, an integrative definition of AI is proposed, tailored specifically for the context of information systems research: "AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals." This definition highlights the functional capabilities of AI systems in generating insights and autonomously taking actions to meet organizational and societal objectives, acknowledging that AI often complements rather than mimics human abilities. (Krause et al, 2020)

In the financial sector, Glogowski and Pisany (2021) described AI as a transformative tool that enhances competitive advantages for financial firms through improved efficiency and productivity, leading to increased profitability. AI facilitates enhanced decision-making, automated execution, better risk management, regulatory compliance, and optimization of back-office processes. But AI techniques alone are unlikely to deliver any competitive gains by themselves because they are easily acquired in the market and are subject to replication. Additionally, the data used to fuel these techniques alone will not be sufficient to create distinct AI capabilities (A. Bharadwaj, 2000).

According to early reports from top companies adopting AI, many businesses currently fail to realize significant operational enhancements. One attributed reason is the time-consuming nature of AI configuration, suggesting that relying solely on AI is insufficient, businesses need a special combination of organizational, human, and physical resources to develop an AI capability that can provide value by setting them apart from rivals. AI capability is defined as it is the ability to choose, coordinate, and make use of its AI-specific resources. (P. Mikalef & M. Gupta, 2021)

So, the objective of this research is to indicate the organizational resources required for Egyptian firms to advance their AI capabilities and, ultimately, improve performance. The Resource Based Theory (RBT) was chosen as the study's underlying theoretical framework because it is seen to be relevant for dynamic and turbulent situations, especially when resource complementarity is encouraged, and organizations create unique capabilities based on their unique resource sets.

Numerous scholarly investigations have outlined the several categories of resources necessary for the development of organizational competencies that propel success (J.B. Barney,1991; P. Mikalef & M. Gupta, 2021). One of the most extensively used classification schemes is made by Grant who divided the resources between tangible resources (like financial and physical assets), human skills (like employee knowledge and abilities), and intangible resources (like synergy, coordination, and strategic direction) classification as this stream of literature (A. Bharadwaj, 2000; M. Gupta, 2016; P. Mikalef & M. Gupta, 2021). We classify the resources that make up an AI capacity using the same classification as this stream of literature

Theoretical Background

The Resource-Based Theory (RBT) and the Resource-Based View (RBV) underscore the significance of a firm's unique resources and capabilities in achieving competitive advantages and enhancing performance. These theories stress the importance of leveraging both tangible and intangible resources, such as IT infrastructure and human skills, to drive organizational success.

Studies indicated that firms with robust IT capabilities tend to outperform their counterparts in terms of profitability and cost-based metrics. Researchers like, Bharadwaj (2000), Melville et al. (2004), and Mikalef et al. (2021) emphasized the integration of IT resources with other organizational capabilities as crucial for achieving competitive advantages and fostering business growth. In strategic management literature, the RBV theory explains how firms attain and sustain competitive advantages by effectively managing their resources. Mikalef et al. (2020) highlighted the positive impact of developing Big Data Analytics Capabilities (BDAC) on market and operational performance, enhancing competitiveness and innovation potential. Furthermore, Wamba et al. (2020) discussed the importance of protecting valuable resources against imitation and substitution to establish a competitive edge. Mikalef et al. (2017) emphasized how valuable, rare, inimitable, and irreplaceable resources, including artificial intelligence (AI), contribute to a firm's overall performance over time. Wade et al. (2004) stressed the value of RBV in understanding how information systems drive firm strategy and performance, underscoring the need for further research to fully grasp the role of information systems in achieving sustained competitive advantage. Chen et al. (2022) argued that the RBV theory elucidates performance differences among firms by highlighting the significance of unique and difficult-to-replicate resources. Dutta et al. (2005) introduced stochastic frontier estimation (SFE) as a method to estimate firm-specific capabilities, showcasing the correlation between high R&D capabilities and market value within the semiconductor industry. Additionally, Barney (2012) explored how firms can leverage market-based assets and capabilities to enhance customer value and gain a competitive edge. Mikalef (2018) discussed how firms can sustain competitive advantage through valuable, rare, inimitable, and non-substitutable resources and capabilities.

Literature Review and Hypothesis Development

The RBT has been used in several research to investigate if and what mix of IT especially Artificial Intelligence and other complementary resources leads to improvements in performance (A. Bharadwaj, 2000; Melville et al, 2004). According to Melville et al, 2004, the RBT enables researcher to create hypotheses that can be empirically tested, by evaluating these hypotheses, the knowledge of the importance of various IT resources and how they affect organizational performance can be improved.

It is evident from the prior debates on the application of AI in business that a great deal of focus has been placed on the potential for these technologies to increase an organization's creativity and performance. T. Amabile, 2019 recorded cases across various industries where the development of AI capabilities has led to advances in organizational creativity. Artificial intelligence can help businesses be more creative by providing innovative ideas and solutions (Amabile, 2020; Paschen et al., 2020). AI capabilities can help businesses to commit more personnel to creative endeavors (Mikalef and Gupta, 2021). H. Jain, 2018 claimed that many manual duties can be automated, giving people more free time to work on creative projects. Based on the previous discussion about how AI can fuel creativity in organizations, we hypothesize the following:

H1: *AI Capability has a positive significant impact on Organizational Creativity.*

> ***H1a:*** *Tangible Resources have a positive significant impact on Organizational Creativity.*
>
> ***H1b:*** *Intangible Resources have a positive significant impact on Organizational Creativity.*
>
> ***H1c:*** *Human Resources have a positive significant impact on Organizational Creativity.*

A thorough analysis of AI's potential and effects on corporate performance has been published. Chaudhuri et al., 2021 suggested that businesses may benefit from artificial intelligence in terms of competitiveness. Similarly, Ghasemaghaei, 2021 advocated that Businesses can obtain precious, uncommon, unique, and priceless resources from Artificial Intelligence Capability.

On the other hand, substantial infrastructure resources (tangible resources: data, hardware devices, software and technical support) are needed for the effective and efficient implementation of AI in businesses, these are explored in much research as Herhausen et al., 2020; Bag et al., 2021c; Chatterjee et al., 2021a; Hwang and Kim, 2021 and Rahman et al., 2021 and Wang &Fan, 2021.

Also, other studies considered the tangible resources, the intangible resources and the employees' skills for the artificial intelligent capability. Intangible resources are the resources that are formed by the special combination of individuals, groups, procedures, and environmental factors that make up organizations. The intangible resources that are identified in the research are inter-departmental coordination, organizational change capacity, and risk proclivity and these resources are significant in gaining business advantages from implemented technology. (A. Bharadwaj, 2000; N. Melville, V. Gurbaxani, K. Kraemer, 2007; G. Schryen, 2013; M. Chui, S. Malhotra, 2018; T.H. Davenport, R. Ronanki, 2018; S. Ransbotham, P. Gerbert, M. Reeves, D. Kiron, M. Spira, 2018).

It was shown in the literature that one of the primary obstacles to adopting AI is the lack of leadership support, which is crucial for its successful implementation. Additionally, for employees to effectively apply AI in the near future, it is essential for them to understand the scope of AI applications and acquire the necessary skills and expertise in using AI systems. According to a study by Davenport and R. Ronanki, 2018, one in three managers are ignorant about the workings of AI technologies. Therefore, it is essential that managers learn about the various AI technology and how they might be used to various organizational roles. Another study by V. Kolbjørnsrud et al., 2016 showed that the capability of managers to organize and start AI installations is crucial factor. Based on the aforementioned claims, we hypothesize the following:

H2: *AI Capability has a positive significant impact on Organizational Performance.*

> ***H2a:*** *Tangible Resources have a positive significant impact on Organizational Performance.*
>
> ***H2b:*** *Intangible Resources have a positive significant impact on Organizational Performance.*
>
> ***H2c:*** *Human Resources have a positive significant impact on Organizational Performance.*

Methodology

This study will use the deductive approach to meet the study objectives and to provide a general evaluation and conceptual framework for the impact of AI capabilities on organizational performance and creativity within the Egyptian market. In addition, descriptive statistics will be conducted to investigate the impact of AI capabilities on organizational performance and creativity through a content analysis approach. Furthermore, an empirical study will be used to test the research hypotheses by collecting and analyzing primary data, utilizing qualitative data to provide a comprehensive understanding of the phenomena. To achieve this, a survey was designed and administered, gathering responses from IT departments' experts of AI-powered organizations in Egypt.

The primary data for this research was collected through a structured survey previously used in Mikalef and Gupta,2021 research. The survey was distributed to 180 participants; however, only 150 responses were deemed valid and used for the analysis. The survey aimed to capture respondents' perceptions of AI capabilities and their effects on organizational performance and creativity.

To test the hypotheses in this study, Structural Equation Modeling (SEM) was employed. SEM was selected due to its capability to evaluate complex conceptual frameworks that involve multivariate analysis. Unlike regression models, SEM enables the simultaneous study of multiple paths. It superseded the regression models empirically and methodologically (Ramli et al., 2018).

Sample Size

Cochran (1963) decides the size of the sample used

$$n = \frac{z^2 * p * (1-p)}{e^2} = \frac{(1.96)^2 * (0.5)(0.5)}{0.1^2} \approx 96.04 \approx 97 < 140$$

Therefore, the sample need to exceed 97 respondents to obtain a margin of error of 0.1

Statistical Analysis

Descriptive Statistics

Table (I): Frequency table for demographics in the sample

Variable	Categories	Frequency	Percentage
Firm Age	≤5	78	55.7%
	6-10	41	29.3%
	11-15	8	5.7%
	>15	13	9.3%
Firm Size	Large (more than 500 employees)	25	17.9%
	Medium (100-500 employees)	51	36.4%
	Small (less than 100 employees)	64	45.7%
Firm Sector	Agriculture; plantations; other rural sectors.	20	14.3%
	Basic Metal Production.	14	10.0%
	Chemical industries.	16	11.4%
	Commerce	29	20.7%
	Education.	3	2.1%
	Financial services; professional services.	33	23.5%
	Food; drink; tobacco.	2	1.4%
	Health services	11	7.9%
	Media	4	2.9%
	Oil and gas production	4	2.9%
	Utility (electricity, water, gas)	4	2.9%

Source: Calculations based on sample using SPSS 26

Observing table I, the majority of the respondents worked in firms aged less than 5 years (78). Around 29% of the firms were aged from 6 to 10 years (41) in the market while only 15% aged more than 10 years (21). The majority of respondents worked in smaller firms (64) in size while the minority worked in large firms (25). The firm sectors mostly represented in the sample was financial services (33), followed by Commerce (29), Agriculture (20) and chemical industry (16).

First Level Analysis

To understand the AI Capability effect on the Organizational Creativity and Performance, a confirmatory factor analysis is first required to ensure that the items utilized to present each variable do not cause multicollinearity and do not affect negatively the reliability and validity of each variable.

Table (II): Confirmatory Factor analysis for the first level analysis

	Items	Loadings	Outer VIF	CA	CR	AVE
AI Capability	AI3	0.865	3.942	0.878	0.912	0.679
	AI10	0.626	1.571			
	AI12	0.911	4.609			
	AI14	0.887	3.719			
	AI16	0.800	2.973			
Organizational Creativity	OC1	0.868	1.930	0.856	0.912	0.776
	OC2	0.875	2.185			
	OC3	0.901	2.505			
Organizational Performance	OP1	0.644	1.213	0.738	0.855	0.667
	OP3	0.928	2.856			
	OP4	0.852	2.554			

Source: Calculations based on sample using SMARTPLS

Observing the reliability of the dimensions, it was found that all Cronbach alpha measures were greater than 0.7 (Taber, 2018). This implies internal consistency. On the other hand all dimensions had composite reliability greater than 0.7 and average variance extracted greater than 0.5 (Sahoo, 2019). This shows that all dimensions are valid. Since VIFs are less than five, this shows how multicollinearity is not an issue in the model (Shrestha, 2020). The loadings of the items were all greater than 0.6 reflecting the importance of the statements (Hoque et al., 2016).

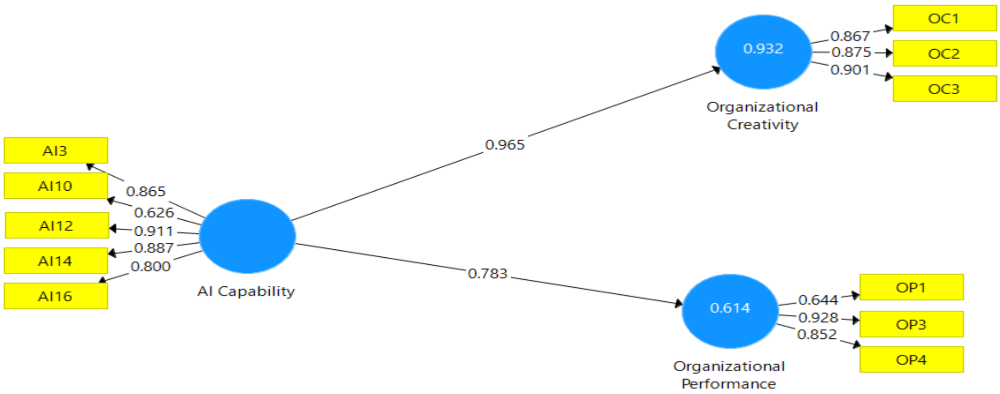
Table (III): Fornell Larker Criterion for first level analysis

	AI Capability	Organizational Creativity	Organizational Performance
AI Capability	0.824		
Organizational Creativity	0.772	0.881	
Organizational Performance	0.746	0.722	0.817

Source: Calculations based on sample using SMARTPLS

Table III provides further delving into validity of the model. The average variance extracted (AVE) for AI Capability is 0.824 and AVE for Organizational Creativity is 0.881. The correlation between Organizational Creativity and AI Capability is 0.772. Since the AVE is greater than the correlation, discriminant validity is established between these two constructs. The AVE for Organizational Performance is 0.817 while the correlations with AI Capability was 0.746 and with Organizational Creativity was 0.722. The AVE is greater than both correlations, confirming discriminant validity. Based on the Fornell-Larcker Criterion, the study demonstrates that the constructs (AI Capability, Organizational Creativity, and Organizational Performance) are distinct from each other (Ab Hamid, 2017). Figure I represent the relationships between variables in phenomenon.

Figure (I): Structural equation Model for first level analysis



Source: Calculations based on sample using SMARTPLS

Second Level Analysis

To delve into more details and understand the further impact of AI Capabilities components, a second level analysis is employed. The sub-variables of the AI Capability is divided into Human, Tangible and Intangible resources.

Table (IV): Confirmatory Factor analysis for the second level analysis of the phenomenon

	Items	Loadings	Outer VIF	CA	CR	AVE
Human Resources	**HR3**	0.908	1.999	0.828	0.920	0.852
	HR6	0.938	1.999			
Intangible Resources	**IR3**	0.764	1.744	0.794	0.875	0.701
	IR8	0.926	2.139			
	IR9	0.814	1.553			
Tangible resources	**TR2**	0.777	2.774	0.855	0.902	0.699
	TR7	0.940	2.428			
	TR11	0.860	2.625			
	TR12	0.755	4.341			
Organizational Creativity	**OC1**	0.857	1.930	0.856	0.912	0.777
	OC2	0.878	2.185			
	OC3	0.908	2.505			
Organizational Performance	**OP2**	0.926	1.829	0.805	0.911	0.836
	OP4	0.903	1.829			

Source: Calculations based on sample using SMARTPLS

Observing the reliability of the dimensions, it was found that all Cronbach alpha measures were greater than 0.7 (Taber, 2018). This implies internal consistency. On the other hand, all dimensions had composite reliability greater than 0.7 and average variance extracted greater than 0.5 (Sahoo, 2019). This shows that all dimensions are valid. Since VIFs are less than five, this shows how multicollinearity is not an issue in the model (Shrestha, 2020). The loadings of the items were all greater than 0.7 reflecting the importance of the statements (Hoque et al., 2016).

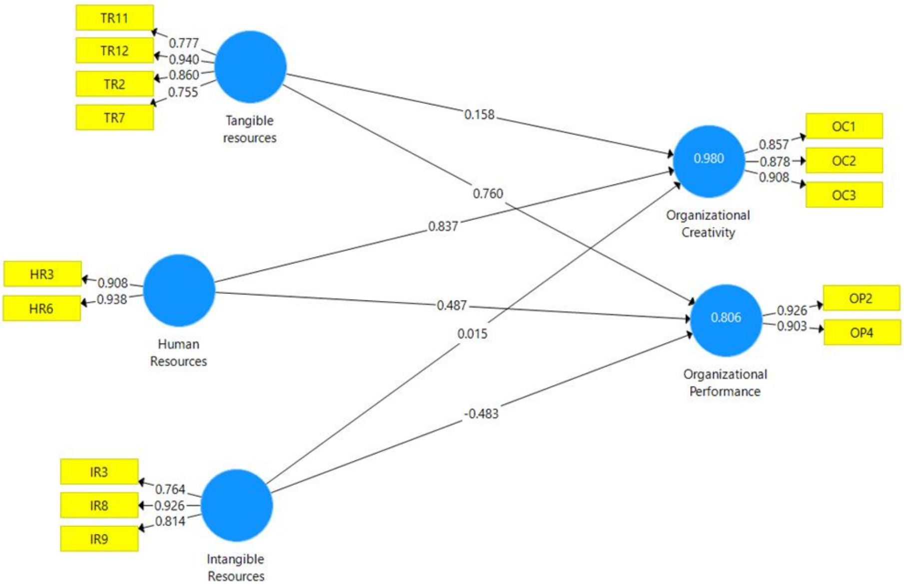
Table (V): Fornell Larker Criterion for discriminant validity analysis for second level analysis

	Human Resources	Intangible Resources	Organizational Creativity	Organizational Performance	Tangible resources
Human Resources	0.923				
Intangible Resources	0.669	0.837			
Organizational Creativity	0.786	0.7	0.881		
Organizational Performance	0.735	0.445	0.819	0.914	
Tangible resources	0.782	0.791	0.708	0.808	0.836

Source: Calculations based on sample using SMARTPLS

Based on the Fornell-Larcker Criterion discriminant validity, the research demonstrates that the constructs (Human Resources, Intangible Resources, Tangible Resources, Organizational Creativity, and Organizational Performance) are distinct from each other (Ab Hamid, 2017). Figure II represent the relationships between variables in phenomenon.

Figure (II): Structural equation Model for second level analysis



Source: Calculations based on sample using SMARTPLS

Table (VI): Path coefficients of the hypotheses for the phenomenon

	Original Sample	Standard Deviation	P Values
AI Capability -> Organizational Creativity	0.965	0.016	0
Human Resources -> Organizational Creativity	0.837	0.075	0
Intangible Resources -> Organizational Creativity	0.015	0.04	0.699
Tangible resources -> Organizational Creativity	0.158	0.082	0.054
AI Capability -> Organizational Performance	0.783	0.037	0
Human Resources -> Organizational Performance	0.487	0.158	0.002
Intangible Resources -> Organizational Performance	-0.483	0.105	0
Tangible resources -> Organizational Performance	0.76	0.189	0

Source: Calculations based on sample using SMARTPLS

At 99% confidence level, AI capability (β=0.965) has a positive significant impact on Organizational Creativity. It is noticeable that, human resources (β=0.837) have a positive significant impact on Organizational creativity. It is observable that Human resources had the highest and most significant impact on Organizational creativity followed by tangible resources. There was no enough evidence that Intangible resources (β=0.015) had an impact on the Organization Creativity.

At 99% confidence level, AI capability (β=0.783) had also a significant positive impact on Organizational Performance. Tangible Resources had a high impact on Organizational Performance such that accompanies with Human resources overcome the negative weak impact of the intangible resources on the organizational performance. It is noticeable that at 99% confidence level both human resources (β=0.487) and tangible resources (β=0.76) had a positive significant impact on Organizational performance.

Table (VII): Model evaluation metrics

Model		SSO	SSE	Q^2	R Square	R Square Adjusted
First level	Organizational Creativity	420	120.589	0.713	0.932	0.931
	Organizational Performance	420	252.174	0.400	0.614	0.611
Second level	Organizational Creativity	420	107.238	0.745	0.980	0.979
	Organizational Performance	280	97.12	0.654	0.806	0.802

First: SRMR=0.022, Chi square= 4130.141, NFI=0.709

Second: SRMR=0.072, Chi square=5230.16, NFI=0.701

Source: Calculations based on sample using SMARTPLS

The R^2 value the model for creativity and perfor mance were 0.932 and 0.614 respectively. This can be explained by stating that the model including the AI Capabilities explains 93.2% and 61.4% of the variation in organizational creativity and organizational performance. However, dividing AI Capability into more in-depth variables caused an improvement in the value of R square. The percentage of variation explained in creativity and performance increased significantly 98% and 80.6%. Considering Q^2 value is greater than zero, it is the measure used for predictive accuracy. As long as it is greater than zero, this shows it was good PLS model. Since the SRMR is a small value close to zero and less than 0.1, this shows that the model was excellent fit for data. In addition, NFI value of both model is slightly higher than 0.7, which is deemed acceptable in social phenomenon (Shadfar & Malek mohammadi, 2013).

Conclusion and Discussion

The increased interest that academics and practitioners have shown in the AI phenomena, especially in the last five years, is what motivated this study. The empirical study investigated the impact of AI capabilities on organizational performance and creativity within the Egyptian market. After studying some insights from RBT and previous literature, eight types of complementary resources are adopted and contributed to the development of an overall AI capability. These resources are classified as the tangible resources that comprised of data, technology, and basic resources, human skills that consisted of technical and business skills, and intangible resources that include the presence of inter-department coordination, an organizational change capacity, and risk proclivity. Finally, the researcher presents multilevel model, in which they tested the research hypotheses through collecting data from 150 questionnaire distributed among IT departments' experts of AI-powered organizations in Egypt.

The results show that AI capabilities can enhance organizations' innovation and knowledge bases, as well as their creative processes and these results are in line with Amabile, 2020 study. Human resources skills that leveraged by AI are noticed to have the highest impact on the organization creativity, followed by tangible resources like data, time and technology. These results are in line with the results of Amabile, 2020, Mikalef and Gupta, 2021 and Raisch and Krakowski, 2021 studies. This can be explained as Artificial Intelligent capabilities take on numerous repeated jobs and provides more solutions when businesses are faced with complicated problems. Also, numerous labor-intensive manual activities that take a lot of time and manpower can also be automated by AI. Businesses are more likely to innovate if they can unleash the potential of their people resources to participate in creative processes.

Also, the results show that firms can significantly benefit from AI in order to achieve and maintain improvements in performance. Tangible resources and human resources skills leveraged by AI proved to have high impact on organizations' performance. These results are in line with the results of Deb S. K. et al., 2018, Mishra A.N. & Pani A.K., 2020, Wambo S. L. et al., 2020 and Mikalef and Gupta,2021 studies. This can be explained as several performance metrics, including cost savings, faster response times, lower production costs, and enhanced customer relationship management, are directly impacted by streamlining operational inefficiencies and using AI to automate processes. However, in order to reap such benefits, AI solutions must be implemented as a component of organizational initiatives and their goal must be understood and shared by all. Organizations may see performance improvements from applications like chatbots, intelligent agents, and even AI techniques for process automation.

Research Implications and Recommendations

Despite significant advancements in artificial intelligence (AI), the journey towards full integration within most firms is still in its early stages. Executives must acknowledge that many of the impending changes are unpredictable, necessitating a degree of experimentation and the simultaneous exploration of multiple possibilities.

The research findings indicate that businesses can significantly enhance their performance by leveraging AI capabilities. To remain competitive, organizations should prioritize integrating AI technologies in sectors where innovation and creativity are crucial. AI's ability to automate repetitive tasks and provide advanced analytical tools can greatly augment human creativity, particularly in processes like idea generation and problem-solving.

The researcher suggests that businesses should focus on embedding AI technologies into areas where innovation drives competitive advantage. Investing in AI that supports creative processes will allow firms to tap into new opportunities and streamline operations, ultimately fostering a more dynamic and responsive business environment.

Also, organizations should establish tailored performance measures to assess AI's impact on various business outcomes, including creativity, productivity, and efficiency. This will enable a more precise understanding of AI's value and its contribution to achieving strategic goals.

The researcher recommends that o fully capitalize on AI technologies, businesses should invest in comprehensive training programs that enhance employees' AI literacy and technical skills. This will empower the workforce to effectively collaborate with AI systems, maximizing their potential and ensuring seamless integration. And Management should foster a culture that supports innovation and recognizes AI's transformative role in reshaping traditional work processes. Encouraging an environment where experimentation and creative thinking are valued will help businesses stay ahead in a rapidly evolving market. Firms should consider making targeted investments in AI technologies that align with their long-term business objectives. These investments should be aimed at enhancing competitive positioning and achieving sustainable growth. Finally, although the study found that the intangible resources of AI capabilities did not significantly impact organizational creativity or could even have a negative impact on performance, successful AI integration requires collaboration across different organizational departments. Businesses should promote the formation of cross-functional teams to ensure AI projects are well-coordinated and aligned with overarching organizational goals.

Limitations and Future Research

Although this study only focuses on Egyptian companies, it makes a valuable contribution to current theoretical advancements and AI capabilities. Going forward, we can expand the developed theoretical framework to include additional industries and nations.

The financial information of the sample firms is not included in the firm performance, which is determined by the respondents' subjective assessments. Future research could take into account both qualitative and quantitative methodologies to examine further relationships and phenomena. This study did not take long-term changes in Artificial Intelligent Capabilities and company performance into account, and it employed data at one point.

The study opens avenues for future research on the long-term impact of AI on organizational creativity and performance. Further research can concentrate also on other aspects of the company, such productivity, market expansion, and R&D capacity. To enhance the model described in this, more organizational characteristics factors will be investigated in subsequent research.

References

Ab Hamid, M.R., Sami, W. and Sidek, M.M., 2017, September. Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion. In Journal of physics: Conference series (Vol. 890, No. 1, p. 012163). IOP Publishing.

Amabile, T., 2019. GUIDEPOST: Creativity. Artificial Intelligence, and a World of Surprises Guidepost Letter for Academy of Management Discoveries. Academy of Management Discoveries. Amabile, T.M., 2020. Creativity, artificial intelligence, and a world of surprises. Academy of Management Discoveries, 6(3), pp.351-354.

Belhaj, M. and Hachaıchi, Y., 2021. Artificial Intelligence, Machine Learning and Big Data in Finance Opportunities, Challenges, and Implications for Policy Makers.

Bharadwaj, A.S., 2000. A resource-based perspective on information technology capability and firm performance: an empirical investigation. MIS quarterly, pp.169-196.

Barney, J.B., 2012. Purchasing, supply chain management and sustained competitive advantage: The relevance of resource-based theory. Journal of supply chain management, 48(2), pp.3-6.

Barney, J., 1991. Firm resources and sustained competitive advantage. Journal of management, 17(1), pp.99-120.

Bag, S., Pretorius, J.H.C., Gupta, S. and Dwivedi, Y.K., 2021. Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. Technological Forecasting and Social Change, 163, p.120420.

Cochran, W.G., 1963. Sampling Techniques, 2d ed., New York; John Willey & Sons.

Chui, M. and Malhotra, S., 2018. AI adoption advances, but foundational barriers remain. Mckinsey and company.

Chaudhuri, R., Chatterjee, S., Vrontis, D. and Thrassou, A., 2021. Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture. Annals of Operations Research, pp.1-35. Chen, D., Esperança, J.P. and Wang, S., 2022. The impact of artificial intelligence on firm performance: an application of the resource-based view to e-commerce firms. Frontiers in Psychology, 13, p.884830.

Czerwińska, T., Głogowski, A., Gromek, T. and Pisany, P., 2021. Digital transformation in banks of different sizes: Evidence from the Polish banking sector. In Fostering Innovation and Competitiveness With FinTech, RegTech, and SupTech (pp. 161-185). IGI Global.

Davenport, T.H. and Ronanki, R., 2018. Artificial intelligence for the real world. Harvard business review, 96(1), pp.108-116.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A. and Galanos, V., 2021. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, p.101994.

Dutta, S., Narasimhan, O.M. and Rajiv, S., 2005. Conceptualizing and measuring capabilities: Methodology and empirical application. Strategic management journal, 26(3), pp.277-285.

Deb, S.K., Jain, R. and Deb, V., 2018, January. Artificial intelligence—creating automated insights for customer relationship management. In 2018 8th international conference on cloud computing, data science & engineering (Confluence) (pp. 758-764). IEEE.

Fountaine, T., McCarthy, B. and Saleh, T., 2019. Building the AI-powered organization. Harvard Business Review, 97(4), pp.62-73.

Gupta, M. and George, J.F., 2016. Toward the development of a big data analytics capability. Information & Management, 53(8), pp.1049-1064.

Ghasemaghaei, M., 2021. Understanding the impact of big data on firm performance: The necessity of conceptually differentiating among big data characteristics. International Journal of Information Management, 57, p.102055.

Herhausen, D., Miočević, D., Morgan, R.E. and Kleijnen, M.H., 2020. The digital marketing capabilities gap. Industrial Marketing Management, 90, pp.276-290.

Hwang, W.S. and Kim, H.S., 2022. Does the adoption of emerging technologies improve technical efficiency? Evidence from Korean manufacturing SMEs. Small Business Economics, pp.1-17.

Hoque, A.S.M.M. and Awang, Z., 2016, April. Exploratory factor analysis of entrepreneurial marketing: Scale development and validation in the SME context of Bangladesh. In Proceedings of the International Social Sciences and Tourism Research Conference (pp. 22-38).

Jain, H., Padmanabhan, B., Pavlou, P.A. and Santanam, R.T. eds., 2018. Call for papers—Special issue of information systems research—Humans, algorithms, and augmented intelligence: The future of work, organizations, and society. Information Systems Research, 29(1), pp.250-251.

Kaplan, A. and Haenlein, M., 2019. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business horizons, 62(1), pp.15-25.

Knowles, E. ed., 2006. The Oxford dictionary of phrase and fable. OUP Oxford.

Kolbjørnsrud, V., Amico, R. and Thomas, R.J., 2016. How artificial intelligence will redefine management. Harvard business review, 2(1), pp.3-10.

Krause, A.E., Mackin, S., Mossman, A., Murray, T., Oliver, N. and Tee, V., Music & Science on 12 June 2020, available online at: https://journals. sagepub. com/doi/full/10.1177/205920 4320931643.

Mikalef, P., Pappas, I.O., Krogstie, J. and Giannakos, M., 2018. Big data analytics capabilities: a systematic literature review and research agenda. Information systems and e-business management, 16, pp.547-578.

Mikalef, P. and Gupta, M., 2021. Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), p.103434.

Melville, N., Kraemer, K. and Gurbaxani, V., 2004. Information technology and organizational performance: An integrative model of IT business value. MIS quarterly, pp.283-322.

Melville, N., Gurbaxani, V. and Kraemer, K., 2007. The productivity impact of information technology across competitive regimes: The role of industry concentration and dynamism. Decision support systems, 43(1), pp.229-242.

Mikalef, P., Krogstie, J., Pappas, I.O. and Pavlou, P., 2020. Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Information & Management, 57(2), p.103169.

Mishra, A.N. and Pani, A.K., 2021. Business value appropriation roadmap for artificial intelligence. VINE Journal of Information and Knowledge Management Systems, 51(3), pp.353-368.

Mikalef, P., Framnes, V.A., Danielsen, F., Krogstie, J. and Olsen, D., 2017. Big data analytics capability: antecedents and business value.

Paschen, J., Wilson, M. and Ferreira, J.J., 2020. Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. Business Horizons, 63(3), pp.403-414.

Russell, S.J. and Norvig, P., 2016. Artificial intelligence: a modern approach. Pearson.

Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D. and Spira, M., 2018. Artificial intelligence in business gets real. MIT sloan management review.

Ramli, N.A., Latan, H. and Nartea, G.V., 2018. Why should PLS-SEM be used rather than regression? Evidence from the capital structure perspective. Partial least squares structural equation modeling: Recent advances in banking and finance, pp.171-209.

Rahman, M.S., Hossain, M.A. and Fattah, F.A.M.A., 2021. Does marketing analytics capability boost firms' competitive marketing performance in data-rich business environment? Journal of Enterprise Information Management, 35(2), pp.455-480

Raisch, S. and Krakowski, S., 2021. Artificial intelligence and management: The automation–augmentation paradox. Academy of management review, 46(1), pp.192-210.

Shadfar, S. and Malekmohammadi, I., 2013. Application of Structural Equation Modeling (SEM) in restructuring state intervention strategies toward paddy production development. International Journal of Academic Research in Business and Social Sciences, 3(12), p.576.

Schryen, G., 2013. Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. European Journal of Information Systems, 22, pp.139-169.

Shrestha, N., 2020. Detecting multicollinearity in regression analysis. American Journal of Applied Mathematics and Statistics, 8(2), pp.39-42.

Sahoo, M., 2019. Structural equation modeling: Threshold criteria for assessing model fit. In Methodological issues in management research: Advances, challenges, and the way ahead (pp. 269-276). Emerald Publishing Limited.

Sheshadri, C., Rana, N.P., Tamilmani, K. and Sharma, A., 2021. The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context.

Taber, K.S., 2018. The use of Cronbach's alpha when developing and reporting research instruments in science education. Research in science education, 48, pp.1273-1296.

Wade, M. and Hulland, J., 2004. The resource-based view and information systems research: Review, extension, and suggestions for future research. MIS quarterly, pp.107-142.

Wamba-Taguimdje, S.L., Wamba, S.F., Kamdjoug, J.R.K. and Wanko, C.E.T., 2020. Impact of artificial intelligence on firm performance: exploring the mediating effect of process-oriented dynamic capabilities. In Digital Business Transformation: Organizing, Managing and Controlling in the Information Age (pp. 3-18). Springer International Publishing.

Wang, M. and Fan, X., 2021. An empirical study on how livestreaming can contribute to the sustainability of green agri-food entrepreneurial firms. Sustainability, 13(22), p.12627.