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RESEARCH ARTICLE

The Impact of Artificial Intelligence on Organizational Agility in Industrial Companies: The Moderating Role of Dynamic Capabilities

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ABSTRACT

The current study examines the impact of artificial intelligence on organizational agility in industrial companies through the moderating role of dynamic capabilities. The descriptive analytical method was used in order to achieve the objectives of the study and answer its questions. The target population in this research consists of industrial companies, as industrial companies are considered among the largest companies that have a direct impact on national income, and try to keep pace with global changes in the field of information technology. The researcher was able to collect (238) questionnaires that were approved to be filled out by employees' industrial companies.The results shows that Artificial Intelligence with it dimension (Expert Systems, Artificial Neural Networks, Algorithms, Machine Learning) has an impact on Organizational Agility in industrial companies. The results also confirm the significant role of the moderate variable (Dynamic Capabilities) in improving the impact of artificial intelligence on Organizational Agility.Artificial intelligence (AI) is crucial for organizations to stay ahead of the curve in the rapidly evolving technology landscape. It is essential to develop an organization's ability to understand, sustainably maintain, build, and deliver business results enhanced by AI, especially in industrial organizations. Agility, characterized by flexibility and responsiveness, is an indispensable asset for organizations to exploit the full potential of AI in enhancing their dynamic capabilities. The literature shows that dynamic capabilities are essential for a firm to successfully adapt, innovate, seize opportunities, respond to changes in its environment, and design new business models and processes. More research is needed to understand the role of dynamic capabilities in the three-way interplay between AI, organizational agility, and AI-enabled agility.The study recommends the use of artificial intelligence programs that rely on neural network techniques to monitor workflow and tasks in a stable and consistent manner. It is also recommended to establish specific procedures for discovering and developing capabilities within the company.

INTRODUCTION

Since the 1990s, technology has made interaction and knowledge consumption more efficient and cheaper (Aceto et al., 2018). The importance of technology and advances in production and marketplaces for goods and services has led enterprises to seek out artificial intelligence and its benefits (Bharadiya et al., 2023). Managers consider it when making decisions because it helps assess the organization's strengths and weaknesses. AI's applications and management quality must be considered (Jarrahi et al., 2023). Organizational agility is needed to improve performance in a fast-changing world where customers' preferences change (Malcom, 2021). Prior research has improved understanding of an organization's environmental adaptability and response strategies (Nafei, 2016). Organizations today seek agility through strategic objectives, resources, and a change vision. More research and development and human resources, especially fast, flexible, and adaptable ones, are needed to achieve this. Additionally, companies should produce high-quality goods. These organizational agility elements boost performance (Zeb-Obipi & Irabor-Ighedosa, 2023).

The issue is the complexity of the simultaneous tasks industrial firms must handle. Digitization must be planned for in business and corporate plans. Sund et al. (2016) suggest reviewing and changing their organizational structure. According to Krotov (2017), businesses must adopt new digital technologies and develop new capabilities to create innovative value propositions. Failure may result in being left behind. Thus, industrial managers lack confidence in starting or implementing strategic digital transformation programs in their firms. McKinsey & Company (2018) found that industrial enterprises have 4–11% digital transformation success rates. This is surprising given the academic literature on digital transformation. The study uses Teece's (2007) dynamic capacity framework to examine how "Digital Transformative Capabilities" (DTCs) evolve over time to recognize, acquire, and reorganize firm assets to address this pressing business problem. In fast-changing situations, "dynamic capability" is crucial. Facilitating change requires dynamic capabilities. Management can speculate on customer preferences, business challenges, and technology. These theories must be tested, improved, and applied. Researchers have mostly studied static and dynamic capabilities that improve firm performance.

Based on the above, the current study examines the impact of artificial intelligence on organizational agility in industrial companies through the moderating role of dynamic capabilities. The impact of artificial intelligence (AI) on organizational agility, particularly in the context of industrial companies, is a topic that requires both theoretical and practical contributions. Theoretical contributions include the conceptualization of organizational agility, which encompasses the ability to rapidly adapt to market changes, customer demands, and technological advancements. A framework has been developed to link AI capabilities to various dimensions of organizational agility, such as strategic flexibility, operational responsiveness, and organizational alignment. Referring to the dynamic capabilities, emphasizing the processes through which organizations adapt, integrate, and reconfigure internal and external competencies to address rapidly changing environments. AI can be conceptualized as a dynamic capability that enhances an organization's ability to sense opportunities, seize them, and reconfigure resources accordingly. Moderation effects are explored under what conditions dynamic capabilities moderate the relationship between AI implementation and organizational agility, identifying potential boundary conditions and the role of resources and competencies. A proposed model proposes that strong dynamic capabilities enhance the positive relationship between AI adoption and organizational agility. Practical contributions include implementation strategies, such as guidelines for AI adoption, dynamic capabilities development, performance measurement, feedback mechanisms, training and culture, and leadership alignment. The hypothesis suggests that industrial companies invest in developing their dynamic capabilities, such as sensing, seizing, and transforming, to enhance efficiency, decision-making, and responsiveness. In conclusion, understanding the moderating role of dynamic capabilities can help industrial companies harness the potential of AI technologies to enhance their agility and responsiveness in an increasingly complex and competitive landscape. Future research should empirically validate the proposed frameworks and models while considering sector-specific nuances and challenges.

LITERATURE REVIEW

Artificial Intelligence

A system that is intelligent and characterized by a rational thinking method and designed to obtain proper conclusions is called artificial intelligence (McCarthy, 2022). The study of intelligent behavior in machines is the goal of artificial intelligence, which is described in a wide and rather circular way. Intelligent behavior, on the other hand, encompasses complex environmental perception, cognition, learning, communication, and action. A long-term objective of artificial intelligence is to create machines that can execute all of these tasks as well as, or even better than, humans (Grace et al., 2018). Sheikhtaheri et al. (2014) included algorithms, expert systems, machine learning, and artificial neural networks as AI applications.

Expert systems express computer programs that imitate the procedures of specialized experts in solving difficult problems in their field of specialization (Hasan, 2021). In this way, the expertise and skills of specialists are transformed into expert systems that benefit users in solving problems. In expert systems technology, the expertise of specialists is programmed and stored in a knowledge base for an information system related to a specific field of knowledge, and through specific types of activities (Leo Kumar, 2019). Thus, the expert system is able to work as a human expert works in solving complex administrative problems.

Artificial neural networks, in contrast, rely on knowledge base systems distributed over a package of systems and programs that run through a large number of processors in a parallel processing style (Sze et al., 2017). These networks interact dynamically with the patterns and relationships contained in the data you process, similarly to how neural networks in humans rely on their operation. The goal of Genetic Algorithms Systems (GA) is to enhance computer systems' problem-solving capacities by simulating biological processes that occur in people (Clune, 2019). It has evolved into a crucial and efficient tool for handling intricate investigational issues. In order to find the best answer, this technology mimics the way human genes work. The core concept is to create a computer program where several decision-making options compete with each other; this is why it is called genetic (Sohail, 2023), as the computerized program uses the methodology of evolution and conflict to reach the optimal solution in the same way in which human genes arise and develop (Kumar et al., 2018). Machine learning, which is sometimes called self-learning, refers to one of the types of artificial intelligence techniques through which computers are empowered with the ability to learn through data or processes and not by using prior programming (Alahakoon et al., 2023). Thus, the computer has a better ability to handle the data and give greater accuracy in the results. Machine learning technology enables the computer to adapt automatically with minimal human intervention.

Organizational Agility

In the early 20th century, a new way of thinking about production and manufacturing called "agile" came up in the discipline of management science. It was initially presented in 1991 as a result of federally supported research at Lehigh University's Yococca Research Institute. Renowned management scientist Peter Drucker popularized the term, which piqued the interest of other academics and professionals in the subject. As soon as they understood it, they set out to clarify it by defining its concept and outlining its many elements.

An organization's ability to adapt quickly and effectively to market turbulence is known as organizational agility, which is a crucial feature for withstanding such challenges (Vasanthan & Suresh, 2022). This is due to its administrative capacity, which enables the organization to promptly implement necessary adjustments in response to circumstances, hence preventing future issues and effectively addressing current difficulties (Rafi et al., 2022). Consequently, agility emerged as a crucial attribute that signifies organizational effectiveness in the competitive landscape, garnering significant focus. Organizations were categorized into two types: agile organizations and traditional organizations (Saha et al., 2017). Environmental changes known as "agility drivers" place firms in a precarious situation and force them to seek out ways to differentiate themselves from the competition. Here you can find statements and data related to the "driving forces for agility" segment. The capacity to respond quickly, competently, flexibly, and with the necessary ability to deal with change is known as agility (Walter, 2021).

According to Baraei & Mizaei (2018), In 1991, a team of researchers from the Iaccoca Institute at Lehigh University came up with the concept of agility in production to describe the behaviors they saw and considered important in the manufacturing process (Yusuf et al., 1999). Researchers found that in order for a company's production system to be successful, it needs to be able to quickly change production models (move from one product model to another) and adjust to new business requirements (in terms of speed, flexibility, responsiveness, and infrastructure, for example).

Dynamic Capabilities

Dynamic capability refers to the necessity of modernizing organizational configurations to meet the evolving environmental conditions. This means that firms become capable of responding rapidly to risks and opportunities in their surroundings as well as searching, exploring, buying, absorbing and employing knowledge of resources, possibilities, and resource orchestration (Salvato & Vassolo, 2018). It also refers to the needs of capitalizing the opportunities presented by the accelerating pace or variation in the demands. The effectiveness of strategic management results from its ability to combine and reform internal and external organizational skills, operational resources, and competences to confront the demands of an increasingly changing environment (Murschetz et al., 2020).

A firm's ability to adjust to changes in its surroundings is determined by dynamic capability, which is described as a stable behavioral inclination concerning how to implement, reform, and rejuvenate and update its basic capabilities (Menghwar & Daood, 2018). However, there are two ways in which dynamic capabilities can be generated. One is through absorptive capacity, which refers to an organization's understanding of and ability to make use of existing capabilities (Engelman et al., 2017). The other is transformational capacity, which involves the ability to take existing capabilities and turn them into new ones (Warner & Wäger, 2019).

Resource-Based View (RBV) theory

The Resource-Based View posits that critical resources are determinants of firm performance. Resources encompass both tangible and intangible assets within an organization (Mikalef & Gupta, 2021). This theory posits that resources that are valuable, rare, inimitable, and irreplaceable can establish a competitive advantage by generating value and enhancing firm performance. This advantage can endure for an extended duration. Businesses can enhance the value of their resources, as the aggregate value of complementary resources exceeds the total of individual resources (Ghasemaghaei, 2021; Mikalef et al., 2021).

Consequently, based on the RBV theory and the framework proposed by Stroumpoulis et al. (2021), the adoption of AI technology in industry may allow companies to cultivate distinct "smart capabilities." Debnath et al. (2014) assert that the aforementioned capabilities should equip companies at basic levels with functions such as sensing, processing, controlling, and communicating, while advanced levels should encompass functions like predicting, healing, and preventing. These capabilities cannot be purchased or transferred; they can only be acquired through time and consistent practice.

The concepts of rarity and inimitability within the Resource-Based View (RBV) are confined to the boundaries of a firm. Firms must sustain relationships with other firms to remain competitive in a dynamic marketplace. Information technology serves as an internal resource and facilitates advanced supply chain capabilities and organizational agility (Liu et al. 2016). The resource-based view (RBV) has been extensively utilized in organizational management research; however, the dynamic capability view (DCV) is more appropriate for explaining firm performance in environments marked by supply chain complexities (Yu et al. 2018). The Dynamic Capabilities View (DCV), grounded in the Resource-Based View (RBV), posits that enhanced firm performance arises from two categories of organizational capabilities: dynamic capability and operational capability.

A framework for strategic management known as the Resource-Based View (RBV) hypothesis focuses on how a company's special assets and competencies might result in a long-term competitive advantage. When considering AI technologies, organizational agility, and dynamic capabilities, the Resource-Based View (RBV) approach may provide significant insights into optimizing these resources.

Hypotheses development

Artificial intelligence has caused and will continue to cause disruption and unpredictability in both the corporate and consumer markets. Artificial intelligence possesses the capacity to establish connections between all individuals and entities. Sheikhtaheri et al. (2014) indicated that applications of artificial intelligence include expert systems, artificial neural networks, algorithms, and machine learning. In their study, Zeb-Obipi & Irabor-Ighedosa (2023) examined the relationship between AI and organizational agility. Internet of Things, neural network, and machine learning have been used as dimensions of artificial intelligence. The organizational agility variable was measured using human resources agility, information technology agility, and innovation agility. The literature evaluation showed a relationship between artificial intelligence and organizational agility. Therefore, the study indicates that increasing artificial intelligence enhances agility. The findings of Mrugalska & Ahmed (2021) indicate that organizational agility is important for an organization to adopt Industry 4.0 technologies because it helps companies deal with the changes that arise with reliance on technologies. Moreover, it also indicates that by adopting Industry 4.0 technologies, companies can significantly enhance their agility ability in different aspects by using different technologies. Chatterjee et al. (2021) stated that Findings based on organizational agility, the relationship between stakeholders, perceived value and ease of AI customer service system, and between employee trust and attitude, attitude influence and behavioral intention as key mediators towards AI was demonstrated. This involves building specific skills and procedures that improve their agility and responsiveness.

Studies indicates a positive correlation between AI and organizational resilience; however, it lacks clarity on the measurement methods and the mechanisms that connect these two variables. The text highlights the significance of organizational resilience in the adoption of industry technologies; however, it lacks a practical framework for companies to implement these findings. Providing practical recommendations to companies based on these findings may be beneficial. According to the above, the following hypotheses can be reached:

- H1: ““There is a positive impact of the impact of artificial intelligence on organizational agility”.
- H1.1: “There is a positive impact of the impact of expert systems on organizational agility”.
- H1.2: “There is a positive impact of the impact of artificial neural networks on organizational agility”.
- H1.3: “There is a positive impact of the impact of algorithms on organizational agility”.
- H1.4: “There is a positive impact of the impact of machine learning on organizational agility”.

The emergence of artificial intelligence (AI)-based technologies has provided manufacturers with fresh prospects to sustain their technological advantage and tackle urgent societal issues. The findings of Abou-Foul et al. (2023) emphasize the positive impact of AI capabilities on sterilization; this relationship is positively moderated by absorptive capacity. Shafiabadi et al. (2023) reported that AI modeling can be used to predict an organization's agility and capabilities. This can work to acquire competencies and capabilities, and utilize resources, in order to achieve strategic objectives more effectively. The investigation conducted by Wamba-Taguimdje et al. (2020) show that companies improve their performance by using AI skills to create dynamic process-based capabilities. According to Baškarada and Koronios (2018), the organizational agility framework proposes five dynamic capabilities (sensing, searching, adjusting, transforming and shaping) that support organizational agility.

The cited studies indicate a positive relationship between AI and organizational capabilities; however, they may insufficiently address the moderating role of dynamic capabilities in the effect of AI on organizational resilience. The results of the studies are confined to a particular context. The studies indicate potential advantages of AI; however, there appears to be insufficient empirical evidence illustrating the effective application of these technologies in practice. Conversely, AI is an evolving discipline, and present findings may be inadequate for forecasting future advancements. According to the above, the following hypothesis can be reached:

"There is a positive effect of the moderating role of dynamic capabilities on the impact of artificial intelligence on organizational agility".

RESEARCH METHODOLOGY

To achieve the objectives of the study and answer its questions, the descriptive analytical method was used, where the descriptive method was used based on the study of the research topic by relying on an appropriate tool used to collect data and information. The analytical method was used to process the collected data, analyze it, and test the hypotheses to reach the results of the study and provide appropriate recommendations for those results.

The Study Population and Sample

The target population in this research consists of industrial companies, as industrial companies are considered among the largest companies that have a direct impact on national income, and try to keep pace with global changes in the field of information technology. As the size of the target population is large. It is relatively difficult to reach everyone, and the time available for data collection is limited. This led to the use of convenience sampling. To achieve the goal of this study, an electronic questionnaire was sent to all industrial companies through the website and e-mail. The researcher was able to collect (238) questionnaires that were approved to be filled out by employees' industrial companies.

Data Collection

To collect the data required to achieve the study objectives, two primary sources were used. Firstly, theoretical and scientific literature was used as starting secondary sources. Which helped the researcher provide data to develop the theoretical framework of the study and develop the study hypotheses. While reliance was placed on secondary sources by collecting data from members of the study sample through a study questionnaire prepared to achieve the goal of the study, which expresses the dimensions and variables of this study.

Reliability Test

In order to confirm whether the questionnaire items were sufficient and reliable, the Cronbach's alpha coefficient was calculated. If the result is more than 0.70, the value is statistically acceptable

(Sekaran and Bougie, 2016). Table (1) shows that Cronbach's alpha falls between 0.955 to 0.967. In other words, the data generated by the study tool is accurate and trustworthy for evaluating the factors, and it is a reliable tool. Reliability was taken into account since all dimensions of the independent and validated variables were above 70%.

Table (1): Cronbach's Alpha Coefficient

	Number of items	Cronbach alpha
Expert Systems	5	0.967
Artificial Neural Networks	5	0.963
Algorithms	5	0.961
Machine Learning	5	0.962
Artificial Intelligence	20	0.955
Organizational Agility	20	0.964
Dynamic Capabilities	10	0.960
Total	**40**	**0.956**

Descriptive Statistical Analysis

The mean of Artificial Intelligence is 3.72, According to Table (2), the mean for the variable "Expert Systems" was calculated to be 3.85. This indicates a high level of agreement among the respondents regarding this variable. when examining the answers to the individual items, the paragraph "The company uses expert systems to improve the decision-making process through information stored in databases and data" appeared in first place with an arithmetic mean 4.00. On the other hand, the item "The company designs expert systems to process administrative and financial events and processes" received the lowest ranking with an arithmetic mean of 3.70.

The mean for the variable "Artificial Neural Networks" was calculated to be 3.72. This indicates a medium level of agreement among the respondents regarding this variable. Upon examining the individual item responses, the item "The company relies on neural network technologies and applications to plan future events" received the highest rank, as the arithmetic mean reached 3.94. In addition, the paragraph "The company uses modern programs based on neural network technologies in order to monitor the progress of work and tasks according to its goals in a stable and consistent manner" obtained the final ranking, and its arithmetic average decreased the rating to 3.57.

The mean for the variable "Algorithms" was calculated to be 3.73. This indicates a high level of agreement among the respondents regarding this variable. Upon examining the individual item responses, the item "Algorithms help the company perform complex calculations to produce consistent and comparable results" received the highest rank, as the arithmetic mean reached 3.83. On the other hand, the item "Algorithms make it easier for the company to reach quick results when there are diverse and complex inputs" came in last place, and its arithmetic mean rating decreased to 3.64.

The mean for the variable "Machine Learning" was calculated to be 3.59. This indicates a medium level of agreement among the respondents regarding this variable. Upon examining the individual item responses, the item "The company's systems are linked to each other simultaneously, in an integrated and effective manner" received the highest rank, as the arithmetic mean reached 3.71. On the other hand, the item "The company's systems are characterized by the automatic ability to detect any tampering" came in last place, and its arithmetic mean rating decreased to 3.57.

Table (2): Descriptive Statistics mean and standard deviation of Artificial Intelligence Dimensions

NO.	Items	Mean	SD	Rank	Importance
1	The company uses expert systems to improve the decision-making process through information stored in databases and data.	4.00	0.636	1	High
2	The company designs expert systems to process administrative and financial events and processes.	3.70	0.496	5	High
3	Expert systems help in gaining knowledge from databases stored in the company.	3.96	0.628	2	High
4	The company uses expert systems to develop solutions to various problems.	3.82	0.687	3	High
5	Expert systems help managers in strategic planning processes.	3.82	0.746	4	High
	Expert Systems	3.85	0.477		High
6	Neural networks contribute to supporting the information properties of the company.	3.69	0.898	3	High
7	The company has a qualified and trained human cadre to deal with neural network technology.	3.69	0.935	4	High
8	The company uses modern programs that rely on neural network techniques in order to monitor the progress of work and tasks according to its objectives and in a stable and consistent manner.	3.57	1.028	5	Medium
9	The company relies on neural network technologies and applications to plan future events.	3.94	0.703	1	High
10	The company uses advanced computer hardware and equipment that is compatible with neural network technology.	3.74	0.729	2	High
	Artificial Neural Networks	**3.72**	0.719		High
11	Algorithms make it easier for the company to reach quick results when there are diverse and complex inputs.	3.64	0.839	5	Medium
12	Algorithms are characterized by their ability to adapt to changes occurring in the company's regulatory environment by developing themselves.	3.77	0.762	2	High
13	Algorithms help the company perform complex calculations to produce consistent and comparable results.	3.83	0.804	1	High
14	The company's algorithms help in performing complex calculations to obtain appropriate and more reliable results.	3.78	0.853	2	High
15	The company relies on algorithms to make decisions about accepting or rejecting a customer.	3.67	0.973	4	Medium
	Algorithms	**3.73**	0.717		High
16	The company's system can automatically handle the problems it may encounter	3.63	0.870	3	Medium

17	The company's systems handle errors in a logical and programmed manner.	3.64	0.869	2	Medium
18	The company's systems are characterized by the automatic ability to detect any tampering.	3.45	0.970	5	Medium
19	The company's systems are linked to each other simultaneously, in an integrated and effective manner.	3.71	0.794	1	High
20	The company's system automatically keeps a copy of the data in the event of a sudden disruption to the company's network.	3.55	0.970	4	Medium
Machine Learning		3.59	0.772		Medium
Artificial Intelligence		3.72	0.606		High

According to Table (3), the mean for the variable "Organizational Agility" was calculated to be 3.92. This indicates a high level of agreement among the respondents regarding this variable. Upon examining the individual item responses, it is evident that "The company has effective communication capabilities between itself and its customers", received the highest average rating of 4.09. On the other hand, Paragraph "The company takes proactive measures to improve operations and capitalize on value-added opportunities", which lower average rating of 3.80.

Table (3): Descriptive Statistics mean and standard deviation of Organizational Agility

NO.	Items	Mean	SD	Rank	Importance
1	The structural relationship between departments in the company is clear and achieves integration and harmony to achieve goals.	3.93	0.732	4	High
2	The company gives its employees sufficient powers to enable them to perform the work they are assigned.	3.85	0.719	8	High
3	The company takes proactive measures to improve operations and capitalize on value-added opportunities.	3.80	0.644	10	High
4	The company applies the principle of equal opportunities among employees.	3.87	0.644	7	High
5	The company provides professional development opportunities for employees with the aim of advancing their abilities and skills.	3.91	0.687	5	High
6	The company has effective communication capabilities between itself and its customers.	4.09	0.662	1	High
7	The company has a staff with the experience and knowledge to achieve its goals.	4.04	0.628	2	High
8	The company is characterized by its knowledge of the capabilities that need to be improved or to provide a better product to its target customer segments.	3.98	0.662	3	High
9	The company uses corrective measures periodically to improve the production process	3.84	0.862	9	High
10	The company is distinguished by its high ability to adapt to changes to meet requirements.	3.89	0.766	6	High
	Organizational Agility	3.92	0.586		High

According to Table (4), the mean for the variable "Dynamic Capabilities" was calculated to be 3.81. This indicates a high level of agreement among the respondents regarding this variable.

Upon examining the individual item responses, it is evident that "The company collects information about its customers through customized databases", received the highest average rating of 3.94. On the other hand, Paragraph “The company sets specific procedures to discover its talented people" which lower average rating of 3.66.

Table (4): Descriptive Statistics mean and standard deviation of Dynamic Capabilities

NO.	Items	Mean	SD	Rank	Importance
1	The company appoints specialized committees to study market needs.	3.87	0.687	2	High
2	The company periodically evaluates its technological capabilities.	3.87	0.674	3	High
3	The company's policies focus on the need to expand its business geographically.	3.85	0.707	5	High
4	The company is keen to benefit from successful practices in other companies.	3.77	0.826	9	High
5	The company's units and divisions cooperate periodically to improve their activities.	3.81	0.835	6	High
6	The company relies in its activities on multidisciplinary work teams.	3.87	0.661	4	High
7	The company makes periodic adjustments to its resources to suit the needs of all its units.	3.78	0.748	8	High
8	The company holds periodic meetings to discuss improving activities and operations.	3.79	0.756	7	High
9	The company collects information about its customers through customized databases.	3.94	0.653	1	High
10	The company sets specific procedures to discover its talented people.	3.66	0.717	10	Medium
	Dynamic Capabilities	3.81	0.589		High

The Test of Hypothesis

To test the first main hypothesis, Multi linear regression analysis was performed.

H1: “There is a statistically significant impact at the level (α≤0.05) of artificial intelligence on organizational agility”.

Table (5): Results of Testing H1

D.V	Model Summery		ANOVA		Coefficients				
	R	R^2	F	Sig F*	variable	B	standard error	T	Sig T*
Organizational Agility	0.773	0.597	86.326	0.000	Expert Systems	0.149	0.081	2.592	0.013
					Artificial Neural Networks	0.191	0.057	3.344	0.001
					Algorithms	0.221	0.073	4.283	0.000
					Machine Learning	0.365	0.062	5.890	0.000

In industrial companies, Artificial Intelligence has an effect on Organizational Agility, as indicated by the correlation coefficient (R = 0.773). Table No. (5) indicates a statistically significant relationship between the independent variable (Artificial Intelligence) and organizational agility, with a computed value of F (86.326) and a significance level (sig = 0.000) less than 0.05. 59.7% of the variation in organizational agility may be explained by variations in artificial intelligence, according to the coefficient of determination (R^2 = 0.597).

Table (5) shows the values of the regression coefficients for the sub-dimensions of the variable (artificial intelligence). The Expert Systems Dimension's computed T value was (2.592) at a significant level (0.013), and its B value was clearly 0.149, as the table shows. It is less than 0.05, indicating a significant positive effect at the significance threshold ($\alpha \leq 0.05$).

In terms of Artificial Neural Networks, B has a value of (0.191). In this dimension, the value of T was determined at a significance level of 0.001, or less than 0.05, as the table clearly demonstrates. This indicates a significant positive influence at ($\alpha \leq 0.05$).

With the B value of 0.221 and the T value of 4.283 at a significance level of (0.000), less than 0.05, where ($\alpha \leq 0.05$), the table clearly shows a significant positive influence in the Algorithms dimension.

With a B value of 0.365 and a T value of 5.890 at a significance level of (0.000), less than 0.05, where ($\alpha \leq 0.05$), the table clearly shows a significant positive influence on the machine learning dimension.

To test the sub-hypotheses, simple linear regression analysis was performed.

H1.1: "There is a statistically significant impact at the level ($\alpha \leq 0.05$) of expert systems on organizational agility".

H1.2: "There is a statistically significant impact at the level ($\alpha \leq 0.05$) of artificial neural networks on organizational agility".

H1.3: "There is a statistically significant impact at the level ($\alpha \leq 0.05$) of algorithms on organizational agility".

H1.4: "There is a statistically significant impact at the level ($\alpha \leq 0.05$ of machine learning on organizational agility".

Table (6): Impact test results H1.1, H1.2, H1.3 and H1.4

V	**Model summery**		**ANOVA**		**Coefficients**			
	R	**R^2**	**F**	**Sig F***	**B**	**standard error**	**T**	**Sig T***
Expert Systems	0.608	0.370	138.701	0.000	0.748	0.064	11.772	0.000
Artificial Neural Networks	0.681	0.464	204.579	0.000	0.555	0.039	14.303	0.000
Algorithms	0.685	0.469	208.263	0.000	0.559	0.039	14.431	0.000
Machine Learning	0.743	0.553	291.659	0.000	0.565	0.033	17.078	0.000

The R-value of (0.806) in Table 6 indicates that there was a positive correlation between the first dimension (expert systems) and the second dimension (organizational agility). The coefficient of determination data reveal that (R^2 = 0.370) while all other components remain constant, meaning that the (Expert Systems) domain accounted for (37%) of the variation in organizational agility. The value of (F) reaching 138.701 at the confidence level (sig = 0.000) showed that the regression's significance was supported at the significance level ($\alpha \leq 0.05$).

R-value of 0.681 for the second dimension indicates that there is a positive correlation between the two dimensions (organizational agility and artificial neural networks). R^2 = (0.464) is the coefficient of determination after all other factors have been taken into account. This means that

46.4% of the variance in (organizational agility) can be attributed to the (Artificial Neural Networks) domain. Moreover, the regression's significance at the level of significance ($\alpha \leq 0.05$) was showcased by the value of (F) reaching (204.579) at the confidence level (sig = 0.000).

The R-value of 0.469 shows that there is a positive relationship between the dimension of organizational agility and the third dimension, algorithms. The coefficient of determination results indicates that, 46.9% of the variance in (organizational agility) was explained by the (Algorithms) domain, assuming that all other variables remain constant. This translates to a 0.395 coefficient of determination. The regression's significance at the $\alpha < 0.05$ significance level was also shown by the value of (F) obtained (208.263) at the level of confidence (sig = 0.000).

The R-value of 0.743 for the second dimension shows that there is a positive correlation between the two dimensions (organizational agility and machine learning). Following the removal of all other variables, the coefficient of determination yields a value of (R^2 = 0.553), indicating that the domain of Machine Learning accounted for 55.3% of the variance in Organizational Agility. Additionally, it was shown that the regression was significant at the level of significance ($\alpha \leq 0.05$) by reaching the value of (F) at (291.659) at the confidence level (sig = 0.000).

H2: "There is a statistically significant impact at the level ($\alpha \leq 0.05$) of dynamic capabilities on the impact of artificial intelligence on organizational agility".

Table No. (7): Test results H2

DV	**IV**	**First model**			**second model**		
		B	**T**	**Sig***	**β**	**T**	**Sig***
Organizational Agility	artificial intelligence	0.737	18.054	0.000	-		
	Dynamic Capabilities × artificial intelligence	-			0.753	12.731	0.000
	R	0.762			0.867		
	R^2	0.580			0.751		
	ΔR^2	0.578			0.749		
	Δ F	325.944			355.251		
	Sig. Δ F	0.000			0.000		

The findings of the hierarchical multiple regression analysis based on two models are shown in Table (7). According to the results of the first model, there is a positive association between organizational agility and artificial intelligence, with a correlation value of R = 0.762. Additionally, the results demonstrated that the Dynamic Capabilities variable had a statistically significant impact on Organizational Agility, with a value of (F = 325.944) and a significance level of (Sig = 0.000), which is less than (0.05).

The determination coefficient's value, R^2 = 0.580, indicates that changes in artificial intelligence have an impact on organizational agility, as measured by changes in organizational agility of (0.580). With a value of 0.737, the impact score value of (B=0.737) indicates that 73.7 percent of the variation in Organizational Agility can be explained by artificial intelligence. This means that an increase of one degree in the level of interest in artificial intelligence leads to an increase in Organizational Agility.

The second model included the modified variable "Dynamic Capabilities" in the regression model. As a result, the correlation coefficient increased to R = 0.867 and the determination coefficient R^2 increased by 75.1%. This percentage and the change in the value of F (355.251) and the level of significance (Sig = 0.000), which is less than (0.05), both indicate that the model is statistically significant.

The results indicate that the modified variable (Dynamic Capabilities) significantly improved the impact of artificial intelligence on organizational agility. The rate of interpretation of the discrepancy in organizational agility increased by 75.1%, from 57.8% to 74.9%. The effect score value β for the modified variable (Dynamic Capabilities) was (0.753), and the calculated T value was (T = 12.731) with a significance level (Sig = 0.000).

Discussion

The results shows that Artificial Intelligence has an impact on Organizational Agility in industrial companies. A positive association was found between the first dimension (Expert Systems) and the second dimension (organizational agility). Also, there is a positive association between the two dimensions (Artificial Neural Networks and organizational agility). There is a positive link between the third dimension (Algorithms) and the dimension (organizational agility). In addition, there is a positive association between the two dimensions (Machine Learning and organizational agility). This has been supported by Zeb-Obipi & Irabor-Ighedosa (2023), Mrugalska & Ahmed (2021), Chatterjee et al. (2021) present these results. The results also confirm the significant role of the moderate variable (Dynamic Capabilities) in improving the impact of artificial intelligence on Organizational Agility, as the rate of interpretation of the discrepancy in Organizational Agility improved by (75.1%), rising from (57.8%) to (74.9%). Organizational agility means the ability of organizations to adapt and change quickly to meet challenges and opportunities in the organizational environment. This can include the ability to make quick decisions, flexibility in dealing with changes, and innovation in processes, products, and services. In this case, dynamic capabilities can be a positive influence between the impact of artificial intelligence and organizational agility.

CONCLUSION

In today's rapidly evolving technology landscape, the development and application of artificial intelligence (AI) has become critical for organizations aiming to stay ahead of the curve. In addition, it is necessary to develop the organization's ability to understand, sustainably maintain, build and deliver business results enhanced by artificial intelligence, whether in terms of services that rely on artificial intelligence technologies or developing the organization's capabilities, or by avoiding the risks and negative consequences that these technologies impose on the organization. Especially in industrial organizations. On the other hand, the fusion of agility and artificial intelligence (AI) stands at the forefront of transformative business strategies. Agility, characterized by flexibility and responsiveness, has become an indispensable asset for organizations striving to exploit the full potential of AI in enhancing their dynamic capabilities. Thus, there is a rich field of investigation between artificial intelligence, dynamic capabilities, and organizational agility that are rapidly emerging, forever evolving, and constantly being investigated and revised. The literature shows that dynamic capabilities are essential for a firm to successfully adapt, innovate, seize opportunities, respond to changes in its environment, and design new business models and processes. Additional analysis and empirical research are recommended to explore the role that dynamic capabilities play in shaping the interaction between AI and agility, and vice versa. Organizations can have diversity in their levels of dynamic capabilities, which is expected to influence the nature of the impact of AI on organizational agility in industrial firms. Overall, more research is needed to understand the precise role of dynamic capabilities in the three-way interplay between AI, organizational agility, and AI-enabled agility. Participating organizations are also urged to design artificial intelligence programs, to create appropriate conditions to facilitate job rotation. The study recommends the use of artificial intelligence programs, which rely on neural network techniques, to monitor workflow and tasks in a stable and consistent manner. It is also recommended to facilitate rapid results by using algorithms to process diverse and complex inputs. The study also calls for proactive action to improve operations and capitalize on value-added opportunities. It also stresses the importance of encouraging the benefit of successful practices in other companies and applying them, according to the company's environment. It is also recommended to establish specific procedures for discovering and developing capabilities within the company.

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