International Journal of Academic and Applied Research (IJAAR)
ISSN: 2643-9603
Vol. 9 Issue 6 June - 2025, Pages: 96-106

A Hybrid Model of Artificial Intelligence Capability in Business Applications

Abubakar Balarabe, Naseer Sanni Ajoge (PhD), Aminu Salihu Zakari

Faculty of Computing, Department of Computer Science, Mewar International University, Nigeria
balarabe@miu.edu.ng
College of Science and Technology, Department of Computer Science, Kaduna Polytechnic, Kaduna Nigeria
ajogenass@kadunapolytechnic.edu.ng,
aminusalihu@kadunapolytechnic.edu.ng

Abstract: *This study presents the design and mathematical evaluation of an enhanced hybrid model of Artificial Intelligence (AI) capability, aimed at improving strategic decision-making and organizational success within business enterprises. Building upon the Resource-Based Theory (RBT) and integrating existing AI capability models by Mikalef & Gupta (2021) and Li et al. (2022), the research identifies and incorporates thirteen additional AI-related factors—such as data, technology, human resources, and organizational change capacity—resulting in a comprehensive model with eighteen critical variables. The model categorizes these factors into external, instantaneous, and temporal components to capture both immediate and time-bound organizational dynamics. Formalized using first-order differential equations and verified through equilibrium analysis, the model demonstrates stability and alignment with strategic goals. The findings underscore the enhanced model's potential to support creativity, knowledge sharing, and sustained performance in AI-driven organizations*

Keywords— Artificial Intelligence, AI Capability, Resource-Based Theory, Knowledge Sharing, Organizational Success, Hybrid Model, Mathematical Verification.

1. INTRODUCTION

One of the things our society can boast of today is the rapid development of science and technology as well as another aspect of computer knowledge such as Artificial intelligence (AI). Artificial intelligence is widely recognized as the next source of business value, a key technology guiding a new wave of technological innovation and industrial transformation (Li, Yan, Yang & Gu 2022), as a result, AI technology is now becoming increasingly important (Townsend et al., 2018).

AI developed into a multidisciplinary discipline in the late 1980s and early 1990's that comprises; Expert systems, Neutral networks, Robotics, Natural language processing (NPL) Speech recognition, and Virtual reality (Ertel, 2018).

Bughin et al. (2017), asserts that the rapid development of AI brings many opportunities and challenges to organizations to acquire key AI technologies. In recent years, the field of AI has witnessed remarkable advancements, transforming the way we interact with technology and shaping industries across the globe, with this development, it is important to note that AI has been used in applications to perform certain tasks in various business organizations including the academia.

The business sector needs to respond faster in the digital age and pay more attention to the competitive landscapes, which can shift more quickly than ever, many companies are embracing new technologies aimed at achieving high performance and competitive advantage (Weill & Woerner, 2017), among these technologies, AI has occupied a prominent position and has attracted attention from both the literature and business organizations. According to Davenport (2018), AI might be the technology force with the greatest disruptive potential currently in use, similarly, a study by Brynjolfsson and Mcafee (2017), also shows how AI is the most important general-purpose technology of our era, particularly with regards to machine learning techniques. The goal of AI is to make computers capable of carrying out tasks that would typically need human intelligence as a result, AI will eventually replace many human-held jobs (Jerrahi, 2018).

Artificial intelligence is also very much useful in knowledge management and in all fields of human endeavor, instrumental in the learning and business environment. It is essential to note that knowledge management (KM) is a key tool for firms to gain a sustainable competitive advantage. Individual knowledge and knowledge sharing are the main aspects of knowledge management for organizational achievement in the information age. The development of AI technology promises several benefits in organizations, which will bring about business value (Enholm et al., 2021).

In order for businesses to achieve their strategic goals, knowledge sharing is crucial since it enables them to collaborate and create new sources of knowledge, update their problem-solving abilities, and become more aware of how other people make decisions (Li et al., 2022).

Although AI have attracted the attention of business organizations in the last decade due to advancement in machine learning, organizations are still struggling to integrate AI into their businesses because they don't understand how to use it strategically (Borges et al, 2020), effective knowledge management will be facilitated by the incorporation of AI techniques into knowledge organizations, which will result in the transformation of individual knowledge into organizational knowledge. (Liebowitz, 2001).

Zheng et al, (2021), asserts that mere adoption of AI tools without appropriate KMPs is not effective. Due to the competitive nature of the business world, high data volume, scarce resources, and the need for speed in decision-making, many organizations are beginning to adopt AI technologies. Knowledge workers in business organizations need to have/develop creative skills and adapt the use of AI in their business in other to bring about creative, innovative, and useful solutions thereby creating an edge in the business world (Botega & da Silva, 2020), one of the key drivers of this progress is the identification of AI capability factors, needed to bring about organization creativity, success and performance. Building on the resource base theory (RBT) of the firm, the study enhanced an AI capability model by hybridization and addition of more factors necessary for the success of an organization. The RBT emerged as one of the most extensively used theoretical approaches for illuminating how disparities in performance within the same industry might be caused by the resources that an organization possesses or have under its control (Barney, 2001).

Grounded in strategic management literature, the RBT asserts that firms compete based on the resources that they have under their control, which providing are valuable, rare, difficult to imitate, and non-substitutable can generate performance gains. As such, resources represent the input of the production process, while a capability is the potential to deploy these resources to improve productivity and generate rents (Mikalef, Pateli, & van de Wetering, 2020).

Hence, the study builds on the RBT and combined the conceptual model of two AI capability, to create a robust and adaptable model. According to Alobaedy (2015), the term "hybrid" in computer science is the combination of two or more different techniques, methods, models, separated naturally from each other, in other to generate something new, which have the ability to take advantage of different techniques, methods, or models combined. In this era of relentless innovation, the quest for AI capabilities that can push the boundaries of what firms can achieve has led to the emergence of more organizations, adapting the use of AI model in their businesses. This model represents a significant milestone in the evolution of AI, promising to revolutionize industries, improve decision-making processes, and unlock new possibilities that were once confined to the realm of science fiction.

In other to study the impact of AI capability on organizational creativity, some scholars have creatively proposed the idea and framework of AI capability, designed its scale and investigated the effect of AI capability on organizational creativity and performance (Mikalef & Gupta, 2021).

However, they did not fully explain how artificial intelligence capability contributes to the improvement of organizational creativity that leads to organizational success.

Islam et.al, (2021), elaborates mainly on employee creativity, and pointed out that employees will not be afraid of being criticized for sharing their thoughts and ideas base on emotional trust. However,

Li et al. (2022), presented an AI capability model, introduced the concept of AI capability and examined its relationship to organizational creativity; they also examined the influence path between AI capability and organizational creativity from the perspective of knowledge sharing, the effect of organization cohesion and how it helps in promoting AI capability. Result from their study shows that AI capability has a positive impact on knowledge sharing, knowledge sharing has a positive impact on organizational creativity and knowledge sharing mediates the relationship between AI capability and organizational creativity. However, existing research lacks some exploration on the effect of organizational level factors to promote organizational success. Some essential factors that are necessary and relevant in enhancing the effect of AI capability in business organization which will help managers and employees in making quick and accurate decision, to be creative and innovate is inadequate, despite the revolutionary potential that AI capabilities may promote (Perifanis & Kitsios, 2023).

None of these literatures were able to show that organization performance leads to organization success. However, Chowdury, (2022), Created and verified a unique theoretical model on knowledge sharing, trust, worker's AI abilities and job clarity to better organization success, also Hussan and Pinky (2023), in their work verified how improved employee performance, leads to overall organization success. Therefore, there's a need to enhance these models to improve the decision-making ability of managers and employees in business organization that will bring about organizational success. To achieve this, we enhanced an AI capability model of (Li et al., 2022) by hybridization and the addition of more factors, necessary for an overall organization success

The aim of this study is to design an enhanced hybrid model of AI capability by hybridization and addition of more factors. We then formulate the mathematical model of the enhanced hybrid model. And evaluate the enhanced model using mathematical verification. The study designs an enhanced hybrid model of AI capability that can be used to influence important decisions in business organizations, through the identification of factors relevant for organization success.

2. LITERATURE REVIEW

2.1 RESOURCE BASE THEORY

Resource base theory (RBT) begins by supposing that firms are bundles of resources and capabilities (Barney, David, Ketchen & Wright, 2011). The RBT of the firm has become one of the most widely applied theoretical perspectives in explaining how the resources that an organization owns or has under its control can lead to differences in performance in the same industry (Barney, 2001).

Resource base theory is a management framework that focuses on a firm's internal resources as sources of sustainable competitive advantage, it suggests that a firm's internal factor such as resources and capabilities, can lead to superior performance when effectively leveraged (Porter 1989). That apart from the technology itself, other human and complementary organizational resources are required to leverage investments (Gupta & George, 2016; Mikalef, Pappas, Krogstie, & Giannakos, 2018). These, and other previous research consistently show how effective the RBT is, in explaining the connection between organizational resources and firm performance.

RBT represents a specific set of theories and frameworks within that perspective, offering more detailed guidance on how to analyze and leverage these resources effectively.

Since the aim of this study is to identify the necessary organizational level factors and enhance the existing AI capability model that will enable business owners make quick and accurate decision which will result in performance gains, the RBT was a suitable choice to serve as the study's underlying theoretical framework.

Figure 1 shows the VRIO framework (Valuable, Rare, Inimitable, organization), the framework was proposed by Jay Barney in 1991, is a business framework that forms part of a firm's larger strategic scheme, is a strategic analysis tool used to assess the competitive advantage of a firm's resources and capabilities. The VRIO model proposes the new criteria of the organizational embeddedness of a resource (Utami & Alamanos, 2023).

Dynamic Capabilities: a concept in strategic management that describes a firm's ability to adapt and innovate in response to changing environments. Dynamic capability is a theory of competitive advantage, (Denrell & Thomas 2016), it emphasizes the importance of a firm's ability to adapt, integrate and change its resource base over time. It is also the capacity to systematically solve problems, enabled by its propensity to sense opportunities and threats, to make prompt decisions and to effectively implement strategic decisions (Ferreira, Coelho & Mountinho 2020).

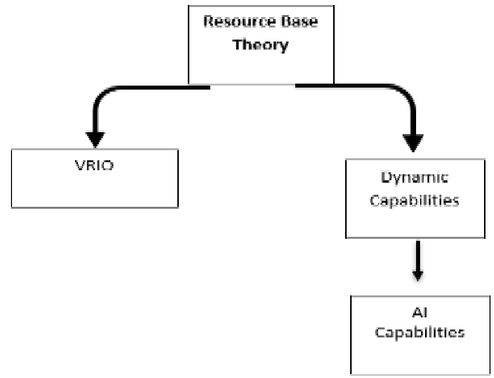

Fig1: Approaches in Resource Base Theory

Modeling here might involve assessing how a firm's resources can be dynamically reconfigured to respond to changing market conditions.

Table 1: Comparison of VRIO and Dynamic Capability Approaches in Resource Base Theory

VRIO	Dynamic Capability
Focus: Focuses on assessing a firm's existing resources and capabilities to determine if they can contribute to sustained competitive advantage	Dynamic capability focuses on a firm's ability to adapt, change, develop and respond to new capabilities over time
Static: Static, assess current resources and capabilities without emphasis on how they evolve over time	Dynamic capabilities are inherently dynamic, as they address a firm's ability to change and adapt, making them particularly relevant in fast-changing industries
Application: help firm in determine their existing resources and capabilities and determine whether they are valuable, rare, difficult to imitate, and organized, to lead to competitive advantage	It emphasizes a company's capacity to learn, innovate, and respond to environmental changes. They help firm's ability to evolve and stay competitive in the long-run.

Base on the features and comparison of the two approaches, AI capabilities are often associated with the "Dynamic Capability" approach (Tigunt & Hossari, 2020). Dynamic capabilities refer to an organization 's ability to adapt, evolve, and innovate in response to changing market conditions and technological advancements. AI capability models involve the development and integration of artificial technologies into an organization's processes, which can enhance its ability to analyze data, make predictions, and make decisions dynamically based on new information. This aligns with the dynamic capability perspective, as organizations with strong AI capabilities can respond more effectively to changes in their environment and gain a competitive advantage.

Therefore, this study is built based on the dynamic capability approach, which describes the ability of a firm to adapt, evolve, and innovate in response to changing market conditions and technological advancements (Teece, 2022). In addition, it will enhance their ability to deal appropriately with their rapidly changing environment (Felsberger et al., 2022).

2.2 Conceptual Research Model of AI Capability

Figure 2 shows Conceptual Research Model which is grounded on the resource base theory of the firm. Mikalef & Gupta (2021), put forward a conceptual research model that seeks to examine the resources that are required to build an AI capability. Empirical result from their study shows that AI has a positive effect on organization creativity and performance. The first true type of integrated intelligent model is fused architecture. Systems that incorporate several techniques and procedures into a single computational model are among them. They exchange knowledge representations and data.

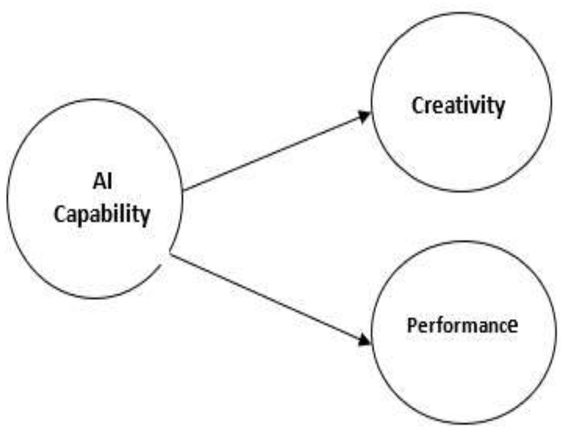

Fig. 2: Conceptual Research Model

2.3 Integrated Artificial Intelligence Capability Model

Figure 3 shows the existing AI capability model and conceptual research model for organizational creativity and performance by Li et al. (2022) and Mikalef & Gupta (2021). Empirical research was carried out to this effect. Mikalef & Gupta proposed a conceptual framework of AI capability model, designed its scale and studied the impact of AI capability on organization creativity and performance. Their empirical study supports the suggested theoretical framework, developed an instrument that provides evidence that AI capability results in increased organizational creativity and performance.

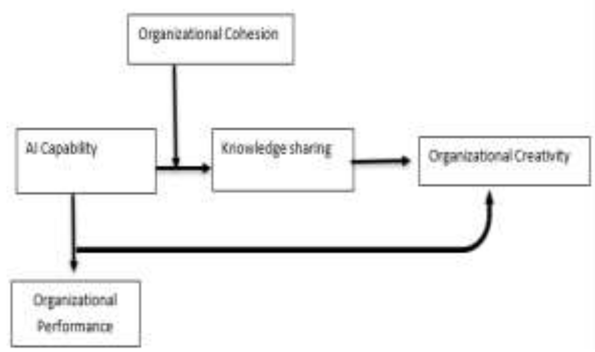

Fig. 3: Integrated Model of AI capability

While Li et al. (2022), presented an AI capability model, which established an Integration model of AI capability, Knowledge sharing and Organizational creativity. They examined the influence path between AI capability and organization creativity from the perspective of knowledge sharing and the effect of organization cohesion on organization creativity, through an empirical survey base on 189 questionnaire data, using multi-level regression analysis and bootstrap method to analyze the influence mechanism, result from their empirical study shows that AI capability has a positive impact on knowledge sharing, knowledge sharing has a positive impact on organizational creativity and knowledge sharing mediates the relationship between AI capability and organizational creativity. The model utilized the RBT essential in the business domain.

Mikalef & Gupta, (2021) put forward the concept of AI capability as the ability of a firm to select, orchestrate, and leverage its AI-specific resources. A novel idea that refers to a company's capacity to choose, organize and use resources specifically for AI, they carried out an empirical research to support and provide evidence that AI capability results in increased organizational creativity and performance, using the resource based theory of the firm, the study identifies the AI-specific resources that creates AI capability and also developed an instrument to capture AI capability of firms, examines the relationship between AI capability, organizational creativity and performance.

2.4 Enhanced integration of AI capability Model Factors

Table 2 shows the integration model factors and the proposed enhanced hybrid model of AI capability model factors. None of these literatures were able to show that organization performance leads to organization success.

Chowdury, (2022), Created and verified a unique theoretical model on knowledge sharing, trust, worker's AI abilities and job clarity that relates to better organization success, while Hussan & Pinky (2023), in their study, verified how improved employee performance, leads to overall organization success. Therefore, there's a need for the inclusion of more factors to show how organization performance leads to organizational success. The factors identified in the model are not robust enough, as there are more factors that can lead to organizational success.

Based on these drawbacks of the integrated AI capability Model, there's a need to enhance these models to improve the decision-making ability of managers and employees in business organization, to achieve this; more factors were included in our work. The present study proposed and enhanced hybrid model of AI capability by the inclusion and identification of more factors. This is to be achieved by addition of more factors obtained from other literature.

A total of thirteen (13) factors such as Data, Technology, Basic Resources, Technical Skills, Business Skills, Interdepartmental coordination, Organizational change capacity, Risk Proclivity, Tangable Resources, Human Resources, Intangible Resources, Collaboration and Organization success are realized in order to have a comprehensive conceptual model, that has eighteen (18) relevant factors to aid business owners (mangers) in making strategic decisions relevant for organization success.

Table 2: Integration of AI model factors and the proposed enhanced model factors

Conceptual Research Model (Mikalef & Gupta, 2021)	Proposed Enhanced Hybrid Model of AI Capability
• AI capability • Organizational creativity • Organizational Performance	• Data • Technology • Basic Resources • Technical Skills • Business Skills • Inter departmental Coordination • Organisational change Capacity • Risk Proclivity • Tangible Resources • Intangible Resources • Human Resources • Collaboration • Organization success.
AI Capability Model (Li et al., 2022)	
• AI capability • Knowledge Sharing • Organizational Cohesion • Organizational Creativity	

3. METHODOLOGY AND DESIGN

3.1 RESEARCH FRAMEWORK

The Research Methodology is shown on figure 4 below. A framework underlying the design structure of the study is given. The framework implemented is adapted from Mustapha, 2019 and Mustapha et al. (2020).

As a result of the complex and dynamic nature of the business environment, this methodology is applicable for formal specification and representation. This research methodology serves as a guide to develop and evaluate the AI Capability model grouped into three (3) stages, the first two 2 stages (Design, and Operational) is used as a basis for the model construction while the last stage involves model evaluation.

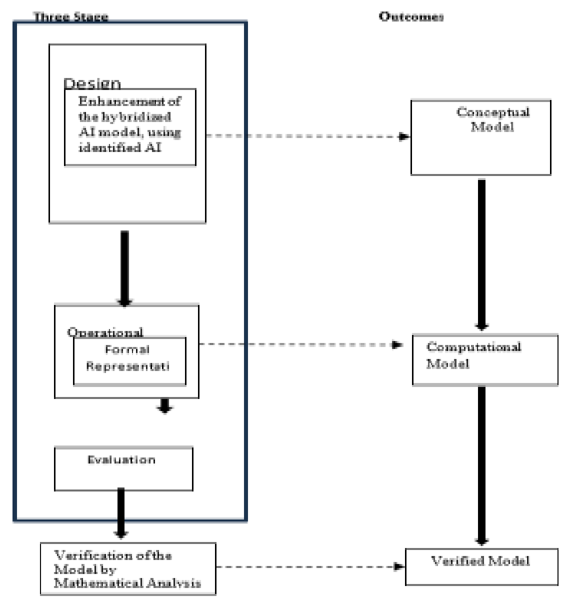

Fig. 4: Research Methodology

3.2 DESIGN MODEL STAGE

In the design model stage, thirteen (13) AI capability factors such as data, technology, basic resources, Technical skills, business skills, interdepartmental coordination, organizational change capacity, Risk proclivity, Tangible resources, Intangible Resources, Human Resources, collaboration, and organizational success were obtained from the resource base theory of the firm and related literatures, combined to enhance the AI capability model, put forward by Mikalef & Gupta (2021) and Li et al. (2022). Each of the factors in the model is represented by a node, and the casual relationships between the factors are shown using flow arrows. To create a model of enhanced AI capabilities, the direct and indirect relationships were taken into account based on the theory of each concept. The model's variables were divided into external, instantaneous, and temporal factors. The external factors are set of input factors to the model, while the instantaneous factors are factoring whose process occur instantly. The temporal factors, are time-bounded factors whose processes occur with many delays in time. The result of this research stage fulfils the first research objective. Activities in the design stage are shown in figure 5 followed the process used by Mustapha (2019).

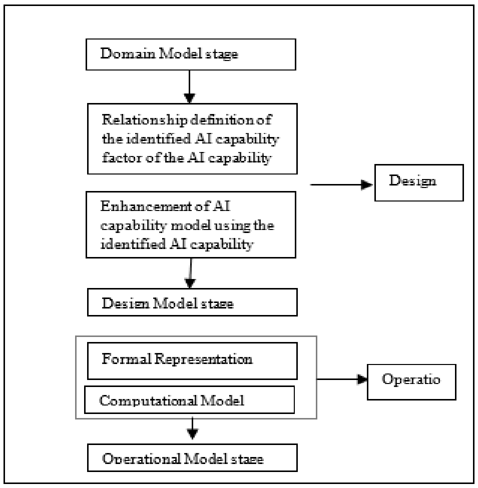

Fig. 5: Design and Operational Model Stage Activities

To demonstrate the design model stage, if A, B, C, D, and E are factors identified from the domain model stage, then the design model can be presented in figure 3.3. if A, B, C, D and E are factors identified from the domain model stage, the relationship between these five factors (A, B, C, D and E) is shown using a set of flow arrows as shown in figure 3.4 obtained based on theories where the factors are identified.

To demonstrate the design model stage, if A, B, C, D, and E are factors identified from the domain model stage, then the design model can be presented in figure 3.3. if A, B, C, D and E are factors identified from the domain model stage, the relationship between these five factors (A, B, C, D and E) is shown using a set of flow arrows as shown in figure 6 obtained based on theories where the factors are identified.

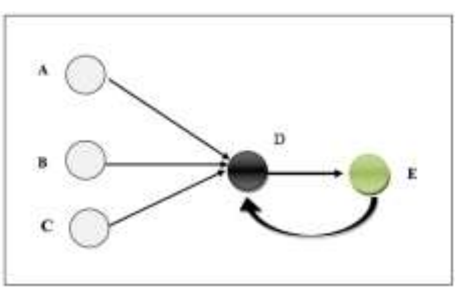

Fig. 5: Example of Design Model

3.3 OPERATIONAL STAGE

At this stage, the conceptual model derived from the design model is formalized. The result of this stage fulfils the second research objective. For example, the mutual representation of the four 4 identified factors (A, B, C, D) determine E. assumptions can be made that the casual interactions of these factors are based on the RBT. For this purpose, it can be assumed that if equation 3.1 and 3.2 are non-zero, or not equal to 1, then the concept conditions stated in table 2 can be formalized conceptually to gain equation 3.3 and 3.4, assuming E is the combination of factors as shown below.

$$E = f[A, B, C, D] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Where $0 \leq A \leq 1$, $0 \leq B \leq 1$, $0 \leq C \leq 1$, $0 \leq D \leq 1$ and $0 \leq E \leq 1$.............................. (3.2)

$$D(t) = \omega_{x1}.A(t) + \omega_{x2}.B(t) + \omega_{x3}.C(t) + \omega_{x4}.E(t) \ldots\ldots\ldots\ldots (3.3)$$

$$\sum_{i=1}^{4} \omega_{xj} = 1$$

Where ω_{x1}, ω_{x2}, ω_{x3}, ω_{x4} are weight parameters of the equations.

$$E(t+\Delta t) = E(t) + \gamma_E.\big(D(t) - E(t)\big).E(t).\big(1 - E(t)\big).\Delta t \ldots\ldots\ldots\ldots (3.4)$$

Equation 3.4. was obtained from the concept of differential equation, the change equation in this process is measured in a time interval between t and t +Δt. the rate of change of all temporal speculations is determined by flexibility rates of γ_E, known as the change rate parameters. (1-E (t)) are the regulating function in the equations.

4. RESULTS AND DISCUSSION

In this study, thirteen (13) factors of AI capability was identified based on the review of related literatures and empirical study as stated above.

The thirteen (13) factors identified in this model were classified into three (3) groups namely, external (input), Instantaneous (mediating) and Temporal factors. The external factors are independent factors that contribute to other factors, while the instantaneous factors are dependent that are time-bounded with no delay, in contrary, the temporal factors are dependent factors that are time-bounded with delay.

4.1 External Factors of the Enhanced Hybrid Model of Artificial Intelligence Capability

Eleven (11) external factors were identified in the enhanced hybrid model of AI capability namely; Data, Technology, Basic Resources, Technical Skills, Business Skills, Interdepartmental coordination, Organizational change capacity, Risk Proclivity, Tangible Resources, Human Resources and Intangible Resources.

Table 3: Summary of External Factors of the Enhanced Hybrid Model of Artificial Intelligence Capability based on the Resource Based Theory of the Firm

Factors	**Symbol**	**Definition**	**References**

International Journal of Academic and Applied Research (IJAAR)
ISSN: 2643-9603
Vol. 9 Issue 6 June - 2025, Pages: 96-106

Data	D_t	These are facts, information, or pieces of knowledge that are collected, stored and analyzed used to make informed decision in other to gain competitive advantage.	Parkins, (2017), Ransbotham et al.(2018).
Technology	T_n	This refers to the infrastructure and equipment necessary for the adoption and implementation of AI within organizations, encompassing all equipment for fast data analysis and execution of complex algorithms, such as GPU-intensive clusters and parallel computing techniques	Mikalef and Gupta (2021), Chui and Malhotra (2018)
Basic Resources	B_r	Emphasizes essential commodities required for organizations to establish AI capabilities.	Mikalef and Gupta (2021), Gupta and George, (2016), Davenport and Ronanki (2018).
Tangible Resources	T_r	Tangible resources refer to physical assets that can be bought, sold, or quantified in monetary terms. This includes financial assets such as cash, investments, and securities, as well as physical assets like property, equipment, and inventory.	Mikalef and Gupta (2021), Barney, (1991).
Technical Skills	T_s	The ability to develop, implement, and manage AI algorithms, as well as to ensure that AI applications align with organizational goals.	Mikalef and Gupta (2021), Wilson, Daugherty & Bianzino (2017).
Business Skills	B_s	Skills needed by managers and employees for a successful implementation and utilization of AI technologies within organization.	Mikalef and Gupta (2021), Davenport and Ronanki (2018).
Interdepartmental coordination	I_c	Collaborative efforts and shared values among different departments within an organization. It is also a state characterized by high levels of shared values, mutual goal commitments, and collaborative behaviors.	Mikalef and Gupta (2021), Ransbotham et al. (2018). Souder (1977)
Organizational-change capacity	O_y	Refers to an organization's ability to successfully transition from old processes to new ones, particularly in the context of adopting artificial intelligence (AI) technologies.	Mikalef and Gupta (2021),
Risk Proclivity	R_p	An organization's inclination towards embracing risk in pursuing new ventures, such as adopting artificial intelligence (AI) technologies.	Mikalef and Gupta (2021), Ransbotham et al. (2018).

Human Resources	H_r	Refers to both technical expertise related to AI technologies and business acumen necessary for effectively integrating AI into operations.	Mikalef and Gupta (2021), Bharadwaj, (2000), Ravichandran and Lertwongsatien, (2005).
Intangible Resources	I_r	Resources considered more challenging for competitors to replicate.	Mikalef and Gupta (2021), Grant (1991).

4.2 Instantaneous factors of the Enhanced Hybrid Model

Three (3) instantaneous factors of the enhanced hybrid model was identified namely: AI capability, Knowledge Sharing, and Collaboration.

. In enhancing the conceptual model of AI capability, relevant factors necessary for organizational success were identified from related literatures, used to enhance the integrated model put forward by li et al. (2022), Mikalef and Gupta (2021).

A total of seven (7) factors in each model was identified included as AI Capability, Organization Cohesion, Organization Performance, Organization creativity and Knowledge sharing.

In the enhanced model, an addition of thirteen (13) AI capability factors were added and represented symbolically using nodes and flow arrows. The nodes represent the states and the flow arrow shows the relationship between the states. The nodes and flow arrows formed the conceptual model. This conceptual model explicitly indicates interaction between factors and the relationships involved based on the resource-based theory.

The casual relationships produced an enhanced conceptual model called "an enhanced conceptual model of AI capability" as summarized in figure 6.

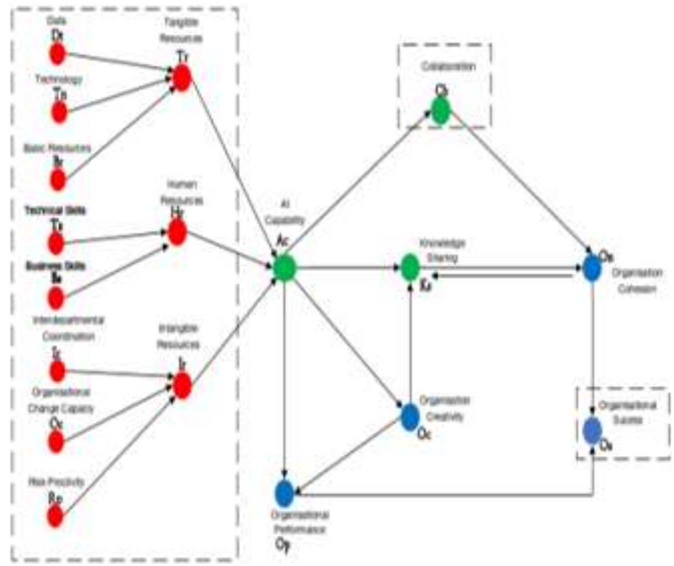

Fig. 6: An Enhanced Hybrid Model of AI Capability

The model is formalized into a set of formal equations, done based on the studies of R, Mustapha (2019, 2020), and Truer (2016a, 2016b, 2016c). The formalization of the model factors is obtained with respect to time (t), Details of the formalization of the external factors are given below.

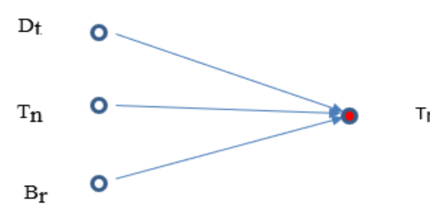

Fig. 7: Casual Relationship of Data, Technology and Basic Resources

Data, Technology, and Basic resources contribute positively to tangible resources. The introduction of data, technology and basic resources in an organization brings about valuable tangible resources. Data provides insights into consumer preferences, market trends, and operational efficiencies, guiding resource allocation. Technology enables the efficient utilization of resources through automation, optimization, and innovation. Basic resources serve as the foundation for tangible outputs, whether raw materials in manufacturing or human labor in service industries.

$$T_r(\mathrm{t}) = \left[\omega_{Tr1}.D_t(t) + \omega_{Tr2}T_{n(t)}\right].B_r(\mathrm{t}) \ \ldots\ldots\ldots\ldots\ldots (3.5)$$

The formalization of tangible resources with respect to time were ω represents the weight of each factor, implying the contribute equally as shown in equation 3.5.

4.3 Verification of the Enhanced Model ff Artificial Intelligence Capability

In other to fulfil the third 3rd objective of this study, which is to evaluate the enhanced model mathematically, the verification of the model is done by using mathematical methods. Verification is the process or technique used to ensure that the model specification and assumptions are correct (Mustapha, 2020).

The aim is to ensure the model achieves its desired objective which is to verify the theoretical and structural analysis of the model. This study carryout equilibrium analysis that described a scenario in which a stable situation has been reached. That is, if the dynamics of the system is to be described by a different equation, then equilibrium levels can be estimated by setting a derivative or all derivatives to zero. One important thing to note is that, an equilibrium condition is considered stable if the system always returns to kits state after small perturbation or disturbances. These equilibrium condition indicates the correctness of the enhanced model.

Mathematical analysis can be used to analyze the dynamic properties of dynamic models in order to understand the structure and correctness of the model through theoretical construct. Examples of such properties are values of the variables for which no change occurs (Stationary points or equilibria), certain valuables in the model converge to some limit value) and certain values will show monotonically increasing or decreasing values over time (monotonicity), others are situations occur in which no convergence occurs, but in the end, a particular sequence of values is represented all the time (limit Cycle).

The existence of reasonable equilibria is a sign of the model correctness. The concept used in this study derived from the concepts of differential equations (D.E) Truer (2016a, 2016b, 2016c).Mustapha, (2019).

To obtain possible equilibria values, for the temporal factors which are the dependent variables, the study first described the temporal equations.

$$\frac{dO_c}{dt} = \beta_{Oc}(A_c - O_c).O_c.(1 - O_c) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

$$\frac{dO_p}{dt} = \gamma_{Op}\big((\omega_{Op1}A_c + \omega_{Op2}O_C\big) - O_p).O_p.(1 - O_p) \ldots\ldots..(2)$$

$$\frac{dO_n}{dt} = \alpha_{On}\big((\omega_{On1}C_b + \omega_{On2}K_s) - O_n\big).O_n.(1 - O_n) \ldots\ldots(3)$$

$$\frac{dO_s}{dt} = \mu_{Os}(\omega_{Os1}O_p + \omega_{Os2}O_n) - O_s).O_s.(1 - O_s) \ldots\ldots\ldots(4)$$

This can be further distributed into

$$(O_C = A_C) \cup (O_C = 1) \cup (O_C = 0) \cup \big(A_C + O_C = O_p\big) \cup \big(O_p = 1\big) \cup \big(O_p = 0\big) \cup (C_b + K_s = O_n) \cup (O_n = 1) \cup (O_n = 0) \cup \big(O_p + O_n = O_s\big) \cup (O_s = 1) \cup (O_s = 0)$$

Thus, it can be concluded these are points were the equilibrium can occur.

That is, when $O_c = A_c, O_c = 1, O_c = 0$ $or\ when\ O_p = A_c + O_c,$ $O_p = 1, O_p = 0$ or $O_S = 1, O_S = 0$

Combining these three (3) conditions, it can be rewritten as a set of relationship in a form $(A \cap C) \cup (A \cap E)$

Therefore, we have,

$$\big((O_C = A_C) \cup (O_C = 1\big) \cup (O_C = 0)) \cap ((A_C + O_C = O_P)(O_P = 1) \cup$$

$$O_P = 0)) \cap ((C_b + K_C = O_n)(O_n = 1) \cup (O_n = 0)) \cap ((O_P + O_n = O_s) \cup (O_s = 1) \cup (O_s = 0))$$

Using distributive law, these equations can be further elaborated into: $(A \cap C) \cup (A \cap E) \cup (A \cap G) \cup (A \cap I) \cup \ldots (C \cap M)$

$(O_C = A_C \cap Ac + Oc = Op \cap C_b + K_C = O_n \cap O_P + O_n = O_s) \cup (O_C = 1 \cap O_P = 1 \cap O_s = 1) \cup \ldots \cup (O_C = 0 \cap O_P = 0 \cap O_s = 0)$.

The temporal factors are used to determine the possible combinations. From the concept of differential equations, (D.E), $F(x) = X^n$

Where x is the possible number of equilibrium points that can occur in a particular temporal factor for example,

$$O_p = A_c + O_c, \quad O_p = 1, and\ O_p = 0$$

And n, is the number of temporal factors in the hybrid model. Since there are four (4) temporal factors, this results in 3^4 (81) possible equilibrium points.

However, it can be problematic to provide complete classification of equilibrium due to large size of possible combinations. Typical cases are analyzed below.

Case 1: $O_P = A_C + O_C$

$A_C = O_C - O_P$ Or $O_C = A_C - O_P$

Considering the factor that receives Op as an input from the casual relationship.

For example, O_s (Organizational Success) receives O_P (Organizational Performance) as input. Therefore, we substitute ($O_P = \gamma_{O_P} A_C + O_C$) equation i, in equation ii.

$$O_P = \gamma_{O_P} A_C + O_C \; \dots\dots\dots\dots\dots\dots\dots\dots\dots (8)$$

$$O_s = \gamma_{O_P} O_P + (1-\gamma) O_n \dots\dots\dots (10)$$

Substituting O_P in equation 10,

$$O_s = \gamma_{O_P} A_C + O_C + (1-\gamma) O_n$$

Assuming $\gamma_{O_P} = 1$

$$O_s = A_C + O_C + (1-1) O_n$$

$$O_s = A_C + O_C$$

Changing the value for $\gamma_{O_P} = 0.5$

From equation 4.10,

$$O_s = 0.5 * O_P + (1-0.5) O_n$$

$$O_s = 0.5 O_P + (0.5) O_n$$

$$O_s = 0.5(O_P + O_n) = 0.5(O_P + O_n)$$

But,

$$O_P = A_C + O_C \; \dots\dots\dots\dots (8)$$

Therefore,

$$O_s = 0.5(A_C + O_C + O_n)$$

When $\gamma_{O_P} = 0$ from equation 4.10,

$$O_s = \gamma_{O_P} O_P + (1-\gamma) O_n$$

$$O_s = 0 + (1-0) O_n$$

$$O_s = O_n$$

5. CONCLUSION

The study presented an enhanced hybrid model of Artificial Intelligence capability in the business domain that can assist managers, business owners in making quick and accurate decisions. The study hybridized and enhanced an AI capability model by integrating two existing AI capability model by addition of more factors to have a robust Conceptual model. the study presented a total of eighteen (18) AI capability factors, five (5), from previous research while a total of thirteen (13) factors were added, these factors were obtained based on the Resource-based theory of the firm and other related literatures, were reviewed and used as a guide in obtaining these factors, the factors were combined using flow arrows to show the casual relationship of one factor to the other, which resulted in a more robust Conceptual AI capability model.

The second objective which is to formalize the model and the obtained factors derived from a conceptual model was expressed in formal specification based on first order differential equation, in particular the study used thirteen (13) factors in design of the enhanced model. The model was verified using the verification analysis method, achieved by using mathematical analysis. Three (3) selected cases from equilibrium points were used to prove how the model converge otherwise known as the stability of the model. Important to show how the model stabilize under certain conditions, despite the presence of small disturbance.

6. References

Abubakar, A. M., Behravesh, E., Rezapouraghdam, H., & Yildiz, S. B. (2019). Applying artificial intelligence technique to predict knowledge hiding behavior. *International Journal of Information Management*, *49*, 45–57. https://doi.org/10.1016/j.ijinfomgt.2019.02.006

Ain, N., Vaia, G., DeLone, W.H., & Waheed,M.(2019). Two decades of research on business intelligence system adoption, utilization and success-A systematic literature review. Decision Support Systems, 125, 113113. https://do.org/10.1016/j.dss.2019.113113.

Alobaedy, M.M.T. *Hybrid Ant Colony System Algorithm For Static and Dynamic Job Scheduling In Grid Computing.* PHD Thesis, Universit5y Utara Malaysia, 2015

Apian, (2019). *PART THREE:* Why Humans, AI Systems, and Robots Needto Get Along at Work – And Why it's So Hard to Do. Retrieved from https://www.appian.com/wpcontent/uploads/2019/03/idg-future-of-workpart-3.pdf

Aziz, A. A., Ahmad, F., Yusof, N., Ahmad, F. K., & Yusof, S. A. M. (2016). Formalanalysis of temporal dynamics in anxiety states and traits for virtual patients (p.20001). https://doi.org/10.1063/1.4960841

Barber, K.D., Garza-Reyes, J.A., Kumar, V. and Abdi, M.R. (2017), "The effect of supply chain management practices on supply chain and manufacturing firms' performance", Journal of Manufacturing Technology Management, Vol. 28 No. 5, pp. 577-609

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of management,27*(6), 643-650.

Barney, J. B., Ketchen, D. J., & Wright, M. (2011). The future of Resource-Based Theory. *Journal of Management*, *37*(5), 1299–1315. https://doi.org/10.1177/0149206310391805

Bayless, S., Kodirov, N., Iqbal, S. A., Beschastnikh, I., Hoos, H. H., & Hu, A. J. (2020). Scalable constraint-based virtual data center allocation. *Artificial Intelligence*, *278*, 103196. https://doi.org/10.1016/j.artint.2019.103196

Bean R. (2017). How Big data is empowering AI and Machine learning at scale, *MIT Sloan management review*

Bencsik, A. (2021). The sixth generation of knowledge management – the headway of artificial intelligence. *Journal of International Studies*, *14*(2), 84–101. https://doi.org/10.14254/2071-8330.2021/14-2/6

Bharadwaj, A. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS quarterly, 24*(1). 169-196.

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*, 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Botega, L. F. D. C., & Da Silva, J. C. (2020). An artificial intelligence approach to support knowledge management on the selection of creativity and innovation techniques. *Journal of Knowledge Management*, *24*(5), 1107–1130. https://doi.org/10.1108/jkm-10-2019-0559

Brynjolfsson, A. Mcafee. The Business of Artificial Intelligence: what it can – and cannot- do for your organization Hav.Bus.Rev. Jul, 10 (2017).

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlstrom, P., Henke, N., & Trench, M. (2017b). Artificial intelligence: the next digital frontier? *Mckinsey and Company Global Institute*. https://apo.org.au/node/210501

Chaki, J., Thillai Ganesh, S., Cidham, S., & Ananda Theertan, S. (2022). Machine learning and artificial intelligence based Diabetes Mellitus detection and self-management: A systematic review. *Journal of King Saud University - Computer and Information Sciences*, *34*(6), 3204–3225. https://doi.org/10.1016/j.jksuci.2020.06.013

Chui, M., & Malhotra, S. (2018). AI adoption advances, but foundational barrier remain. *Mckinsey and Company*. 34

Chowdhury, S.,Budhwar, P., Dey, P. K., Joel-Edgar,S., & Abadie,A (2022). AI –employee Collaboration and Business Performance: Integrating Knowledge-Based View, socio-technical systems and organizational socialization framework. Journal Of Business Research, 144,31-49. https://doi.org/10.1016/j.jbusres.2022.01.069

Conboy, K., Mikalef, P., Dennehy, D., & Krogstie, J. (2020). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. *European Journal of Operational Research*, *281*(3), 656–672. https://doi.org/10.1016/j.ejor.2019.06.051

Colson, E. (2019). What AI-driven decision making looks like. *Harvard Bus Rev.*

https://hbr org/2019/07/what-ai-driven-decision-making-looks-like. Accessed, 30

David .J. Teece, *DYNAMIC Capabilities 2022, In* the Scholar Entrepreneur.

Davenport, T. H. (2018). *The AI advantage: How to put the artificial intelligence revolution to work*. MIT Press.

Danyluk, A., & Buck, S. H. (2019). Artificial Intelligence Competencies for Data Science Undergraduate Curricula. *Proceedings of the . . . AAAI Conference on Artificial Intelligence*, *33*(01), 9746–9747. https://doi.org/10.1609/aaai.v33i01.33019746

Derozier, V., Arnavielhe, S., Renard, E., Dray, G., & Martin, S. (2019). How Knowledge Emerges From Artificial

Tigunt, B., & Hosarri, H. (2020). Big Data Analytics and Artificial Intelligence: A Meta-Dynamic Capability Perspective. *International Conference on Business Management & Sustainability (ICMIS) 2020.* http://dx.doi.org/10.2139/ssrn.3709077.

Townsend, D. M., & Hunt, R. A., McMulen, I.S., & Sarasvathy, S.D. (2018). Uncertainty, Knowledge problems, and entrepreneurial action, *The Academy of Management Annals*, 12(2), 659-687. https://doi.org/10.5465/annals.2016.0109

Utami, H.N., & Alamanos, E. (2022). Resource based theory: A review. In S. Papagianidis (Ed), TheoryHubBook. http://open.ncl.ac.uk.

Wamba-Taguimdje, S. L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal, 26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: humans and AI are joining forces. *Harvard Business Review, 96*(4), 114-123.

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2018). Artificial Intelligence and the Public Sector Applications and Challenges. *International Journal of Public Administration*, *42*(7), 596–615. https://doi.org/10.1080/01900692.2018.1498103

Zhao, J.L., Fan, S., & HU, D., (2014). Business challenges and research directions of management analytics, in the big data era. *Journal of Management Analytics,* 1(3), 169-174.

Zheng, T., Ardolino, M., Bacchetti, A. and Perona, M. (2021), “The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review”, International Journal of Production Research, Vol. 59 No. 6, pp. 1922-1954.