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Enhancing Internal Integration Through Ai: A Resource-Based View With Data-Driven Culture As Moderator

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Abstract. This study examines the impact of artificial intelligence (AI) usage on internal integration within large industrial firms in Jordan. It investigates the moderating role of data-driven culture in this relationship. Grounded in Resource-Based View theory, we develop and test a conceptual model proposing that AI usage positively influences internal integration, with this effect being stronger in organizations with a well-established data-driven culture. Data collected from 345 large industrial firms in Jordan undergoing digital transformation were analyzed using structural equation modeling. Results indicate that AI usage significantly enhances internal integration by facilitating cross-functional coordination and information sharing. Furthermore, a data-driven culture strengthens this relationship, highlighting the importance of cultivating appropriate organizational values and practices when implementing AI technologies. This study contributes to the literature by empirically validating the AI-internal integration relationship in a developing economy context and identifying data-driven culture as a crucial contingency factor. For practitioners, our findings suggest that successful AI implementation requires both technological integration and cultural alignment.

Keywords: Artificial Intelligence, Internal Integration, Data-Driven Culture, Resource-Based View (RBV) Theory

1. Introduction

Based on a plan drawn up by the Ministry of Jordan Industry and Trade, to establish factories and companies to produce goods. This plan resulted in several industries working in Jordan, such as mining, chemical, agricultural, tissue, and electrical industries (Jarrar & Jaradat, 2022). Due to rapid advances in digital technology present significant opportunities and risks, including big data, cloud computing, AI, Internet-of-Things technology, blockchain, and 5G. These technologies affect the sustainable development and competitiveness of supply chains (Frederico et al., 2020; Ning & Yao, 2023). So, technology cannot be ignored as essential for building relationships among supply chain (SC) partners, providing a fast and standardized communication method (Sharma et al., 2024), and based on the complexities of the interconnected global economy and external uncertainties (Zhang et al., 2024). Jordan's industrial sectors faced supply chain disruptions due to poor collaboration and weak technological infrastructure.

The Jordan Industry Chamber explained that the manufacturing sector is vital to Jordan's economy, creating jobs, attracting quality investments, opening international markets, and enhancing the image of Jordanian products. It directly contributes approximately 25% of GDP and fosters economic and social growth. That is presented in Figure 1. Nonetheless, an incomplete Industry 4.0 roadmap, unexamined AI, big data, and IoT hinder AI implementation. Infrastructure and regulatory issues impede AI investments (Almashawreh et al., 2024). A turbulent environment further affects the supply chain, highlighting the need to rethink its structure and design (Kopanaki, 2022), particularly amid geopolitical tensions and technological disruptions (Ma & Chang, 2024).

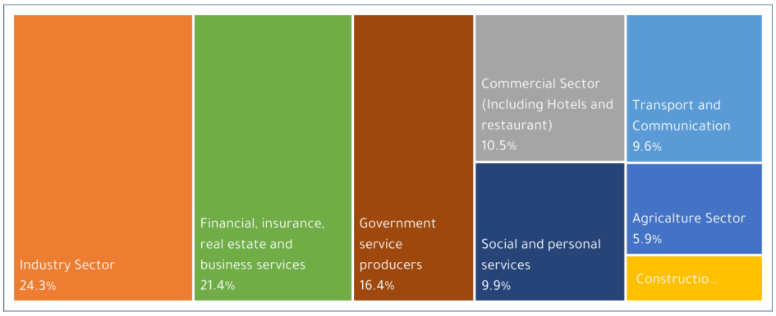

Fig.1: Jordan Gross Domestic Product (GDP)

https://jsf.org/uploads/2022/12/manufacturing

Thus, there is increasing attention on the challenges and opportunities in manufacturing, particularly regarding AI and unstructured data in business (Zhang et al., 2024). Allioui et al. (2024) suggest that AI's rapid evolution could transform internal integration, fostering both superficial connections and deep communication. Strategic planning and skilled supply chain management help organizations address challenges and seize opportunities (Hader et al., 2022). They also enhance decision-making speed, providing a competitive edge over previous technological waves. The expected impact of these technologies calls for immediate engagement from top management (Selvarajan, 2021; Hossain et al., 2022; Donthireddy, 2024). Management decisions aim to foster internal integration by linking existing data repositories as AI resources. This initiative is influenced by variables that shape a culture of data usage, integrating processes for productivity (Malik et al.2023; Cui et al., 2023).

This strategy combines AI with a resource-based view, focusing on resource integration and transitioning from external adoption to internal capabilities that enhance user experience (Willie, 2025; Chen et al., 2022). Through sharing real-time information (Hader et al., 2022). Thus, companies must establish a data-driven culture to create and enhance value while fostering collaboration across different functions (Wamba et al., 2024). A data-driven culture enhances AI collaboration among remote workers, transforming integration challenges into positive outcomes (Fügener et al., 2022). This integration enables the effective use of AI, empowering individuals to solve complex problems. Organizational integration drives continuous improvement, innovation, and success in the business landscape (Bahoo et al., 2023).

Several studies have been conducted on the effects of artificial intelligence systems on integration at various levels and from different angles, but not from the point of view of resource enhancement in the production chain (Wu et al.2022). The results obtained from studies conducted in this field have not achieved the desired benefits, nor the results that were hoped for to improve work, reduce losses, and produce goods of good quality and at competitive prices (Jum'a, 2023). In addition, the desired goals of the long-term plan, such as a proper infrastructure that meets the needs of companies regarding basic services and increasing the labor force to work in this sector, have not been achieved (Broo et al., 2022).

While integrating AI into business processes is crucial for competitiveness and innovation (Bahoo et al., 2023), traditional logistics has changed significantly over the past 20 years, requiring most businesses to rethink and restructure their global production networks (Sun et al., 2022). To address these challenges, businesses need strong supply chain strategies and technologies to streamline both internal and external operations (Bahoo et al., 2023). Additionally, developing models and frameworks is necessary to facilitate implementation. Thus, the aim of the paper is to highlight the importance of enhancing internal integration using artificial intelligence systems and to determine the moderating effect of data-driven culture on the relationship between AI and internal integration. Some of the expected questions that the paper aims to answer are:

1. Does the artificial intelligence enhance the internal integration?
2. Could the AI affect internal integration with a data-driven culture?

Wamba et al. (2024) suggest a connection between a data-driven culture and leading-edge technologies. Tiwari (2021) and Wu et al. (2022) studies indicate that in the future, more attention should be paid to examining how each resource can provide an advantage regarding internal integration, and researchers in developing nations have yet to explore these issues extensively, as the literature gives little attention to developing countries (Alkhatib, 2022). It remains unclear how a data-driven culture influences the relationship between AI and internal integration from the RBV perspective (Zhu & Li, 2023). To our knowledge, no study exists on the link between AI and internal integration based on the resource-based view (RBV).

This paper is structured into six sections. Section 2 presents the theoretical framework. Section 3 reviews the relevant literature and develops the hypothesis, establishing the study's foundation. Section 4 outlines the methodology, while Section 5 covers the results and discussion. Finally, Section 6 concludes with the study’s implications, contributions, and limitations.

2. Theoretical Framework

This study aims to explore ways to enhance internal integration in Jordan’s industrial sectors. The Resource-Based View (RBV) theory, articulated by Barney (1991, 2021), provides the foundation for the analytical framework. Barney’s model defines firm resources as a combination of assets, capabilities, processes, attributes, information, and knowledge, all of which are controlled by the firm. These resources enable the firm to develop and implement strategies that enhance efficiency and effectiveness. Barney posits that firms should adopt a capability-based approach to integrate diverse internal resources and capitalize on unique external opportunities (Barney et al., 2021).

The Resource Based View (RBV) theory has emerged as a leading theory in strategic management and is considered one of the most influential theoretical frameworks in management literature (Barney, 2021; Pereira & Bamel, 2021). RBV theorists have developed a strategy for enhancing firm performance through available resources to attain a sustainable competitive advantage (Adnan et al., 2018; Pereira & Bamel, 2021; Collins, 2022). The RBV is founded on three fundamental premises (Barney, 2021). The first premise asserts that an organization is a bundle of somewhat unique resources and that some firms are better endowed with these resources than others. The firm's resources (AI, Internal Integration, and Data-Driven Culture) are considered any capabilities that the firm possesses to compete with others; for example, Internal Integration is regarded as a tangible resource, while social and technological aspects, such as AI and Data-Driven Culture, are considered intangible resources (Chen et al., 2021). Differences in relative resource endowments result in disparities between firms. Only those resource differences that are perceived as valuable by competing firms lead to superior performance (Azeem et al., 2021). Resources or capabilities are "valuable" if they enable a firm to implement strategies that enhance its effectiveness and efficiency (Azeem et al., 2021; Wu et al., 2022). The natural assumption is that these differences must persist to some extent over time.

The second assumption states that the strategic resources of organizations within an industry are not homogeneously distributed. Arraya (2016), Andersén (2021), and Nikmah et al. (2021) confirm this assumption that the strategic resources of firms within an industry are not uniformly allocated. Cuthbertson & Furseth (2022) point out that organizations in an industry will be heterogeneous concerning the strategically relevant resources they control, and that these resource differences will significantly determine the competitive advantage of firms. For all effective organizations in any given industry, success must therefore be based solely on differences in resource endowments. Firms may differ in the types and amounts of resources they control; hence, these differences will account for variations in observed performance (Elia et al., 2021; Liu et al., 2023). Without such capabilities, the mere possession of attractive resources is insufficient to achieve a competitive advantage. Resources must also be rare (Varadarajan, 2023; El et al., 2022). Competitive advantage based on such resources cannot be imitated or copied by a follower. Finally, the third assumption states that firms' resources are not perfectly mobile across organizations. It is implied that the mobile resources are taken by the players. The resulting advantage for the organization might likely decline over time in the absence of additional influences. The RBV suggests that the differences between firms in strategic resources may persist over time (D'Oria et al., 2021).

The resource-based view (RBV) describes how the internal characteristics of firms, specifically their capabilities and resources, are the fundamental determinants of competitive advantage (Adnan et al., 2018; Chen et al., 2021; Lubis, 2022). Moreover, RBV requires support from a specific internal culture known as a "data-driven culture" (Lee et al., 2024). The effective organization of internal capabilities depends on a culture that is adept at utilizing them (Wamba et al., 2024). Merging internal information and data within organizations enhances efficiency while improving communication and collaboration across departments. Irfan & Wang (2019) noted that accelerating the flow of raw materials and information during integration can significantly enhance efficiency (Mehta et al., 2024). Mikalef & Gupta (2021) assert that AI improves performance. Hirsch (2018) observed that advances in AI and machine learning are reshaping the human-machine dynamic, enabling more integrated interactions (Ristyawan, 2020). Furthermore, the RBV theory asserts that in volatile markets, firms with unique, rare, and inimitable resources gain a sustainable competitive advantage and achieve superior performance (Barney, 1991).

3. Literature Review and Hypothesis Development

Today's business world is fast-paced and complex, requiring a high level of integration within organizations. The resource-based view and other key theories emphasize the importance of diverse activities and capabilities for success. However, there is a lack of knowledge regarding which resources best support internal integration initiatives (Alsheyadi et al., 2024; Wu et al., 2022).

This study focused on large industrial companies in Jordan that have already undergone digital transformation. It aims to analyze the effect of AI on internal integration and examine how a data-driven culture moderates this effect.

3.1. Internal Integration

Internal integration is the process by which a firm links and develops internal resources and capabilities to create expertise and knowledge beyond the boundaries of a single department or functional area. This supports external integration activities and ultimately enhances goal alignment and performance (Amoako et al., 2022). Departments are considered silo areas, with information on sales orders, production capacity, and inventory of raw materials or finished products segmented across different systems (Elofsson & Virdebrant, 2022). This aspect, known as internal integration (II), is fundamental to driving organizational transformation. The rapid advances in telecommunications and computing have significantly improved information sharing within organizations. Today, stakeholders value business intelligence over mere access to raw data. As a result, organizations require dedicated teams and centralized resources to generate actionable insights. This shift in approach embodies internal integration (Li et al., 2021). This integration must be pursued across all departments within the organization, from management to the shop floor (Oubrahim et al., 2023). By adopting an integrated strategy, firms can align the information systems of different supply chain partners (Khalil et al., 2022).

However, internal integration also entails synchronizing business processes and information flow (Ganbold et al., 2021). ElMokadem & Khalaf (2023) highlight that this integration fosters departmental collaboration, breaking down silos between functions and facilitating faster information sharing to enhance customer value. Pham and Verbano (2022) emphasize that strategic collaboration across company functions is essential for success. In manufacturing, internal integration of operations is a prerequisite for pursuing external integration initiatives (Khan & Wisner, 2019).

This framework empowers employees to monitor pertinent environmental information and swiftly identify challenges that could jeopardize their safety. In response, they can take immediate action to protect themselves (Han & Huo, 2020). Achieving this level of integration requires effective communication, knowledge sharing, and alignment between departmental goals and the organization's overarching objectives. A harmonious blend of marketing and operations enhances brand performance, aids in risk management, and creates lasting competitive advantages (Yu et al., 2021). A firm's internal operations and supply chain must be fully integrated to ensure smooth information flow across various functions, including production planning, account management, transportation, warehouse operations, technical support, and collections. This integration is essential for fostering customer focus, identifying core competencies and stakeholders, and establishing long-term strategic goals (Saragih et al., 2020).

Internal integration (II) is the core competence derived from linking internal activities to best support the client at the lowest cost (Pulido Martínez et al., 2014; Oubrahim et al., 2023). Departments are considered silo areas, with information on sales orders, production capacity, and inventory of raw materials or finished products segmented between different systems (Elofsson & Virdebrant, 2022). This integration must be pursued across all departments within the organization, from management to the shop floor (Oubrahim et al., 2023). By adopting an integrated strategy, firms can align the information systems of different supply chain partners (Khalil et al., 2022).

While parts of the firm have become more integrated in recent years through investments in technological platforms, the goal of integration is a long process. The management and shop levels remain more segregated (Zhang et al., 2023), and differences in information systems, technology platforms, and the professional culture of different departments hinder implementation across the organization (Fachridian et al., 2024). Internal integration also entails synchronizing business processes and information flow (Ganbold et al., 2021). Vveinhardt & Sedziuviene (2022) pointed out that organizational resistance and a lack of managerial commitment have stalled the integration process. Khan & Umar (2024) refer to the requirements for integration in a firm's departments as technically viable. Despite this, in manufacturing, internal integration of operations is a prerequisite for pursuing external integration initiatives (Khan & Wisner, 2019). El Mokadem & Khalaf (2023) highlight that this integration fosters departmental collaboration, breaking down silos between functions and facilitating faster information sharing to enhance customer value. Pham and Verbano (2022) emphasize that strategic collaboration across company functions is essential for success.

Achieving this level of integration requires effective communication, knowledge sharing, and alignment between departmental goals and the organization’s overarching objectives (Yu et al., 2021). This framework empowers employees to monitor relevant environmental information and quickly identify challenges that could threaten their safety. In response, they can take immediate action to protect themselves (Han & Huo, 2020). Additionally, a harmonious blend of marketing and operations enhances brand performance, aids in risk management, and creates lasting competitive advantages (Yu et al., 2021). A firm’s internal operations and supply chain must be fully integrated to ensure a smooth information flow across various functions, including production planning, account management, transportation, warehouse operations, technical support, and collections. This integration is essential for fostering customer focus, identifying core competencies and stakeholders, and establishing long-term strategic goals (Saragih et al., 2020). Thus, information modeling is proposed as a method to foster integration management. Integration requires mutual agreement across departments on the information content, structure, and frequency of sharing. The join/vert approach of information documentation facilitates discussions about the system's technical, functional, and human aspects (Abuezhayeh et al., 2022; Alshawabkeh et al., 2024).

3.2. Artificial Intelligence

AI is a branch of science dedicated to developing intelligent machines capable of performing tasks that intersect with various human cognitive processes, including reasoning, learning, perception, linguistic comprehension, logical reasoning, and decision-making (Sarker, 2022). Recent technological advancements have made AI more prevalent in organizations (Olan et al., 2022). Leveraging large datasets and AI's pattern recognition capabilities, organizations can enhance evidence-based decision-making in management. AI systems also provide deeper insights, revealing patterns within complex data (Bauer et al., 2023).

Although AI-enabled systems are used in various industries worldwide to improve economic growth, reduce costs, and enhance products, AI is being utilized in mainframes to better handle skills and execution for predicting product failures, recognizing events that require investigation, and tuning product specifications (Yi & Ayangbah, 2024). According to Mikalef and Gupta (2021, p. 2), "AI capability" refers to "a firm's ability to use its AI resources." The successful implementation of AI in organizations depends on its alignment with their culture and resources. Data-driven organizations derive greater benefits from AI than those lacking such a culture (Szukits & Móricz, 2024). In contrast, there has been extensive research on barriers to AI adoption, with end-users claiming that there is no business case for AI (Laato et al. 2022). As many companies are still on the sidelines attempting to learn more about AI’s potential, which has been further emphasized by firms operating on the fringes of change (Vassakis et al. 2025), these firms often express a dislike for having insufficient domain knowledge or experience implementing similar projects elsewhere, as well as for having an underdeveloped internal AI culture or inadequate leadership and teamwork (Haugen, 2021; Hermandinger, 2023). Even academics are still grappling with the issue (Chen et al. 2022; Hansen et al. 2024).

However, causality models from different data streams and knowledge included in a rule-based framework assist in understanding anomalies and provide an explanation of why they occur (Nadim et al., 2023). While data has long been a critical resource, AI enables organizations to extract unexpected strategic insights from it (Dubey et al., 2022). Besides, AI has rapidly evolved into a well-established field, impacting numerous industries and significantly transforming organizational strategies and operational frameworks (Allioui & Mourdi, 2023). Various applications of AI and its procedures are successfully transforming industries worldwide. However, most of these procedures and applications are kept confidential. Hence, their knowledge is insufficient (Rashid & Kausik, 2024; Kulkov, 2021).

This has not yet created a buzz, as significant sums are needed to establish a foothold (Shi et al., 2024). There is limited literature on AI's effects on internal integration processes in organizations (Wamba, 2022); even so, the AI capabilities are expected to bring substantial changes within organizations (Ng et al., 2021).

3.3 Data-Driven Culture

Many scholars define a culture as data-driven when organizations explicitly acknowledge it in public documents (Javed & Akhlaq, 2024). A data-driven culture is characterized by the extent to which data-driven values, beliefs, and behaviors are shared among members of an organization, including their commitment to data-driven principles, data and analytic product development, and data-led decision-making (Yu et al., 2021; T. W. Wong & W. T. Ngai, 2022). This culture fosters decision-making based on data-driven insights and prioritizes information processes to differentiate through smart analytics (Javed & Akhlaq, 2024). Ababneh (2021) confirms that organizational culture consists of shared values, norms, and assumptions that influence how managers guide employee behavior. According to Gupta & George (2016, p. 1053), a data-driven culture is defined by "the extent to which all members, including executives, rely on data-driven insights to make decisions." This paradigm represents a shift from intuition-based decision-making to data-informed strategies (Asfahani, 2024).

In today's fast-changing business environment, decision-making must incorporate data insights alongside experience and judgment. Real-time insights significantly enhance decision-making, particularly in times of uncertainty, and foster innovation and creativity (Venkatachalam et al., 2022). An acceptable level of belief in data-driven innovation is crucial for effectively influencing performance, while data challenges and regulations moderate the impact on innovative outcomes (Al-Khatib, 2025). Developing a data-driven culture is complex and raises concerns about resource allocation and costs, which can impact an organization's dynamics. However, scalable data-driven technologies, including AI and machine learning (ML) tools, have reduced the costs associated with cultivating such a culture (Venkatachalam et al., 2022). Even so, although technology can reveal insights, it is people who drive action. Critical data skills, including statistical or computational expertise, are rare and can be easily taken by competitors (Baiod & Hussain, 2024). On the other hand, rather than minimizing ambiguity, data-driven intelligence may create new sources of emergence, violation, and conflict in organizations if they do not conform to existing cultures and norms (Yu et al., 2022). The lack of understanding of the roles of varying ideas and cultural norms in the development of data-driven innovations limits managers' efficacy in strategic planning and implementation (Kumar et al., 2021).

Dubey et al. (2019) argue that organizations with strong data-driven cultures are more competitive since they promote the use of data and analytics in driving decisions rather than gut instinct, thus fostering an explorative mindset and a more open approach to innovation (Almazmomi et al., 2022). The emerging large volumes of structured and unstructured data accumulated by organizations must be treated as critical resources (Dubey et al., 2019; Tayefi et al., 2021). Treating data as a key asset unlocks substantial business value (Ghafoori et al., 2024). Companies that refine their data-heavy processes are more likely to realize AI's benefits and use it to enhance both operations and strategy. A data-driven culture strengthens an organization's ability to maximize AI's potential. Effective data utilization and management indicate an organization's readiness for this shift (Rajagopal et al., 2022). However, such transformation relies on the readiness of organizations, including human and technological infrastructure, cultures, and norms, which should be adequately addressed from the data architecture perspective (Bahyan et al., 2024).

A data-driven culture helps organizations leverage and capitalize on data-related capabilities while also developing better analytics capabilities (Zhu & Li, 2023). Organizations that minimize biases, provide data quality metrics, and adopt data-driven strategies can be classified as data-driven (Kumar et al., 2023). Additionally, leveraging AI in operations provides firms with a competitive edge and enhances performance. Successful AI implementation depends on a data-driven culture that eliminates organizational silos (Arshad et al., 2024). The data-driven culture reflects the shared belief that data can drive improved decision-making and that employees should have the freedom and skills to work with and contribute to data (Varma & Dutta, 2023). It supports capability development and the innovation-driven project cost structures of data-driven consultants (Soltani et al., 2025). There are mixed findings on how these factors impact resource selection and innovation (Jum'a et al., 2024).

3.4 Artificial Intelligence and Internal Integration

Castañer and Oliveira, (2020) define internal integration as a seamless link among related functions within an organization, emphasizing the need for coordination across various organizational efforts. Supporting this notion, Shukor et al., (2021) highlight that both technology and human resources are essential for effective internal integration.Within the production landscape, all economic sectors exhibit interdependence. Poor integration in supply chain management can lead to inefficiencies in planning and production, resulting in surplus inventory, reduced profits, and, ultimately, business failure. Internal integration is crucial for supply chains as it fosters alignment and collaboration to achieve shared goals and ensure the efficient delivery of products and services. Gouda &Tiwari (2024) argue that this integration is fundamental to the sustainability and success of manufacturing firms. To remain competitive and enhance performance, organizations must adopt advanced technologies.

The growing presence of robotics in industries, driven by AI advancements, is increasingly evident (Oosthuizen, 2022). This technological shift contributes to economic growth and job creation (Wamba, 2022) while profoundly transforming production systems and industrial operations (Riahi et al., 2021). AI’s ability to process vast amounts of structured and unstructured data enhances supply chain management by improving the accuracy of data related to supply, demand, and inventory. Consequently, AI facilitates more effective decision-making in complex scenarios (Helo & Hao, 2022; Pournader et al., 2021). Despite AI's existence for over fifty years, its application in solving supply chain challenges remains underdeveloped. Although recent advances have improved internal integration processes, the complexity of supply chain systems and the inadequacy of existing frameworks have hindered its full adoption (Sharma et al., 2022; Ganesh & Kalpana, 2022). Based on this understanding, the following hypothesis is proposed:

***H1**: Artificial intelligence usage will have a positive effect on internal integration.*

3.5 The Moderating Effect of Data-Driven Culture on AI Use and Internal Integration

A data-driven culture reflects an organization's perspective on using data for decision-making in management and operations. Zhang et al. (2020) argue that a data-driven corporate culture serves as an internal driver for an organization’s assimilation of Big Data Analytics and AI (BDAI). Given the growing importance of AI and its widespread adoption across organizations, it is necessary to understand how process moderation influences its effectiveness (Olan et al., 2022). If a data-driven culture enhances AI’s benefits, organizations must carefully evaluate the costs of retention and attrition against the unclear benefits and expenses of investing in AI (Wong & Ngai, 2023; Akter et al., 2021).

A data-driven culture encourages employees to incorporate data into decision-making processes, which is critical for organizational success. Culture can either facilitate or impede the effective use of data analytics (Almazmomi et al., 2022). As an internal value, a data-driven culture enables employees to integrate data-driven insights into their decision-making, refining processes and improving products. Encouraging consumer involvement in decision-making can further promote internal integration (Dubey et al., 2022). The role of internal integration highlights the theoretical and practical value of a data-driven culture. The relationship between AI and internal integration is expected to strengthen as organizations increasingly embrace data-driven practices (Olan et al., 2022; Benzidia et al., 2021). Based on these insights, the following hypothesis is proposed:

H2: *A stronger data-driven culture will enhance AI's positive effect on internal integration.*

Based on the reviewed literature, the researchers developed a conceptual model, as shown in Figure 2.

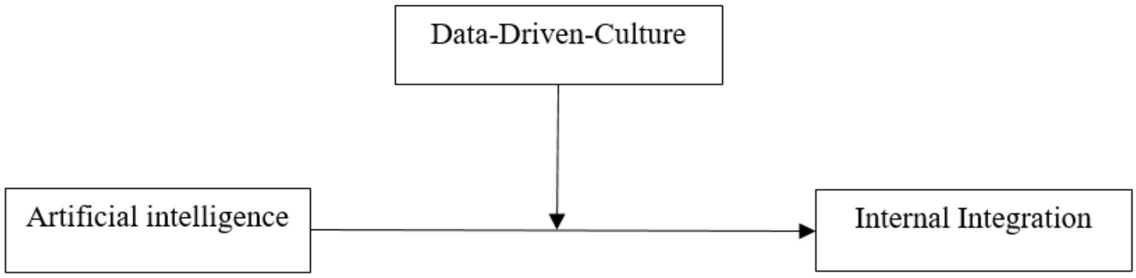

Fig.2: Conceptual Model

4. Methods

This conceptual paper explores the methodological framework for conducting research on the effect of artificial intelligence on internal integration with the moderating effect of a data-driven culture in organizational contexts. This study proposed the utilization of a self-administered questionnaire as a key tool for data collection. Primary data were collected through surveys distributed via a Google Forms link. The proposed survey design is partitioned into several thematic areas: a filter question related to whether the company applied digital transformation, seven items related to the demographics of respondents, seven items examining the role of AI in enhancing internal integration, six items focusing on internal integration, four items investigating the influence of a data-driven culture as a moderating factor, and three items on general questions regarding the marker variable. The questionnaire employs a five-point Likert scale, ranging from (1) "Strongly Disagree" to (5) "Strongly Agree," to gauge respondents' attitudes effectively toward AI and internal integration. Meanwhile, in the data-driven culture section, a seven-point Likert scale was employed, ranging from 1="Strongly Disagree" to 7="Strongly Agree." The survey is expected to take approximately two to three months to complete.

In this study, the unit of analysis is at the organizational level. The target sample for this study consists of top managers and middle managers from various industrial sectors in Jordan, providing a relevant context for the investigation. Additionally, a pilot study is proposed to pre-test the questionnaire, ensuring the reliability and validity of the constructs measured. This pre-test would involve preliminary data collection from a smaller subset of respondents, with plans for a larger final sample to enhance the robustness of the findings. The researcher has sent 345 online surveys to large companies within Jordan's industrial sector. According to G*Power software, the minimum required sample size for this study is 95 firms. A purposive sampling technique was employed to select companies that implement artificial intelligence, totaling approximately 293 firms, based on the Amman Chamber of Industry report. The final sample was determined using a filter question.

Once data collection is complete, the data will be cleaned and prepared using SPSS and analyzed using SmartPLS 4, a variance-based second-generation multivariate analysis tool. Through this methodological lens, the paper aims to contribute to understanding the dynamic interplay between AI integration and internal integration with a data-driven culture in organizational frameworks.

5. Results and Discussion

This conceptual study offers several key insights into how artificial intelligence (AI) usage can enhance internal integration within large industrial firms, especially in developing economies like Jordan. Drawing on the Resource-Based View (RBV), we argue that AI functions as a strategic organizational resource that can improve coordination, communication, and data exchange across departments. However, the effective utilization of this resource is not solely a technical challenge; it is equally a cultural one. The primary conceptual proposition advanced in this study is that AI, when embedded within a strong data-driven culture, becomes significantly more effective in driving internal integration. A data-driven culture acts as a complementary capability that enables the organization to extract value from AI systems. This synergy creates a dynamic capability—allowing firms not just to possess technological tools, but to use them effectively and adaptively to enhance performance.

Traditional RBV literature emphasizes tangible and intangible resources as sources of competitive advantage (Kant, 2021). This paper extends the RBV by highlighting the combinatory effect of AI (a technological resource) and a data-driven culture (an intangible cultural capability) in driving internal integration, a key operational capability. Conceptually, AI supports internal integration by automating workflows, generating predictive insights, and enabling real-time communication across departments. These features reduce organizational silos and promote horizontal collaboration. Internal integration is one of the factors that directly utilizes the results of AI techniques (Rana et al., 2022). Thus, for successful internal integration, organizations must implement operational systems and monitor them closely. Unlike other capabilities, a well-developed data-driven culture is difficult for competitors to replicate, as it is deeply rooted in the shared understanding, values, and expertise of the workforce (Barbala et al., 2024).

This study presents two main hypotheses:

- H1: AI usage positively influences internal integration.
- H2: A data-driven culture moderates the AI-II relationship, amplifying the positive effect when the culture is more data-driven.

While technology adoption is important, this paper stresses that the realization of value from AI depends on the cultural readiness of the firm. AI usage is largely influenced by its benefits and data availability (Merhi, 2023). A data-driven culture encourages openness to insights, trust in data, and decentralized decision-making—all of which amplify the integrative capacity of AI (Liu et al., 2022). In contexts like Jordan, firms are not adequately utilizing AI capabilities due to the absence of a data-driven culture (Ayoub & Aljuhmani, 2024). Companies face challenges at several levels, including infrastructure, data quality, process design and integration, talent acquisition and retention, change management, and strategy (Liu et al., 2022). Since the cost of purchasing and implementing such techniques is enormous, it is expected that only larger companies with more expertise in data science and AI will adopt AI technology (Haleem et al., 2022). This conceptual framework offers a pathway for leveraging existing cultural or managerial strengths to enhance the impact of AI, where firms may face resource constraints or organizational inertia. By nurturing a data-driven culture, even firms with limited technological infrastructure can begin to reap the integrative benefits of AI. These advancements can help organizations cultivate unique, hard-to-replicate practices, leading to lasting performance improvements. This study aims to provide future researchers with insights into the evolving dynamics of Jordan's industrial sectors, particularly within a landscape shaped by AI and data-driven cultural shifts.

6. Conclusion, Implications and Limitations

6.1. Conclusions and Implications

This study advances our understanding of how artificial intelligence influences internal integration processes within organizations, particularly in the Jordanian industrial context. Our conceptual model, grounded in Resource-Based View theory, proposes that AI usage enhances internal integration by facilitating cross-functional coordination and information sharing, with this relationship being strengthened in organizations that have a well-established data-driven culture. This research makes three key contributions. First, it extends the literature on AI implementation by identifying internal integration as a critical outcome variable affected by AI adoption. Second, it highlights the contingent role of organizational culture in successful technology implementation, specifically identifying data-driven culture as a crucial moderator in the AI-internal integration relationship. Third, it provides empirical insights from an understudied developing economy context, addressing calls for more diverse geographical perspectives in technology management research.

For practitioners, our study suggests that successful AI implementation requires both technological integration and cultural alignment. Specifically, managers should focus on cultivating a data-driven culture characterized by evidence-based decision-making practices and collaborative data sharing across departments prior to or alongside AI implementation. For policymakers in Jordan and similar developing economies, our findings highlight the importance of supporting both technological infrastructure development and organizational culture change to maximize the benefits of digital transformation initiatives in the industrial sector.

6.2 Limitations and Suggestions for Future Research

Despite these contributions, our study has limitations that present opportunities for future research. The focus on large industrial firms in Jordan may restrict the generalizability of findings to smaller organizations or different cultural contexts. Future studies should examine these relationships in diverse organizational settings, industry sectors, and national contexts. Additionally, longitudinal research designs could provide valuable insights into how the AI-internal integration relationship evolves over time as organizations advance in their digital transformation journeys.

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