The Impact of Open Innovation on Firm Performance in the Age of the Fourth Industrial Revolution: The Mediating Role of Big Data Analytics and Artificial Intelligence Capabilities

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Abstract

This study aims to ascertain whether implementing open innovation as a crucial source of competitive advantage positively influences performance. Additionally, it seeks to verify whether companies' utilization of big data analytics and artificial intelligence technologies positively moderates the relationship between open innovation and performance. This study used a structured questionnaire to collect data from a random final valid sample of 294 Jordanian companies operating in diverse industries. A simple and hierarchical regression was applied to verify the proposed hypotheses utilizing the SPSS V. 28 statistical program. The analysis suggests that open innovation execution positively impacts performance among sampled companies. Among the various technologies of the Fourth Industrial Revolution, big data analysis does not have a positive moderating effect on the relationship between the two variables. In contrast, the utilization of artificial intelligence technology has a positive moderating effect on this relationship. In other words, companies investing effort and resources into open innovation may not see performance improvements when simultaneously implementing big data analytics. Conversely, the simultaneous implementation of artificial intelligence technology alongside open innovation may lead to higher performance outcomes. These findings offer insights into the importance of strategic decisions regarding technology adoption for enhancing performance in the context of open innovation.

Keywords: Open Innovation (OI), Fourth Industrial Revolution, Big Data Analytics, Artificial Intelligence (AI), Moderation Analysis, Jordan.

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تأثير الابتكار المفتوح على أداء الشركات في عصر الثورة الصناعية الرابعة: الدور الوسيط لقدرات تحليلات البيانات الضخمة والذكاء الاصطناعي

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ملخص

تهدف هذه الدراسة إلى التحقق مما إذا كان تطبيق الابتكار المفتوح، كمصدر حاسم للميزة التنافسية، يؤثر بشكل إيجابي على أداء الشركات. بالإضافة إلى ذلك، تسعى الدراسة إلى التحقق مما إذا كان استخدام الشركات لتحليلات البيانات الضخمة وتقنيات الذكاء الاصطناعي يعدل بشكل إيجابي العلاقة بين الابتكار المفتوح والأداء. استخدمت هذه الدراسة استبيانًا منظماً لجمع البيانات من عينة نهائية عشوائية وصالحة مكونة من 294 شركة أردنية تعمل في قطاعات صناعية متنوعة. تم تطبيق الانحدار البسيط والمتعدد الهرمي للتحقق من الفرضيات المقترحة باستخدام برنامج SPSS V.28 الإحصائي. تشير النتائج إلى أن تطبيق الابتكار المفتوح يؤثر بشكل إيجابي على الأداء بين الشركات التي شملتها العينة. ومن بين التقنيات المختلفة للثورة الصناعية الرابعة، لا تمتلك تحليلات البيانات الضخمة تأثيراً معدِّلاً إيجابياً على العلاقة بين المتغيرين. على النقيض من ذلك، فإن استخدام تكنولوجيا الذكاء الاصطناعي له تأثير معدّل إيجابي على هذه العلاقة. بعبارة أخرى، قد لا ترى الشركات التي تستثمر الجهد والموارد في الابتكار المفتوح تحسينات في الأداء عند تطبيق تحليلات البيانات الضخمة في نفس الوقت. وعلى العكس من ذلك، قد يؤدي التطبيق المتزامن لتكنولوجيا الذكاء الاصطناعي جنباً إلى جنب مع الابتكار المفتوح إلى تحقيق نتائج أداء أعلى. تقدم هذه النتائج رؤى حول أهمية القرارات الاستراتيجية المتعلقة بتبني التكنولوجيا لتعزيز الأداء في سياق الابتكار المفتوح.

الكلمات المفتاحية: الابتكار المفتوح، الثورة الصناعية الرابعة، تحليلات البيانات الضخمة، الذكاء الاصطناعي، التحليل المعدِّل، الأردن.

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Introduction:

Adapting and growing amidst competition in a rapidly changing business environment are vital goals for companies (Allioui & Mourdi, 2023). Innovation remains a key source of competitiveness, maintaining its traditional importance and significance in the modern context (Mirghaderi et al., 2023). The Creative Destruction Theory depicts innovation as driving change by viewing products and customers from fresh perspectives, departing from existing frameworks (Jurek, 2024). Since then, innovation has been regarded as an essential element of corporate competitiveness. Through innovation, companies continuously provide customers with new products and services to meet their needs and drive growth (Freund & Stanko, 2018; Lee et al., 2021). Additionally, operational innovation boosts corporate performance and efficiency (Trieu et al., 2023). Gui et al. (2024) emphasized a more detailed concept of innovation, delineating product and process innovation.

Open innovation (OI), as proposed by Chesbrough (2003), suggests that tapping into external knowledge sources is crucial for enhancing innovation, as opposed to relying solely on internal resources (Chesbrough & Appleyard, 2007). Chesbrough et al. (2024) emphasized the need for companies to transition from the outdated Closed Innovation model to embracing OI.

The dual nature of scientific and technological advancements is a key factor shaping the business landscape and fostering corporate competitiveness (Wei, 2023). These advancements present both opportunities and threats to businesses. This duality arises because companies that can adeptly grasp the direction of these scientific and technological advancements can thrive, while those that fail to do so risk falling behind competitors (Su, 2023). Among recent scientific and technological developments, the most significant is arguably the Fourth Industrial Revolution or Industry 4.0 (Morrar et al., 2017). This revolution differs from previous scientific and technological changes in that it is fundamentally reshaping not just individual companies but society as a whole (Da Silva et al., 2024; Yun et al., 2023). Predicting the direction of these future changes poses considerable challenges.

Some frequently mentioned components or drivers of this Fourth Industrial Revolution include Big Data Analytics (BDAs), Artificial Intelligence (AI) technologies, the Internet of Things, Blockchain, Drones, 3D printers, Augmented Reality (AR), Virtual Reality (VR), and Cloud Computing (Da Silva et al., 2024; Nagy et al., 2018). Among these, Big Data

Analytics enables businesses to discover trends and patterns in changing customer preferences, facilitating decision-making toward securing competitive advantages. In other words, big data analytics enables companies to anticipate customer needs and secure more revenue swiftly (Khalil et al., 2023). On the other hand, artificial intelligence integrates knowledge from various fields, including computer science, engineering, and statistics, to design machinery and equipment for enhanced human convenience and performance (El Koufi et al., 2024).

Given the recent prominence of OI as a recognized source of competitive advantage for firms, alongside the emerging electronic technologies of the Fourth Industrial Revolution, such as big data and AI, considerable attention has been drawn to their interplay (Almeida, 2024). Big data analytics can facilitate the formation of more resilient and open innovative mechanisms (Bogers et al., 2018). The literature recognizes that big data analytics is critical to improving firm performance by utilizing OI strategies (Arias-Pérez et al., 2022). Similarly, AI is pivotal in encouraging innovation by offering new ideas and reviving the invention process. AI allows organizations to process internal and external knowledge to develop actionable insights, making it essential for future OI practices (Kuzior et al., 2023).

However, several gaps have arisen in the literature. Numerous prior research studies concentrated on innovation performance and neglected other performance measures (Greco et al., 2016; Bertello et al., 2024). Furthermore, most existing studies have estimated the effects of inbound and outbound OI on performance separately, even though they exist simultaneously within the company, which hinders their synergetic effect on performance and produces inconsistent results (Mazzola et al., 2016; Zhang et al., 2024). The literature also shows that significant attention is paid to the consequences of OI on performance in large companies, compared to SMEs, which leads to a deficiency in the existing body of knowledge (Carrasco-Carvajal et al., 2023). Moreover, there is a slight investigation into how different technologies affect OI and performance relationships (Bogers et al., 2018; Yao et al., 2024). A comprehensive understanding of the performance improvement outcomes resulting from OI requires evaluating how such technologies maximize the benefits of OI (Broekhuizen et al., 2023; Schäper et al., 2023; Andrade-Rojas et al., 2024).

Furthermore, to date, there is no firm consensus regarding the influence of OI on corporate performance. Although much prior research revealed that practicing OI positively impacts performance, others suggested an "inverted U-shaped relationship" or even an adverse influence on performance (Bernal et al., 2019; Rumanti et al., 2021; Schäper et al., 2023). This is due to the lack of inclusion of situational or contextual factors or firms' capabilities in these studies' investigation of OI and its relationship to performance.

Previous research on corporate performance measurement was essentially positioned on internal organizational factors and capabilities, heavily relying on readily available financial metrics and traditional, frequently historical, datasets (Pugna et al., 2019). This approach was fundamentally limited by the data infrastructure and analytical techniques prevailing at the time, which were not equipped to handle the size, pace, and variety of information now characterizing big data. Therefore, the systematic application of big data analytics to measure corporate performance was largely absent from earlier studies (Sardi et al., 2023). Furthermore, the very concept of "big data analytics" as a distinct and powerful tool for performance measurement was nascent or unknown to many researchers and practitioners; therefore, even conducting perception-based studies on its potential or adoption in the context of corporate performance was not viable due to a widespread lack of awareness and understanding of the subject itself (Adewusi et al., 2024).

For example, reviewing the work of Laursen & Salter (2006), in which they contend that excessive openness poses risks, including information overload, they do not investigate the aspect of big data analytics: on how big data tools could eagerly mitigate these risks through handling and prioritizing their massive external knowledge. In the same vein, Chesbrough (2015) expresses the positives of OI, but his views are inclined to be universal, as OI is beneficial for any company. This is why a contextualist or an integrationist approach investigates whether the relationship further should be used (Yun et al., 2017; Stahl et al., 2023). Recent research, such as Mikalef et al. (2019), illustrates how big data analytics strengthen decision-making agility; hence, seldo do they integrate this with OI, creating a fragmented understanding.

A key consideration in previous studies approaching AI technology to measure corporate performance is their lack of apprehension of today's capabilities of AI with its complexity and volume of relevant information (Batistič & van der Laken, 2019). Earlier studies utilizing AI did not fully realize its potential, as they underestimated the challenges of data quality, preparation, and integration needed for adequate AI comprehension. Besides, the ethical considerations were not yet fully crystallized, which could influence the applicability of AI-driven performance predictions (Hezam et al., 2025).

Also, previous studies investigating the relationship between OI and performance often overlooked the role of AI technology and big data analytics. Viewing earlier studies such as Chesbrough (2006) and West & Bogers (2014), it is noticed that they rarely considered how AI technology amplifies performance, even though their main investigation was about OI enhancing performance. Recent studies, such as Natalicchio et al. (2017), concentrate mainly on large companies with vast prior AI capabilities, ignoring the spectrum of company sizes. This creates scope for research into how companies of different sizes perceive AI technology and its benefits to their outcomes. Also, while research by Brynjolfsson & McElheran (2016) and Huang & Cheng (2024) shows that AI capacity enhances operational efficiency, the investigations did not account for performance in a holistic view; they focused narrowly on short-term productivity gains, while overlooking variables such as long-term innovation or stakeholders' value.

Additionally, the literature has ignored the moderating role of organizational, environmental, market, and technological factors. Therefore, the role of these factors in evaluating the effects of OI practices on performance remains unsupported (Liao et al., 2020). Finally, prior research has primarily focused on studying big data analytics capabilities' direct influences on diverse facets of corporate performance, such as innovation or financial outcomes. However, the scarcity of studies examining the intermediation function of big data analytics capabilities in OI consequences is observable, mainly in organizational conditions that pose significant data acquisition and handling challenges (Arias-Pérez et al., 2022). There also remains a shortage in the research connecting AI and OI (Kuzior et al., 2023). Also, previous research investigating relationships between OI, big data analytics, AI technology, and corporate performance recognized the prospects of the Fourth Industrial Revolution; hence, there still exists a sparse understanding of how the joint endorsement of OI with both big data analytics and AI technology collectively changes companies' performance in our current era. This study investigates two technologies that align with the industrial revolution, leveraging OI to drive performance, and represents the gap that this research aims to address.

Based on the above discussion, further research is needed to examine the relationship between OI, AI, big data analytics, and corporate performance. Against this backdrop, this study aims to determine if implementing OI, a key competitive advantage, can boost corporate performance outcomes. Additionally, this study seeks to verify whether companies' utilization of big data analytics and AI technologies moderates the relationship between OI and their performance. To achieve this, empirical research was conducted on companies operating in the Jordanian market. Therefore, the research problem is articulated in the investigation of the moderating effect of big data analytics and AI technology on the relationship between OI and performance in Jordan.

This study is expected to address the knowledge gaps mentioned earlier and contribute to the related literature in several ways. First, the present study relied on operational and financial performance indicators rather than innovation performance to obtain a holistic view of OI's effects on performance. This is reflected in the methodology through asking in the survey about sale revenues, operating profit, market share, and investment returns, for example, to measure performance in its financial aspect, as depicted in the questionnaire items in the methodology section. Second, the outbound and inbound activities have been used as one construct to measure OI in this study, which enables the evaluation of their synergic effect on corporate performance. This was displayed in the methodology through five question items referring to Van de Vrande et al., (2009), Popa et al., (2017), Carrasco-Carvajal et al. (2023), and Rumanti et al. (2023). Third, this study combined SMEs and large companies to expand the existing knowledge. Fourth, this study examined the impact of big data analytics and AI technologies on the relationship between OI and corporate performance, utilizing hierarchical regression analysis to assess their moderating role in performance outcomes. This advances our understanding regarding their intermediation role in the relationship between the two main variables under investigation and addresses the knowledge shortage in the literature. Finally, to the best of the author's knowledge, this is one of the very few studies that address this subject in Jordan and the Arab region in general, which advances the literature interested in contextual factors.

Research and Literature Review:

Open Innovation:

The concept of 'innovation' was proposed by Schumpeter, who also established the concept of capitalist market economies. Tushman and Anderson (2018) expanded on this with the concept of 'technological innovation'. Tidd and Bessant (2020) indicated that scholars considered innovation across dimensions: 'product innovation', involving the creation of new products through new technologies, and 'process innovation', which focuses on improving efficiency through the new allocation of resources and the development of capabilities.

The issue with previous research on innovation is that it relied heavily on the ‘closed innovation’ model, which indicates that innovation is entirely an internal generation process of ideas; the classic department in which this is achieved is R&D (Dasgupta, 2023). This outlook remained in previous studies for a long time. It postulated that knowledge from external interactions is mere market transactions rather than a fundamental component of the innovation process itself (Šundić, 2014). Thus, earlier papers focused on R&D capability and intellectual property protection, but the dynamic did not extend beyond the organization’s boundary, thereby neglecting the investigation and utilization of external ideas and opportunities (Ansari, 2013). Past innovations were influenced by factors such as research and development budget allocation, economies of scale, and the acquisition and effective utilization of skilled human resources (Chesbrough, 2003). However, future innovations are driven by factors such as efficient research and development, technology adoption from external sources, and the integration of diverse capabilities (Dodgson et al., 2008; Błach & Klimontowicz, 2021). Recent innovations emphasize absorbing and utilizing external technology and knowledge through collaboration with various external stakeholders, along with integrating diverse innovation-related capabilities (Laursen & Salter, 2006; West & Bogers, 2014).

Based on this future-oriented perspective of innovation, Teece (2007) argued that actively leveraging external knowledge sources enhances innovation outcomes, while Chesbrough (2003) asserted that the paradigm of innovation within firms should shift from ‘closed innovation’ to ‘open innovation’. Recognized as the founder of the ‘open innovation’ paradigm, Chesbrough (2006) highlighted the importance of firms overcoming internal limitations and actively leveraging diverse external sources of knowledge and innovation for sustainable improvement in innovation outcomes. He proposed that firms’ traditional ‘closed innovation’ approach should transition to the more contemporary and future-oriented ‘open innovation’, driven by technological development. In this context, open innovation refers to a more aggressive and proactive utilization of both internal and external sources of innovation, particularly concerning research and development activities and new product development processes. Specifically, open innovation expands innovation activities and efforts beyond the firm’s boundaries; it seeks to embrace external knowledge and innovative ideas, integrating them with internal capabilities and resources to enhance firm performance (Čirjevskis, 2021; Yun et al., 2023).

OI enables firms to transcend reliance on internal research and development to sustain competitive advantages (Portuguez-Castro, 2023). By embracing external technological achievements and ideas, firms can reduce innovation costs, increase the likelihood of success, and maximize value creation (Abdurrahman et al., 2024). OI comprises inbound and outbound approaches. Inbound OI involves acquiring external technologies and ideas for innovation, while outbound OI involves transferring internal technologies to external entities, aiming to commercialize them through new avenues (Leitão et al., 2020; KV & Hungund, 2022). OI entails leveraging external resources for innovation throughout the research, development, and productization processes. The ability to 'internalize' external ideas and technologies and utilize them in various ways determines the firm's openness to innovation (Stanisławski, 2020). However, many factors influence OI behavior within business organizations, including environmental dynamism, public policies (Leitão et al., 2020), entrepreneurial orientation, organizational legitimacy (Jing et al., 2023), adoption of an open business model, proficiency in knowledge management, absorptive capacity, organizational preparedness, and collaborative capabilities (Salimi et al., 2023), knowledge sharing, and network formation capability (Klarin et al., 2021; Alvarez-Meaza et al., 2023; Saint-Paul, 2024).

Big data analytics:

Information and communication technology has become an indispensable management element in the information age. Among these technologies, big data analytics is a critical technological advancement of Industry 4.0 (Elgendy & Elragal, 2016). Big data analytics enables businesses to uncover customer trends and make market-oriented decisions, ensuring a competitive advantage (Gnizy, 2020). By harnessing big data analytics, businesses can more easily explore shifts in customer trends and perceptions, enabling swifter prediction of customer needs and facilitating the creation of desired value (Holmlund et al., 2020). Moreover, it reduces operational risks, enhances efficiency, and fosters smoother collaboration among businesses and stakeholders (Brewis et al., 2023).

As one of the key technologies of Industry 4.0, big data analytics refers to the methods and techniques used to manage and analyze vast amounts of information, leveraging advancements in information and communication technology to generate value. In broader terms, big data analytics encompasses the management and analysis of massive datasets. This includes data generated over short periods, numerical and text data, and structured and unstructured data (Abdelmajied, 2022).

Various related technologies and models are utilized to execute big data analytics, including statistics, data mining, machine learning, artificial neural networks, and deep learning (McGuire et al., 2012). These techniques and models allow vast amounts of data to be processed and interpreted, enabling more precise and informed decision-making. Furthermore, the importance of big data analytics continues to grow as it enables businesses to make more adaptive strategic choices (Duan & Da Xu, 2021).

Big data analytics enables the cost-effective collection, processing, and analysis of large volumes of data, which would be challenging using traditional methods (Kambatla et al., 2014). It facilitates the exploration of important topics and creates value from volumes of information. Additionally, big data analytics processes and analyzes unstructured data like documen*-+ts, text, images, audio, video, and social media data, enhancing value creation (Elgendy & Elragal, 2016).

Artificial Intelligence Technology

AI is broadly categorized into two domains: the study of human thought processes and the development of machines, usually computers, that mimic human cognition to solve problems (Wang et al., 2021; Huawei Technologies Co., 2022). Current AI research areas include machine learning, artificial neural networks, and deep learning (Gupta et al., 2021).

Machine learning refers to algorithms that computers use to capture patterns or types in data by mimicking human perception and learning, allowing them to predict new data values (Attaran & Deb, 2018). Compared to traditional prediction methods, machine learning is preferred for predictions in cases with more variables, and the effects of variables on outcomes are more complex (Murdoch et al., 2019).

An artificial neural network refers to a machine-learning model that mimics or reflects the process and structure of human perception. Computers learn from data and solve problems by assigning weights through a ‘synaptic’ structure, mimicking human neural networks for learning, analysis, and storage (Kariri et al., 2023). It is generally defined as a machine-learning field (Kurucan et al., 2024). According to Kumar (2005), artificial neural network models are highly effective in non-parametric decision-making processes;

they provide superior predictive results compared to traditional regression models that assume normal distribution.

Deep learning, a component of artificial neural network frameworks, delves further into complex neural networks. Deep learning refers to models using multiple hidden layers of neural networks. It mimics the structure of the human brain, assigning weights to solve given problems more effectively (Kufel et al., 2023). Deep learning utilizes multiple hidden layers to perceive given decision-making situations in a hierarchical structure, allowing for more accurate predictions compared to other prediction methods or models (Lai, 2019). Unlike traditional machine learning, deep learning automatically extracts features from data, providing another advantage. Consequently, deep learning models are particularly promising for natural language and image processing fields (Hang, 2018).

AI machine learning models have been grouped into supervised (e.g., Naive Bayes, logistic regression, decision trees, K-nearest neighbor, random forest, support vector machines, and artificial neural networks) and unsupervised (e.g., principal component analysis, latent Dirichlet allocation, and kernel density estimation techniques from distribution mapping) (Jardim et al., 2023).

Corporate performance

Today, corporate or organizational performance is the most frequently used dependent variable in organizational research (Almatrooshi et al., 2016). However, it remains one of the vaguest and most loosely defined concepts (Tulcanaza-Prieto et al., 2021). However, the definition of corporate performance is a surprisingly open question, and few studies use consistent definitions and measures. Due to economic considerations, corporate performance has become an important study variable with implications not only for processes at the organizational level but also for how individual and collective processes are modeled (Solanki & Baroda, 2024). Consequently, defining, conceptualizing, and measuring performance have not been easy. Researchers have different opinions and definitions of performance, making it a controversial issue among organizational scholars (Rompho, 2024).

Corporate performance is a measure of how effectively a corporation uses its, both human and non-human, resources to accomplish its mission and deliver value to its stakeholders. It also refers to the extent to which a corporation achieves its objectives and goals (Usman et al., 2024). Also, corporate performance is the corporation's ability to achieve its objectives by using resources efficiently and effectively (Rompho, 2024).

Corporate performance has been categorized into operational, financial, and market-based. Operational performance can be subdivided into market share, new product introduction, product/service quality, marketing efficiency, and customer satisfaction (Marei et al., 2024). In addition to financial/economic performance criteria, operational performance measures include market share, new product introduction, product/service quality, and marketing efficiency (Al-Dweiri et al., 2024). Comparable approaches include the Balanced Scorecard or economic models (Kaplan & Norton, 1992), which integrate financial and operational criteria for customer value, innovation, and internal business improvement. Financial performance is typically evaluated using accounting measures (e.g., profitability metrics such as return on assets, return on investment, return on sales, and return on equity) (Rahi et al., 2024), market-based measures (e.g., stock returns), or a combination of accounting and market-based measures (e.g., price-to-earnings ratio) (Sanjaya & Yoelencia, 2024). Given the criticisms toward accounting-based measures, several authors propose market-based measures as better indicators of overall performance (Alomari & Aladi, 2024). Stock market data are assumed to reflect investors' estimates of a company's future potential and thus focus on the long-term value of the enterprise (Sanjaya & Yoelencia, 2024). Assuming that investors evaluate companies appropriately (perfect markets), stock market data are considered prudent performance indicators for listed companies (Alomari & Aladi, 2024). However, the idealistic assumption of perfect markets and the high percentage of unlisted companies severely limit their widespread use.

Research Hypotheses and Model:

In a previous study on OI, Leitão et al. (2020) conducted empirical research that categorized OI activities into inbound and outbound and investigated factors influencing them, such as environmental impact. Their findings revealed that the application of inbound and outbound innovation, along with public policies, positively and significantly impacts the eco-innovative performance of the studied companies. Jing et al. (2023) explored whether entrepreneurial orientation impacts OI through organizational legitimacy. Their empirical analysis revealed that organizational legitimacy has a positive mediating effect on the relationship between entrepreneurial orientation and OI.

A recent study by Salimi et al. (2023) was conducted to establish a framework outlining the key factors affecting OI in startup enterprises. The study explores how OI gives companies a competitive advantage, considering the moderating influence of environmental dynamics. Their research shows that organizational entrepreneurship, adoption of an open business model, proficiency in knowledge management, absorptive capacity, organizational preparedness, and collaborative capabilities significantly influence OI in startups. Additionally, implementing OI strategies increases the chances of startup success by gaining a competitive advantage. Notably, Salimi et al. (2023) highlight the positive moderating role of environmental dynamics in shaping this relationship.

Furthermore, Alvarez-Meaza et al. (2023) examined the influence of knowledge sharing and network capability on innovation behavior. Their results showed that knowledge sharing positively influences OI behavior. Oltra et al. (2018) also found that OI directly and positively influenced performance.

Adopting OI by organizations is a successful strategy that helps them gain a competitive edge in the long term and enhance their performance (Jutidharabongse et al., 2024). Many factors drive organizations' utilization of OI, including increasing the innovation rate due to globalization, technological advancements, new discoveries, and the worldwide information and communications revolution (Carrasco-Carvajal et al., 2023). Research has demonstrated the significance of OI activities in corporate performance (Liao et al., 2020). These research studies have found that OI positively affects corporate performance (Chelliah et al., 2023; Rumanti et al., 2023; Rabie et al., 2024; Rumanti et al., 2023; Wang et al., 2024) and concluded that a high level of practicing OI leads to higher organizational performance (Bertello et al., 2024). Based on these results, this study hypothesizes that:

Hypothesis 1 (H1): Implementing OI positively impacts company performance.

Recent studies related to big data analytics include proposals by Aspiranti et al. (2023) for using big data analytics in activating OI practices. Del Vecchio et al. (2021) assert that employing big data analytics enhances OI activities. Arias-Pérez et al. (2023) discovered that organizations can optimize OI's impact on performance through big data analytics capabilities.

Big data analytics greatly enhances corporate capability to benefit from OI practices and maximize performance (Bogers et al., 2018). It enables firms to obtain a substantial amount of data from external parties and interpret it to gain valuable insights, ultimately reducing the cost of implementing OI. Prior research has highlighted the intermediary role played by big data analytics in improving performance through the application of OI. These studies asserted that big data analytics positively moderates the relationship between OI and corporate performance (Bogers et al., 2018; Karaboğa et al., 2019; Arias-Pérez et al., 2022; Alkhatib & Valeri, 2024; Al Nuaimi et al., 2024). Based on these results, the second hypothesis states that:

Hypothesis 2 (H2): The use of big data analytics positively moderates the relationship between OI implementation and performance.

AI can increase the effectiveness of OI processes by identifying the sources of OI ideas and selecting the appropriate ones (Čirjevskis, 2022; Kuzior et al., 2023). It also contributes to building corporate OI capacities, reviving and enhancing innovation techniques, and presenting more in-depth understandings of developing fresh solutions and methods, making AI an integral part of the successful implementation of OI strategies (Babashahi et al., 2024; Zhang & Huang, 2024). In the context of OI and firm performance, previous studies underscored that utilizing AI technologies positively affects OI and corporate performance. Sahoo et al. (2024) explored the relationship between AI capabilities, OI, and business performance within B2B companies. Drawing on social-technical systems and contingency theories, the research utilizes survey data from 398 multinational B2B firms and employs structural equation modeling. Results reveal that AI capabilities positively impact OI practices, subsequently enhancing business performance. However, the influence of AI capabilities on business performance was only partially mediated. Similarly, Liao et al. (2020) and Bahoo et al. (2023) found that AI enhances OI, improving organizational performance. Therefor, the third hypothesis is stated as follows:

Hypothesis 3 (H3): The adoption of AI technology positively moderates the relationship between OI implementation and performance.

The conceptual framework illustrating the research variables and their relationships is depicted in Figure 1.

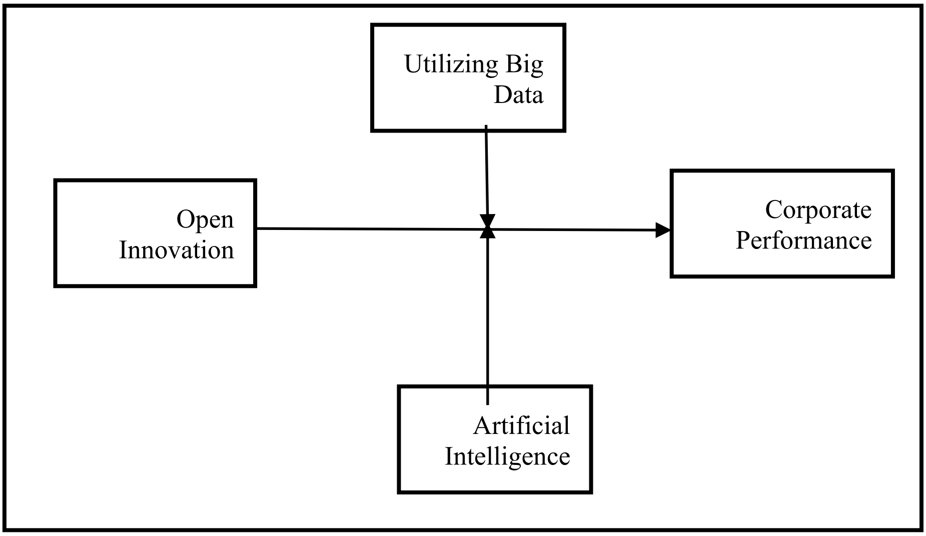

Figure 1. Conceptual Model of the Study

Methodology

Method and Procedures

This study employed a quantitative approach with the application of a survey. It is known that survey research aims to produce statistical data from specific samples by collecting data on a particular population or on subjects of knowledge understood by it, such as the company they work for (Bourque et al., 1997). When using survey research, several advantages can be highlighted: it constructs empirical data by acquiring data from a representative sample that can be generalized to a population, and it generates a large amount of data quickly (Rea & Parker, 2014). Furthermore, survey research has become widely accepted as an authentic way to understand relevant issues that management faces. Accordingly, a structured questionnaire was distributed via email to collect data from a random sample of 294 Jordanian companies operating in diverse industries from 15 September 2023 to 15 January 2024. The number of valid questionnaires accounts for 892 questionnaires. Data collected from the targeted companies in different industries; a total of 892 questionnaires were initially distributed to these companies. However, the successfully received questionnaires were

460, resulting in a response rate of 51.6% (460/892). Following the data validation process, incomplete responses from questionnaires with a significant number of missing values were removed, as these could introduce bias. Also, questionnaires with straight lining were removed, as selecting the same response option for all items indicates a lack of meaningful engagement. Thus, 294 questionnaires were considered valid and suitable for analysis. This represents a valid response rate of questionnaires (294/460 = 63.9%) received, indicating good, returned data. The population is large, with an estimated number of companies exceeding 160,000. Based on these grounds, following standard sample size determination guidelines for large populations (Bougie & Sekaran, 2019), a target of approximately 384 responses is often recommended for a margin of error of 5% with a 95% confidence level. However, the valid responses remaining for the final analysis were 294 companies, which is a strong response rate for organizational surveys (Anseel et al., 2010; Church & Waclawski, 2017). The final analytical sample size of 294 companies is considered statistically robust. It has allowed us to conclude that the population is fulfilling the study's objectives. Besides, it is adequate and comparable to studies based on the same or similar measures in Jordan (e.g., Yousef, 2024; Almashawreh, 2023). The unit of analysis was the company, as it is the specific entity subjected to the random selection process. Since the purpose of the study is to expand the existing knowledge, diverse companies were combined. Consequently, the simple random sampling included 294 companies from this large population, making it representative due to the population's vastness. In other words, considering a sample of 294 companies randomly from a population known to incorporate diverse industries provides a strong likelihood that the sample includes representation from across these sectors.

Variables Measurement

The independent variable, outbound and inbound OI, was assessed using a ten-item measurement adopted from Van de Vrande et al. (2009), Popa et al. (2017), Carrasco-Carvajal et al. (2023), and Rumanti et al. (2023). Corporate performance, the dependent variable in this study, was measured based on the work of Slater and Narver (1994) and Hwang et al. (2023) using a five-item scale. The measurement of the first moderator variable, Big Data analytics (BDAs), was adopted from the scale developed by Mikalef et al. (2019) and contains five items. The measurement of the second moderator variable, AI technology, was adopted from the scale developed by Dubey et al. (2020) and Chatterjee et al. (2023), and it contains five items. Table (1) exhibits the items used to measure each construct and their sources.

Participants' responses were measured on a 5-point scale to all scale measurements.

Table (1) Survey items

Research Concepts	Survey Items	Sources
Open Innovation (OI)	IOI1: "Direct customer participation in innovation processes."	(Carrasco-Carvajal et al., 2023), (Popa et al., 2017), (Rumanti et al., 2023), and (Van de Vrande et al., 2009)
	IOI2: "Activities are established through an external network foundation to foster innovation processes, resulting in the acquisition of external knowledge or human capital."	
	IOI3: "Participation in new and established companies to gain access to their knowledge and obtain other synergies."	
	IOI4: "Employing R&D services from universities, public research institutions, or suppliers."	
	IOI5: "Purchasing or utilizing the intellectual property of other companies, such as patents, copyrights, or registered brands, in order to profit from their external expertise."	
	OOI6: "Developing new business based on the company's internal expertise."	
	OOI7: "The organization sells service or product patents to other organizations."	
	OOI8: "The organization sells service or product licenses to other organizations."	
	OOI9: "Organizations offer new methods used by internal organizations in other organizations."	
	OOI10: "The organization seeks to gain other benefits from the internal innovations that have been carried out."	
Big Data Analytics	BDAs1: "Degree of access to very large, unstructured, or fast-moving data for analysis."	(Mikalef et al., 2019)
	BDAs2: "Degree of integrating data from multiple sources into a data warehouse for easy access."	

Research Concepts	Survey Items	Sources
	BDAs3: "Degree of integrating external data with internal to facilitate analysis of business."	
	BDAs4: "Degree of adopting different data visualization tools."	
	BDAs5: "Degree of adopting new forms of databases, cloud-based services, and open-source software for big data analysis."	
AI technology	AI1: "We possess the infrastructure and skilled resources to apply AI information processing systems."	(Chatterjee et al., 2023) and (Dubey et al., 2020)
	AI2: "We use AI techniques to forecast and predict environmental behavior."	
	AI3: "AI-enabled machines have the computational abilities to perform like humans."	
	AI4: "AI technology helps automate business operation activities."	
	AI5: "AI-enabled machines possess intellectual capabilities."	
Performance (PER)	PER1: Degree of sales revenue increase over the past two years.	(Slater and Narver, 1994) and (Hwang et al., 2023)
	PER2: Degree of operating profit increase over the past two years.	
	PER3: Degree of market share increase over the past two years.	
	PER4: Degree of increase in investment returns over the past two years.	
	PER5: Degree of increase in asset returns over the past two years.	

Empirical Analysis

Classification of Research Targeted Companies

A survey of 294 companies in Jordan, mainly in major cities like Amman, was conducted to test the hypotheses. The cities were chosen based on research accessibility due to their large populations. The companies surveyed were classified based on demographic criteria and according to their industry sectors, as shown in Table (2). The breakdown of companies by industry sector is as follows: 95 in consumer goods manufacturing, 25 in capital goods manufacturing, 42 in components and materials, 32 in intermediate goods manufacturing, 98 in the service sector, and two companies classified as other industries.

Table (2): Classification of Sample Companies by Industry

Industry	Number of Firms	Percentage
Finished Products (Consumer Goods)	95	32.2
Finished Products (Capital Goods)	25	8.5
Components and Materials	42	14.2
Intermediate Goods	32	10.9
Services (Technology/Programs, etc.)	98	33.2
Other	2	1.0
Total	294	100.0

As indicated in Table (3), the companies surveyed were categorized by personnel count: 92 companies had 20 employees or fewer, 110 had 21 to 40 employees, 47 had 41 to 60 employees, and 45 had over 60 employees.

Table (3) Classification of Sample Companies by Number of Employees

Number of Employees	**Number of Firms**	**Percentage**
0-20 employees	92	31.3
21-40 employees	110	37.4
41-60 employees	47	16.0
Over 60 employees	45	15.3
Total	294	100.0

Validity and Reliability of Research Concepts

The reliability and validity of the four research concepts, OI implementation, big data analytics, AI technology, and performance, were verified. The exploratory factor analysis and Cronbach's alpha analysis results are presented in Table (4). The validity of the four research concepts was confirmed through exploratory factor analysis, wherein OI execution was defined as Factor 1, BDAs as Factor 2, AI technology as Factor 3, and performance as Factor 4 (Table 4). Exploratory factor analysis (EFA) is an explorative examination used to find the components within a set of variables (Pallant, 2020). It is used to regulate the number of factors that affect a variable and to analyze which variables fit together to group them into categories to reduce the amount of data (Fabrigar & Wegener, 2012). All research concepts exceeded the loading value criterion of 0.6, indicating their appropriate validity as research concepts. Cronbach's alpha analysis was conducted to validate the reliability of the four research concepts. The results of this analysis are shown in the rightmost column of Table 4. The four research variables exceeded the commonly accepted threshold of 0.7, demonstrating sufficient reliability regarding the Cronbach alpha coefficient (DeVellis & Thorpe, 2021).

Table (4) Exploratory Factor Analysis Results for Concepts and Actual Items

Concept	Item	Factor 1	Factor 2	Factor 3	Factor 4	Cronbach's alpha
Open Innovation	OI1	0.868	0.189	0.202	0.188	0.927
	OI2	0.839	0.288	0.197	0.207	
	OI3	0.819	0.251	0.188	0.195	
	OI4	0.806	0.239	0.221	0.171	
	OI5	0.775	0.147	0.175	0.209	
	OI6	0.881	0.172	0.193	0.162	
	OI7	0.784	0.144	0.211	0.195	
	OI8	0.801	0.201	0.224	0.164	
	OI9	0.805	0.195	0.183	0.241	
	OI10	0.779	0.153	0.144	0.223	
Big Data Analytics	BDAs1	0.188	0.815	0.119	0.204	0.911
	BDAs2	0.196	0.859	0.172	0.193	
	BDAs3	0.174	0.822	0.168	0.188	
	BDAs4	0.237	0.890	0.228	0.217	
	BDAs5	0.207	0.901	0.207	0.158	
AI technology	AI1	0.110	0.182	0.877	0.144	
	AI2	0.184	0.201	0.883	0.176	

Concept	Item	Factor 1	Factor 2	Factor 3	Factor 4	Cronbach's alpha
	AI3	0.141	0.238	0.861	0.206	0.909
	AI4	0.119	0.224	0.928	0.194	
	AI5	0.192	0.173	0.916	0.188	
Performance	PER1	0.158	0.097	0.101	0.841	0.907
	PER2	0.085	0.113	0.088	0.837	
	PER3	0.246	0.124	0.139	0.829	
	PER4	0.287	0.215	0.227	0.753	
	PER5	0.259	0.078	0.115	0.751	

Testing of Research Hypotheses:

To validate the hypotheses, empirical analyses were conducted using simple regression models and adjusted (or hierarchical) multiple regression models. Hypothesis 1, which posits that the execution of OI positively influences performance, was tested using a simple regression model. The results are presented in Step 1 of Tables 5 and 6, with OI execution set as the independent variable and performance as the dependent variable. Both variables were operationalized by averaging the responses to the five 5-point scale survey items specified in the previous section's variables measurement. As shown in Step 1 of Tables 5 and 6, the F-statistic value, indicating the overall significance of the regression model, was 158.874, significant at the 1% level, which can be considered a significant predictor of the dependent variable. The coefficient of determination, representing the explanatory power of the regression model, was 0.504, in which it could be said that the independent variables explain 50.4% of the total variability, also, with an adjusted coefficient of determination of 0.502, which in a more conservative estimation indicates that approximately 50.2% of the total variability in performance is explained by the model, after accounting for the independent variables. The regression model's constant was 1.901, and the coefficient for OI execution was 0.533, indicating that the higher the OI execution is, the better the performance is, because it is a positive sign. Both yielded t-statistic values exceeding 10, indicating significant results at the 1% level. Collectively, these results support Hypothesis 1, affirming that OI execution positively impacts performance.

Table (5) Results of the Initial Regression Model and Verification of the Moderating Effect of Big Data Analysis Utilization

Variable	Step 1			Step 2		
	B	Standard Dev.	t-value	B	Standard Dev.	t-value
Constant	1.901**	0.132	15.002	0.893	0.498	1.802
Open innovation	0.533**	0.041	13.011	0.601**	0.172	3.701
Big Data Analytics	-	-	-	0.299*	0.149	2.114
OI X BDAs	-	-	-	0.039	0.051	0.885
R2	0.504			0.529		
Adjusted R2	0.502			0.524		
Δ R2	-			0.025		
F Statistics	158.874**			159.992**		

Table (6): Results of the Initial Regression Model and Moderating Effect Verification of AI Technology Utilization

Variable	**Step 1**			**Step 3**		
	B	**Standard Dev.**	**t-value**	**B**	**Standard Dev.**	**t-value**
Constant	1.901**	0.132	15.002	3.228**	0.058	49.896
Open innovation	0.533**	0.041	13.011	0.081**	0.021	3.997
AI technology	-	-	-	0.942**	0.033	35.117
OI X AI	-	-	-	0.277**	0.008	45.071
R2	0.504			0.564		
Adjusted R2	0.502			0.559		
Δ R2	-			0.060		
F Statistics	158.874**			189.991**		

Hypothesis (2) was validated in the second stage of the present study using hierarchical regression analysis. To validate Hypothesis 2 (Table (5), Step 2), variables such as OI execution, big data utilization, and the interaction term (the product of OI execution and big data utilization, representing the moderating effect) were used as independent variables; performance was the dependent variable. The results showed that the F-statistic was significant at the 1% level, with R-squared and adjusted R-squared values of 0.529 and 0.524, respectively. This indicates an improvement compared to the basic regression model in Step 1, which indicates that BDAs with Open Innovation collectively explain 52.9% of the variance in the dependent variable. The B value of 0.299 indicates that for every one-unit increase in big data analytics, the dependent variable is predicted to increase by 0.299 units. The interaction between OI and BDAs with a B value of 0.039 suggests that the interaction between OI and big data analytics does not significantly predict the dependent variable. The slight increase in R-squared to 52.9% indicates that the variables in Step 2 collectively explain 52.9% of the variance in the dependent variable. The change in R-squared further explained an additional 2.5% of the variance in the dependent variable.

However, only the coefficient of the OI execution variable was significant at the 5% level. In contrast, the coefficients of the other terms were not significant, as indicated by their low t-values. While the regression model showed significance, most coefficients, barring one, were insignificant, indicating that the hierarchical regression model lacked significance. Therefore, it can be concluded that Hypothesis 2, which posited a positive moderating effect of big data analytics execution on the relationship between OI execution and performance, is not supported.

Hypothesis 3 was validated in the third stage of the present study, also using hierarchical regression analysis. The independent variables included OI execution, AI technology utilization, and their interaction term, representing the moderating effect. Performance was the dependent variable. The results of this validation are summarized in Step 3 of Table (6) below. As shown in the right part of the table, the F-statistic of the second hierarchical regression analysis was 189.991, indicating significance at the 1% level and confirming the model's significance. The positive coefficient (0.081) indicates that a one-unit increase in OI is linked with a prospective increase of 0.081 in the dependent variable. However, the significant decrease in the coefficient for OI when AI technology and interaction are incorporated suggests that a substantial portion of the variance in the dependent variable, previously attributed solely to OI, is now explained by AI technology and/or its interaction term. The coefficient of 0.942 signifies an influential positive association with the dependent variable when controlling for OI and the interaction term. This suggests that higher levels of AI technology are tightly linked to increases in the dependent variable. The positive coefficient (0.227) indicates a positive interaction effect. Thus, it can be deduced that the relationship between OI and performance relies on the level of AI technology, and vice versa. In other words, when companies are engaging with OI, it influences performance, but this becomes even stronger when higher levels of AI technology are used.

Furthermore, the coefficients of determination—R-squared and adjusted R-squared—increased significantly to 0.564 and 0.559, respectively, compared to the initial regression analysis in Step 1. This suggests that the second regression model better explains the data. The model's constant was 3.228, with coefficients of 0.081 for OI execution, 0.942 for AI technology utilization, and 0.277 for the interaction term. These coefficients exhibited high t-values and were significant at the 1% level. Considering these results, the second hierarchical regression model is deemed significant, and Hypothesis 3 is supported. Therefore, it can be concluded that AI technology utilization has a positive moderating effect on the relationship between OI execution and performance.

Discussion:

The study's findings indicated that deploying OI had a substantial impact on performance, supporting the first hypothesis, which posits that implementing OI will positively impact a company's performance. The result confirmed the importance of the environmental impact, which is conceptualized in this study. The results reported that OI accounts for 50.4% of the variability in companies' performance. This is a substantial explanatory power for OI as a predictor. Nevertheless, again, the importance of the OI role is stressed as being detrimental to performance. This aligns with the contentions of Oltra et al. (2018) and Leitão et al. (2020), as discussed in the literature, which imply the significance of external knowledge apprehension in motivating organizational success. This result also provides insights beyond the exclusive focus on startups in the works of Salimi et al. (2023), regarding OI assistance for collaboration and leveraging capabilities. Thus, it is meriting attention by companies to allocate their resources to foster an open, innovative culture. The influence of OI aligns in the same vein with current research that postulates OI as a driver of competitive advantage (Jutidharabongse et al., 2024) and an enhancer of innovation behavior (Alvarez-Meaza et al., 2023), and overall organizational success (e.g., Chelliah et al., 2023; Rabie et al., 2024).

The second hypothesis indicated that the use of big data analytics positively moderates the relationship between OI and performance. The findings revealed that big data analytics with OI collectively explain 52.9%

of the variability of the dependent variable. This improvement in explanation over the previous result indicates that utilizing more BDAs with OI leads to greater performance. Further indication from the B value for big data analytics in the results indicates that a one-unit increase in big data analytics is associated with a 0.299-unit expected increase in performance. So far, this supports the recognition of big data analytics as a possibility for organizations to enhance their ability to collect, process, and extracts insights from extensive data, thereby expecting to improve their performance. This insight is in line with previous endeavors that stressed the big data analytics enhancement of performance (e.g., Bogers et al., 2018; Karaboğa et al., 2019; Arias-Pérez et al., 2022). However, the results showed that the interaction between OI and big data analytics on performance is not supported. This contradicts the general propositions of previous studies mentioned above, in which there is a consensus on the activation of OI, while there are big data analytics (e.g., Del Vecchio et al., 2021; Aspiranti et al., 2023).

This result indicates that big data analytics does not moderate the innovation–performance relationship and needs reflection. One possible explanation could be deduced from the measurement of performance itself. It was measured through perception, which may not fully capture the intricate synergistic benefits that vitalize the interplay between OI and big data analytics. In scrutinizing the results of Arias-Pérez et al. (2022), they found that the effect of big data analytics with OI is greater on financial performance than non-financial performance. This illustrates that the relationship could be clearer if more “hard” data were employed, which is reflected more upon in the implications and recommendations sections below.

Furthermore, it could be explained by delving into the insights provided by Al Nuaimi et al. (2024), which speculates that successful big data analytics implementation depends on addressing critical enablers and overcoming associated challenges. The respondents might not have experienced these enabling aspects. Thus, without culture and literacy of data, top management support, and compliance frameworks, the expected synergistic effects might not be realized. All combined could have impeded the statistical significance of performance.

Moreover, while big data analytics is considered essential, it might have functioned more as an enabler of the current processes rather than a direct driver of performance on the same scale as AI technology. Although big data analytics have been available for some time, many companies continue to face resistance in effectively implementing and leveraging it across their organizations (Adewusi et al., 2024). Challenges related to data quality, data integration, analytical talent scarcity, and turning insights into actionable strategies can weaken its direct impact on overall company performance. AI technology, although more recent in widespread application, might be grasped or implemented in ways that lead to more visible or immediate improvements, mainly if focused on specific high-impact areas. It could also relate to the context of Jordanian companies, as OI and AI technology could be stronger differentiators or more critical for success than the size of big data analytics endorsement.

Regarding the third hypothesis, which says that adoption of AI technology positively moderates the relationship between OI implementation and performance. The hypothesis is accepted, illustrating that the interaction between OI and AI technology significantly influences performance. As mentioned above, this relationship was more pronounced than the interaction between OI and big data analytics to foretell performance. Thus, companies engaging in OI will exhibit competent performance, and this advantage becomes even stronger when they utilize various levels of AI technology. The more evident influence of this hypothesis is in line with previous literature such as Čirjevskis (2022) and Kuzior et al. (2023), illustrating that AI technology can increase the effectiveness of OI processes through locating resources, ideas, and optimizing selection. Furthermore, the apparent influence suggests that AI technology acts as a synergistic power to stimulate companies in their processing and analysis of knowledge acquired through OI for better outcomes. These results provide an imperative for managers to strategically incorporate AI technology, as also implied by Babashahi et al. (2024).

Overall, the results can be attributed to the influence of OI, which involves customizing products that meet customer needs. Therefore, AI technology, which focuses on addressing diverse issues and streamlining processes, is more relevant or suitable than big data analysis, which is primarily concerned with data processing and management. OI and AI technology align with practical problem-solving and customer-driven convenience and automation. Consequently, companies can expect higher performance when simultaneously pursuing both approaches and concentrating their investments and efforts in that direction. The results demonstrate that OI is a driver of performance, which aligns with previous research emphasizing the value of external knowledge and integration (Chesbrough, 2015). This signifies that companies that engage with OI practices, such as external knowledge and innovative ideas, are open to external sources, strengthening their ability to innovate and adapt, which ultimately drives performance. Similarly, AI technology emerged as a solid trigger of performance, corroborating studies stressing AI's role in decision-making, easing workflow, and uplifting customer experiences (e.g., Zhang & Huang, 2024).

Research Implications

Implications for theory:

This research explores the significance of innovation in businesses from a new perspective. This is achieved by leveraging the concept of OI, which is flexible and can incorporate a broader range of innovation factors (environment, market, etc.), unlike traditional internal innovation approaches. Previous studies have focused on a “closed innovation” model, which is driven internally by organizations and emphasizes a firm’s generation of ideas and development, primarily through internal R&D. This is why earlier academic work often focused on optimizing internal capabilities for innovation efficiently, thereby, neglecting the exploration of external ideas and ways to the market that are vital to the concept of OI. In incorporating big data analytics and AI technology, a new mechanism of the influence of OI and performance is featured. Hence, this research is outpacing some research that established a direct link between innovation and performance. This study moves beyond this depiction by proposing a moderating effect through OI, which is translated into better performance. This is also informative to existing theoretical frameworks where these factors are upheld in isolation. The connections are explored novelly through data from Jordan; the outcomes of this investigation have theoretical and practical ramifications. Finally, it could help uncover the value and usefulness of big data analytics and AI technology for organizations, as well as aiding decision-making in innovative efforts.

Implications for practice:

The findings provided a theoretical foundation for assessing the ability of big data analytics and AI technology to affect a firm's performance. Given the limited number of studies on the relationship between OI and performance in Jordanian companies, management practitioners and academics have the chance to acquire new knowledge. This theoretical conceptualization may also influence future investigations in the relevant fields. The goal of this study is to investigate how the concept of OI influences performance in the light of openness in pertinence to variables, which are big data analytics and

AI technology. The study findings indicate a significant impact of OI on performance. In the moderation analysis, more precise than big data analytics, AI technology showed moderating effects on the relationship between OI and performance. These results imply that while big data analytics technology focuses on interpreting data, AI technology aims at problem-solving and optimization. Therefore, in innovation activities, particularly OI involving customized product development, AI is more suitable and can synergistically enhance performance.

These technologies, particularly those examined here, are expected to have broader applications across various fields, such as trade and international logistics, improving performance and enhancing competitiveness. Organizations should foster a culture of OI by actively seeking external knowledge and collaboration, while also investing in and utilizing AI technologies. The industry could uphold actions in developing transparent processes for external knowledge apprehension while, at the same time, building internal AI capabilities (e.g., employing AI talent, training in AI, and AI infrastructure). Given the synergy between OI and AI technology, companies can explore efforts that combine these two, such as using AI-powered platforms to connect with prospective partners and employing AI to discern external data for new development ideas. Although BDAs are less predictive than AI technology, they remain important. Therefore, firms can secure data management practices and employee training to support AI technology, OI, and their employment. However, the study's findings may have limited generalizability due to the focus on Jordanian companies.

Managers in organizations are recommended to strategically invest in developing dynamic BDA and AI capabilities as a component of their innovation processes. This could involve transitioning from traditional data collection methods to a more complex data framework, thereby gaining and leveraging talent in data science and AI. More importantly, organizations should assign greater value to data-driven decision-making and AI insights in the context of innovation. In the context of Jordan, companies could actively uphold BDA to locate and track market trends and optimize product development cycles. It could also be achieved more quickly when organizations lacking these capabilities partner with or outsource to focus on translating data and AI models into actionable strategies for process improvement and internal efficiency.

For policymakers, it is necessary to create initiatives and committees to endorse digital literacy. In educational systems, developing the current curricula would be an opportunity to adopt digital literacy, enabling the workforce to utilize such tools efficiently. Hence, considerations for regulations should accompany such steps, in terms of ethical AI usage and data sharing transparency. Moreover, training programs provided will be beneficial, specifically if they are backed up with certifications accredited by official bodies. Finally, it is recommended to establish partnerships that connect the public and private organizations to sustain programs and training to equip learners with relevant BDA and AI competencies.

Conclusion, limitations, and future research:

The present study investigated whether companies in the Jordanian market improve performance using OI. Additionally, it examined whether various technologies of the fourth industrial revolution, specifically big data analytics and AI, positively moderate the relationship between OI and performance. An empirical analysis was conducted on 294 companies in Jordan using surveys.

The first hypothesis, asserting that OI execution has a positive impact on performance, was confirmed. To achieve the second research objective, the results of the moderation analysis using multiple regression analysis revealed that while the execution of big data analytics does not exhibit moderating effects, the execution of AI technology shows positive moderating effects on the relationship between OI execution and performance. These findings suggest that companies focusing their investment on OI execution may experience performance boosts due to synergies with AI technology. However, the study suggests that such synergistic effects are less likely to be expected from the execution of big data analytics.

These results imply that while big data analytics technology focuses on interpreting data, AI technology aims at problem-solving and optimization. Therefore, in innovation activities, particularly OI involving customized product development, AI is more suitable and can synergistically enhance performance.

This study may be limited by the use of survey questions, which could introduce respondent bias and affect the results. Future research could use structured and unstructured interviews to address this issue. Future research could also explore the mediating role of big data analytics and AI between OI and performance in different settings and cultures, integrate OI with quality management practices, and explore aspects related to environment, social, and governance considerations alongside performance.

One more limitation of this study is that it is cross-sectional in design, which means that establishing causality is not possible. Since the inherent nature of cross-sectional studies is to capture relationships between variables at a single point in time, rather than following up their evolution over time. Thus, longitudinal research is recommended. The study is conducted in Jordan, but research applying the conceptualization elsewhere could bring interesting insights.

Collecting data on this subject from different nations could bring more insights, as cultural differences could play a significant role. One approach is to contextualize national culture within the framework of future studies. Additionally, future research could employ objective measures for performance, if feasible, and expand considerations by exploring alternatives to measuring open innovation, BDA, and AI technology. Finally, within the proposed relationships in this study, future endeavors can investigate possibilities of including mediating or moderating variables that influence the assigned relationships, thereby contributing to a more holistic understanding of how companies can endorse these technologies for improved performance.

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