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ORIGINAL

Analysing the artificial intelligence of e-marketing adoption in the b2b enterprise market

Análisis de la inteligencia artificial de la adopción del marketing electrónico en el mercado empresarial B2B

khalid Thaher Amayreh[1], Ali (Mohammad Ali) Alqudah[2], Firas Rashed Wahsheh[3], Khaled (Yousef Issa) Alshboul[4], Tariq Abdelhamid Ali Mussalam[5], Omar (Mohammad Ali) Alqudah[6], Mohammad alzoubi[7]

[1]Department of Business Management, Amman Arab University, Amman, Jordan.
[2]Department of design graphic, Al-Zaytoonah University, Amman, Jordan.
[3]Department of Management Information Systems, Ajloun National University, Ajloun, Jordan.
[4]Department of Management Information System, Irbid National University, Irbid,Jordan.
[5]Department of E-marketing, Irbid National University,Irbid, Jordan.
[6]Department of E-marketing Department, Irbid National University, Irbid, Jordan.
[7]Irbid National University, Business Intelligence and Data Analysis, Jordan.

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ABSTRACT

Introduction: this research examines the factors influencing the adoption of e-marketing by B2B organizations in Jordan and its impact on overall business performance. It draws on relationship marketing, innovation adoption theories, and integrates concepts from Artificial Intelligence Driven Big Data Analytics (AI DBDA) and Cognitive Service Analytics (CSA). The study is framed around the Diffusion of Innovation (DoI) theory and the Technology Acceptance Model (TAM), providing a comprehensive view of the determinants that drive e-marketing adoption.
Method: a quantitative research approach was employed, using Structural Equation Modelling (SEM) for data analysis. A survey was administered via a Google Form, collecting 226 valid responses from B2B organizations in Jordan. The theoretical framework was tested using advanced statistical techniques to evaluate the relationships between e-marketing adoption and various influencing factors.
Results: the findings indicate that e-marketing adoption is significantly influenced by AI-DBDA, CSA, perceived compatibility, relative advantage, perceived ease of use, and market performance. These factors were found to be crucial in determining the extent to which B2B organizations in Jordan embrace e-marketing.
Conclusions: this study emphasizes the importance of environmental factors, such as technological capabilities and organizational perceptions, in the adoption of e-marketing. The results contribute to the limited empirical research on e-marketing adoption in developing countries, offering insights into how these factors enhance business performance. These findings suggest that for successful e-marketing implementation, organizations need to focus on technological innovations and alignment with their business objectives.

Keywords: Cognitive Service Analytics; TAM; DOI; Big Data Analytics; Structural Equation Modeling.

RESUMEN

Introducción: esta investigación examina los factores que influyen en la adopción del e-marketing por parte de las organizaciones B2B de Jordania y su impacto en el rendimiento empresarial global. Se basa en el marketing relacional, las teorías de adopción de innovaciones e integra conceptos de la Analítica de Grandes Datos Impulsada por Inteligencia Artificial (AI DBDA) y la Analítica Cognitiva de Servicios (CSA). El estudio se

enmarca en la teoría de la Difusión de la Innovación (DoI) y el Modelo de Aceptación de la Tecnología (TAM), proporcionando una visión integral de los factores determinantes que impulsan la adopción del e-marketing.
Método: se empleó un enfoque de investigación cuantitativo, utilizando el Modelo de Ecuaciones Estructurales (SEM) para el análisis de datos. Se administró una encuesta a través de un formulario de Google, recogiendo 226 respuestas válidas de organizaciones B2B de Jordania. El marco teórico se puso a prueba utilizando técnicas estadísticas avanzadas para evaluar las relaciones entre la adopción del e-marketing y diversos factores influyentes.
Resultados: los resultados indican que la adopción del e-marketing se ve influida significativamente por la AI-DBDA, el CSA, la compatibilidad percibida, la ventaja relativa, la facilidad de uso percibida y el rendimiento en el mercado. Estos factores resultaron cruciales para determinar hasta qué punto las organizaciones B2B de Jordania adoptan el marketing electrónico.
Conclusiones: este estudio subraya la importancia de los factores ambientales, como las capacidades tecnológicas y las percepciones organizativas, en la adopción del marketing electrónico. Los resultados contribuyen a la limitada investigación empírica sobre la adopción del e-marketing en los países en vías de desarrollo, ofreciendo una visión de cómo estos factores mejoran el rendimiento empresarial. Estas conclusiones sugieren que, para implantar con éxito el marketing electrónico, las organizaciones deben centrarse en las innovaciones tecnológicas y en la alineación con sus objetivos empresariales.

Palabras clave: Analítica Cognitiva de Servicios; TAM; DOI; Big Data Analytics; Modelado de Ecuaciones Estructurales.

INTRODUCTION

The proliferation of novel technologies and the Internet has garnered significant attention from scholars, policymakers, and practitioners during the last two decades. Consequently, academics have used many established theoretical frameworks to study how individuals and organisations embrace and spread new technology. In addition, recent studies on the acceptance and utilisation of information technology have been driven by the aim of identifying characteristics that contribute to effective implementation in a marketing setting (Canhoto et al., 2020; Grover, Purva, et al., 2020). Although the exploration of non-objective variables impacting purchasing choices in the business community is a positive advancement, there is a significant lack of study examining these aspects specifically in relation to the adoption of innovative practices within the business community. Managers' choices to accept innovation are known to be impacted by a range of behavioural and subjective characteristics, as acknowledged by many studies (Mohan et al., 2017; Henriques et al., 2019; Kusiak, 2019). According to Brown et al. (2019), the service sector is making significant contributions to wealth creation. However, they argue that there has not been a thorough analysis of the sector's substantial role in producing and using innovation. Therefore, although there is a growing focus on customer centricity in the SMEs markets, it is remarkable that only a limited number of studies have investigated how firms engage in innovation for their industrial customers (Salunke et al., 2019; Heirati & Siahtiri, 2019), and none have examined the subjective factors that impact managers' choices to innovate and embrace new offerings. This study addresses this gap by investigating the mechanisms through which AI-DBDA capability and CSA capability impact e-marketing adoption in the decision-making process of the business industry. Innovation adoption pertains to the degree to which B2B decision-makers embrace novel offerings proposed by a supplier (Behl et al., 2021; Akter et al., 2021).

The acceptance of innovation in industrial markets is crucial for the success of firms (Martin et al., 2016; Altay & Pal, 2022). Due to the high expenses and intricate nature of industrial acquisitions, the implementation of new ideas has been seen as a purposeful process for managing potential risks (Joachim et al., 2018). Therefore, due to the importance of managing uncertainty in making these judgements, rational decision-making processes have been the primary focus of academic discussions on the adoption of innovative behaviours (Bag, Gupta, & Kumar, 2021). Hence, a company's choice to embrace new ideas may also be swayed by subjective factors that are unique to managers and owners, such as the company's dedication to maintaining a partnership with a supplier. Marr (2020) and Hinsch et al. (2020) provide empirical findings derived from leaders' perspectives on how their organisations will influence business strategy throughout the big data analytics age and AI.

However, Existing study offers little empirical data and mostly relies on anecdotal accounts to investigate the influence of AI-BDA culture on resilience and agility in the adoption of e-markets. By 2022, it is projected that the allocation of marketing funds towards AI implementation service analytics will surpass 11 %, based on available statistics. According to Watson et al. (2021), total spending on AI is projected to surpass $125 billion by 2025. The global adoption of AI technologies by tech-savvy corporate clients is seeing a significant increase (Brock & Wangenheim, 2019) as a result of the introduction of diverse service improvements. AI allows healthcare customer suppliers to implement predictive maintenance for their valuable equipment, enhancing performance, minimising costs, and reducing time. This enables clients to benefit from a further personalised, engaging service experience, and consistent (Hallikainen et al., 2019). Therefore, this research offers several contributions. Initially, we develop and verify the construct of cognitive service analytics capacity, which integrates the skills of machines and marketers in digital B2B marketplaces.

This research marks an attempt to delve into the application of AI for analyzing services in business markets. Instead of displacing marketers and machines, the use of AI technology enhances their capabilities. In addition, the study evaluates how the adoption of AI in the market impacts the abilities of services and models the effects on market performance and service innovation. This research seeks to address the increasing need for investigations into AI-driven advancements in service offerings within business markets, as indicated by research studies (Huang & Rust, 2018; Kumar et al., 2020; Grewal et al., 2020; Kumar et al., 2021). Moreover, our research offers insights for marketing professionals in the industry on how to address challenges related to leveraging AI technology to improve service analysis capabilities by fostering teamwork between machines and marketers.

LITERATURE REVIEW

Extending the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DoI)

In recent years, numerous scholars have sought to extend the frameworks of TAM and DoI to enhance their predictive capabilities regarding technology adoption and user acceptance over time. Notable contributions to this field have been made by Ajzen (2020), Alshami et al. (2022), and Rifki & Ikhsan (2023). While both models incorporate elements that elucidate the adoption and dissemination of new technologies, they often overlook critical factors that may influence the acceptance, dissemination, and integration of emerging technologies.

To achieve a comprehensive understanding of e-marketing strategy adoption among business-to-business (B2B) enterprises, it is essential to enrich these models by integrating additional elements that consider both internal and external influences on organizations operating in this domain. This endeavor necessitates a thorough review of the literature surrounding technology assimilation in organizational contexts to identify key factors that may impact the execution of e-marketing practices.

A systematic review was conducted to assess the literature pertaining to the adoption of new e-marketing technologies. Despite the rapid growth of research in this area over the past decade, it is evident that much of the literature has focused primarily on this timeframe. The literature review revealed that researchers in this field have relied not only on the components of DoI and TAM but also on various other factors. Key variables influencing the adoption of new technology include robust support from upper management, distinct product attributes, organizational readiness regarding scale and cost, availability of financial and technical resources, information intensity, industry competition, the quality of national infrastructure, security concerns, governmental influence or support, consumer willingness to embrace technology, support from technology suppliers, global orientation of the company, and owner proficiency.

To address these insights, the researcher will incorporate the capabilities of data-driven analytics (DBDA), cognitive service analytics (CSA), and market performance into the frameworks of DoI and TAM. This study framework (Figure 1) was developed based on prior findings to examine the influence of these variables on AI-driven e-marketing adoption by B2B organizations in Jordan. Additionally, some studies have utilized the DoI and TAM in tandem to investigate various aspects impacting novel technologies. Research by Al-Zoubi (2023) and Al-Zoubi et al. (2023) has highlighted a significant relationship between TAM and IDT, noting parallels between “complexity” and “relative advantage” in IDT, and “perceived ease of use” and “perceived usefulness” in TAM. The current study primarily focuses on three critical components: perceived ease of use, perceived compatibility, and perceived relative advantage (or usefulness).

H1: Perceived relative advantage (PRA) positively impacts attitudes towards e-marketing adoption.

H2: Perceived ease of use (PEU) positively influences attitudes towards e-marketing adoption.

H3: Perceived compatibility (PC) positively affects attitudes towards e-marketing adoption.

Artificial Intelligence-Driven Big Data Culture

The term “big data” has gained significant traction recently; however, due to the rapid evolution of computing power and technology, it may soon become outdated. Big data capabilities empower organizations to leverage vast datasets through artificial intelligence (AI), facilitating a shift from intuition-based decision-making to a more data-centric approach.

AI enhances business operations by providing insights derived from substantial amounts of data. It also plays a crucial role in analyzing unstructured information, which constitutes approximately 85 % of big data analytics (Caos et al., 2021). Advancements in technology, tools, and social media platforms have transformed market detection and management, effectively improving data collection and sharing among stakeholders (Kankanamge

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et al., 2021; Altay & Pal, 2022). While there is a growing body of literature emphasizing the potential of AI and big data analytics (AI BDA) in enabling companies to adapt quickly and sustainably, research remains in its infancy. Many organizations are hesitant to acknowledge the role of these technologies in enhancing their decision-making processes (Al-Zoubi et al., 2023; Behl et al., 2021).

The primary barrier to the acceptance of AI-driven data analysis in business lies in the complexity of the technology and the shortage of specialized skills necessary to address market challenges effectively. Furthermore, a lack of an organizational culture that embraces intelligence, big data, and analytics may hinder the uptake of technologies aimed at improving market support initiatives (Grover et al., 2020). Pizzi et al. (2020) assert that fostering a data-centric culture can significantly influence technology adoption. Numerous studies have explored how organizational culture impacts operations management (Sandvik et al., 2014; Zanon et al., 2021).

H4: AI-driven big data culture positively influences attitudes towards e-marketing adoption.

Cognitive Service Analytics Capability

In B2B digital marketplaces, the potential for AI to aid in understanding and predicting service scenarios is significant; however, addressing real service challenges often reveals limitations in knowledge and expertise (Kakatkar et al., 2020). Organizations tend to approach decision-making with caution when relying solely on analytical tools, as these tools are still maturing. Service providers are leveraging AI to enhance the capabilities of their customer service agents (CSAs) (Huang & Rust, 2020).

Today, AI is utilized to automate tasks such as managing account details, processing billing reports, and analyzing contracts. Both humans and machines now collaborate in delivering services that require cognitive and emotional engagement, such as negotiating prices and providing recommendations. Ernst et al. (2015) emphasize the significance of technology in advancing service analytics to improve CSA proficiency.

The collaborative use of AI and human expertise in service management is vital. Cognitive technologies must possess the ability to conduct data analysis, including identifying patterns and anomalies under uncertainty, as well as learning from data to enhance their efficiency progressively. The skills of managers who can harness the insights of service managers and data scientists are also crucial for a comprehensive understanding of the technology. The successful acquisition of this technology and the development of innovative marketing capabilities depend on ongoing research, training, and development.

H5: CSA capability positively influences attitudes towards e-marketing adoption.

AI and Market Performance

Successful AI deployment requires suitable hardware and software, as well as a knowledgeable and skilled workforce capable of seamlessly integrating AI into industry marketing processes and platforms (Saunder, 2020). An effective AI service combines AI with human intelligence to enhance decision-making in industry markets (Huang & Rust, 2020). Transforming comprehensive AI services into distinct offerings is essential for improving market effectiveness and profitability.

Based on the principles of dynamic capabilities, we propose that AI services can enhance the effectiveness of industry marketing strategies by continuously updating and refining their analytical capabilities (Kumar et al., 2020). In the past two decades, advancements in AI have led to the emergence of robust cloud service platforms, such as Amazon Web Services, which have effectively served numerous B2B clients, including Netflix, Twitch, LinkedIn, Facebook, and Apple, significantly improving market performance (Tse et al., 2020). Although several recent studies (Huang & Rust, 2018; Al-Zoubi, 2020; Kumar et al., 2020) have indicated a connection between AI services and market performance, empirical research examining this relationship remains scarce.

H6: E-marketing adoption positively influences market performance.

Table 1. Comparison of AI-DBDA Culture and CSA Capabilities

Aspect	AI-DBDA Culture	Cognitive Service Analytics (CSA) Capabilities
Definition	A culture that emphasizes the integration of big data analytics and artificial intelligence to inform decision-making processes.	The ability to leverage AI-driven analytics to understand, predict, and improve service scenarios in marketing.
Key Dimensions	- Data-driven decision-making - Continuous learning and adaptation - Collaboration between data scientists and marketers	- Pattern recognition - Predictive analytics - Real-time insights and recommendations
Applications	- Enhancing customer segmentation - Optimizing marketing campaigns based on data insights - Informing product development strategies	- Automating customer interactions - Providing personalized marketing solutions - Enhancing customer service experiences through data analysis

Impact on Adoption	Fosters an environment that encourages the use of advanced technologies, leading to higher adoption rates of e-marketing tools.	Improves the effectiveness of marketing strategie s by providing actionable insights, thereby facilitating technology adoption.

Summary of Unique Roles in E-Marketing Adoption

The integration of AI-DBDA culture and CSA capabilities plays a pivotal role in the adoption of e-marketing strategies. The AI-DBDA culture promotes a data-driven approach, enabling organizations to make informed decisions and swiftly adapt to market changes. For instance, a company that utilizes AI-driven analytics to segment its customer base effectively can tailor marketing messages that resonate with specific demographics, increasing engagement and conversion rates.

On the other hand, CSA capabilities empower businesses to understand customer behavior and preferences in real-time. For example, a CSA tool that analyzes customer interactions can provide insights into common queries or pain points, allowing marketers to refine their strategies and enhance customer experiences. Together, these constructs not only facilitate the adoption of e-marketing technologies but also ensure that businesses can leverage data and analytics to drive performance and improve market outcomes.

Overview of the framework

The current research has developed a comprehensive framework for analyzing the implementation of Electronic Marketing, which subsequently impacts the overall performance of a corporation. This model is grounded in the principles derived from the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DoI) frameworks. Additionally, it incorporates components related to client creativity and the risks associated with AI e-marketing adoption.

Figure 1 illustrates the graphical representation of the model, highlighting the intricate relationships among key constructs related to AI-driven analytics and market performance in B2B organizations. Researchers frequently utilize the TAM and DoI in the field of information and communication technology (Alzoubi & Alzoubi, 2020), reinforcing the relevance and applicability of these frameworks in understanding technology adoption in diverse contexts.

Detailed Legend and Component Explanation

1. Cognitive Service Analytics (CSA) Capability: This construct refers to the organization's ability to utilize AI-driven insights to enhance decision-making processes. CSA capability enables businesses to analyze customer data effectively and adapt their marketing strategies accordingly.
2. AI-Driven Big Data Analytics (AI-DBDA) Culture: This element represents the organizational culture that promotes data-driven decision-making. A strong AI-DBDA culture encourages employees to leverage data and analytics in their daily operations, fostering innovation and responsiveness to market changes.
3. Perceived Ease of Use (PEU): This variable indicates how easy the new e-marketing technologies are perceived to be by users. Higher PEU is associated with increased willingness to adopt these technologies.
4. Perceived Compatibility (PC): This construct measures the degree to which the new technology aligns with existing values and past experiences of potential adopters. Greater compatibility leads to a higher likelihood of technology acceptance.
5. Perceived Relative Advantage (PRA): This variable assesses the perceived benefits of adopting the new technology compared to current practices. A higher perceived advantage can drive adoption rates.
6. E-Marketing Adoption: This central node represents the decision by B2B organizations to implement e-marketing strategies. It is influenced by the aforementioned constructs.
7. Market Performance: This outcome variable reflects the effectiveness of marketing efforts in driving business success, including customer engagement, revenue growth, and competitive advantage.

Relationships

- Direct Relationships: Arrows between the constructs indicate direct influences. For instance, CSA capability directly impacts e-marketing adoption, which in turn affects market performance.
- Moderating Effects: Some variables may act as moderators. For example, a strong AI-DBDA culture may enhance the positive effects of CSA capability on e-marketing adoption.

By providing this detailed legend and clearer labeling of each component in the framework, readers can easily grasp the relationships and dynamics at play without needing to refer back to the text. This clarity enhances the overall comprehensibility of the framework and its implications for B2B organizations in Jordan.

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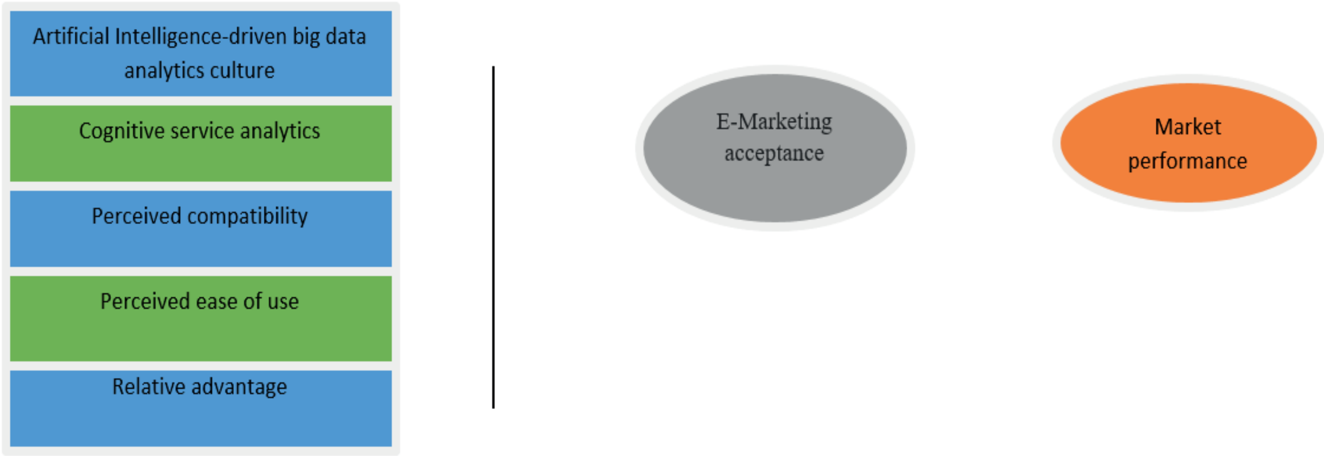

Figure 1. Research Framework

Comparison with existing studies

In recent years, the role of Artificial Intelligence (AI) and Big Data Analytics (BDA) in transforming marketing strategies has been a focal point of many studies, especially in business-to-business (B2B) contexts. The comparison between AI-Driven Big Data Analytics (AI-DBDA) Culture and Cognitive Service Analytics (CSA) Capabilities is crucial to understanding how these two concepts shape the adoption of e-marketing strategies within B2B organizations. In this section, we compare the current study's framework with recent state-of-the-art research on these two constructs.

AI-DBDA Culture has become increasingly important as organizations seek to integrate advanced analytics and AI tools into their decision-making processes. Research by Grover et al. (2020) and Pizzi et al. (2020) highlights the growing significance of a data-driven culture, where businesses rely on AI-powered insights to make informed decisions across various functions, including marketing. A robust AI-DBDA culture promotes continuous learning, collaboration between data scientists and marketers, and adaptability in the face of changing market conditions. This aligns with findings from Brock and Wangenheim (2019), who argue that companies that embrace AI-driven decision-making can gain a competitive advantage by enhancing their ability to segment customers, optimize marketing campaigns, and develop targeted strategies based on real-time data. Thus, in the context of our study, AI-DBDA Culture represents an organizational environment that encourages the use of AI and BDA to improve the effectiveness of e-marketing strategies.

On the other hand, Cognitive Service Analytics (CSA) Capabilities focus on leveraging AI to enhance customer service interactions and improve marketing outcomes. This includes using AI to analyze customer data, recognize patterns, and predict future behaviors. Studies by Huang and Rust (2020) and Ernst et al. (2015) suggest that the integration of AI into customer service can significantly improve both the quality and efficiency of customer interactions. CSA tools enable organizations to provide personalized recommendations, automate routine tasks, and make real-time decisions that enhance the overall customer experience. This is further corroborated by Huang and Rust (2018), who emphasize the importance of combining AI with human expertise in service marketing. The success of CSA depends not only on the technology itself but also on how well it is integrated into organizational practices, fostering collaboration between AI systems and human service providers.

When comparing AI-DBDA Culture and CSA Capabilities, it is clear that while both play distinct roles, they are highly complementary. AI-DBDA Culture forms the foundation for integrating AI and BDA across an organization, ensuring that all departments, including marketing, are empowered to make data-driven decisions. Without a supportive culture, even the most advanced AI tools may not be effectively adopted. Conversely, CSA Capabilities focus more specifically on enhancing the marketing and customer service functions through AI-powered insights and automation. The synergy between the two constructs is crucial. As highlighted by Kankanamge et al. (2021), fostering a strong AI-DBDA Culture within an organization not only enhances the adoption of CSA tools but also ensures that these tools are used to their fullest potential to improve customer service and marketing effectiveness.

Further studies such as Al-Zoubi (2023) and Alshami et al. (2022) have shown that organizations that cultivate a data-centric culture are better equipped to leverage AI technologies like CSA for strategic marketing initiatives. These studies underline the importance of organizational culture in promoting AI adoption and enhancing the capabilities of CSA tools. In this regard, our research extends the existing body of knowledge by highlighting the complementary roles of AI-DBDA Culture and CSA Capabilities in driving the adoption of e-marketing technologies within B2B organizations.

The comparison with recent works indicates that the integration of both AI-DBDA Culture and CSA Capabilities offers a more comprehensive understanding of how organizations can use AI and Big Data Analytics to enhance their marketing strategies. While AI-DBDA Culture creates the conditions for AI adoption across the organization, CSA Capabilities provide the specific tools and methodologies to optimize marketing and customer service outcomes. Together, these two elements play a vital role in the successful implementation of AI-driven e-marketing strategies, ultimately leading to improved market performance and competitive advantage.

METHOD

Sampling Justification and Representativeness

Data were collected in September 2023 through a reputable market research firm in Jordan, which maintains a panel of 11,000 participants with diverse demographic backgrounds. This firm ensures that the panel includes companies from various industries within the B2B sector, allowing for a more comprehensive understanding of AI adoption patterns across different sectors. Preliminary analyses indicate observable differences in AI adoption rates based on industry characteristics, such as technology, manufacturing, and services, highlighting the sample's representativeness of the broader B2B market in Jordan.

Sample Size and Data Robustness

A total of 226 responses were collected for the main study. While this sample size may seem modest, it is important to discuss its adequacy for Structural Equation Modeling (SEM). A post hoc power analysis was conducted to assess the statistical power of the results, confirming that the sample size is sufficient to detect meaningful effects. Additionally, SEM can be effectively utilized with smaller sample sizes, provided that the model is appropriately specified and assumptions are met. Future research could benefit from larger sample sizes to enhance the robustness and generalizability of the findings.

Methodological Limitations

While SEM is an appropriate analytical choice for this study, it is important to acknowledge its limitations, particularly when applied to smaller or heterogeneous samples. The potential for biases in data collection must also be addressed. Responses may have been influenced by industry-specific trends, leading to skewed perceptions of AI adoption. To mitigate these biases, efforts were made to ensure a balanced representation of industries in the sampling process. Furthermore, the study's reliance on self-reported data may introduce additional biases. Future research should consider longitudinal designs or larger, more homogenous samples to validate the findings and explore the dynamics of AI adoption more thoroughly.

The method for delineating and quantifying components is detailed in table 2, which was used for the main investigation.

Table 2. Construct measurement and sources

Variables	No. items	References	Measure
Big data analytics	5	(Salunke, 2019)	5-point Likert Scale
Cognitive service analytics	15	(Altay & Pal, 2022)	5-point Likert Scale
Perceived compatibility	3	(Ajzen, 2020, Behl, 2021)	5-point Likert Scale
Perceived ease of use	4	(Ajzen, 2020)	5-point Likert Scale
Relative advantage	5	(Ajzen, 2020)	5-point Likert Scale
E-Marketing acceptance	5	(Ajzen, 2020)	5-point Likert Scale
Market performance	4	(Huang & Rust, 2020)	5-point Likert Scale

Main Study

Out of 3640 tries, a panel of B2B service analytics managers provided a total of 405 answers. After carefully scrutinising the data quality requirements, including missing values, speeders, screening questions, flatliners and attention-checking questions, we performed an analysis on 226 legitimate responses from service managers that specialise in AI-enabled analytics. The poll participants are mostly from the ICT services sector (25 %), followed by the financial and banking services sector (35 %), professional services sector (14 %), insurance services sector (11 %), media and advertising sector (29 %), and supply chain and logistics sector (8 %).

The qualitative results were utilised to capture the specific circumstances of the research. All the measurement scales employed in the research were adapted from previous research studies, as indicated in Table 4. These scales were used to assess various aspects such as the acceptance of e-market analytics (Ajzen, 2020), cognitive analytics technology (Bag et al., 2021), cognitive analytics information (Grewal, 2020), cognitive problem solving (Tse et al., 2020), cognitive knowledge and skills (Altay & Pal, 2022), cognitive training and development, and perceived compatibility of big data analytics. In Brock's & Wangenheim's (2019) study, the analysis took into account factors such as the ease of use of a service or product, its comparative benefits, the extent of e-marketing strategy adoption, and the resulting market performance evaluation. Each aspect was evaluated using a 7-point Likert scale, which ranged from 1 (strongly disagree) to 7 (strongly agree).

RESULTS

The structural equation model aligned the findings with the research objectives. The presence of missing data could be due to a participant not answering one or more survey questions. We conducted a thorough analysis on the frequency and nature of missing values for each measurement item to validate the data's integrity. Upon reviewing the data, we found only a small amount of missing information. To address this, the missing data was replaced with the median factor responses for each measurement element. Outliers are data points that deviate significantly from the average values of a particular variable (Hair, 2017). In addition to analysing histograms and boxplots, the standardised (z) value of each variable was examined for univariate disclosure. In Hair's (2017) study, a case is considered an outlier if its standard score is equal to or more than 4,0. An outlier is defined as a Z-score that exceeds 4 or falls below -4.

Measurements Model

Multiple tests were conducted to verify the reliability and accuracy of the measures used in this study. The dependability of the measures was evaluated using the internal consistency approach, which included measuring the composite reliability (CR) values. We improved the CR category that evaluated the composition of the formulation. All components included in the study had CPVs greater than 0,7, which is deemed suitable in the field of social sciences (Table 1). We conducted a comprehensive assessment to determine the loading of all components, considering various factors. We determined that a criterion of 0,6 was appropriate. An additional indicator of internal leg weariness is a Cronbach's alpha (CA) value over 0,7 (Behl et al., 2021; Al-Zoubi, 2023). The AVE values were computed for the specified measures, and convergence was successfully attained, with the suitable value being 0,5. AVE scores reflect the differences caused by measurement errors. All average values (AVE) observed in this experiment are more than 0,5 (table 2), showing a significant level of convergent convergence. We used the Fornell-Larcker test and heteroscedasticity analysis to evaluate discrimination. The Fornell-Larcker test assesses the relationship between the square root of the AVE of one latent variable and the other latent variables. The inquiry findings suggest the presence of triadic discrimination since the extracted variance AVE of the latent variable was greater than its correlation with the other components, as shown in table 3. Analysis: This study examines the correlation between two integrators and compares it with the autocorrelation of each construct. When the connection between two variables is stronger than the correlation between the variables themselves, it can compromise profitability. This study incorporates dependable control and validity, and the acquired data is enough for analysis.

Table 3. Measurement Model

Factors	Loading	CA	CR	AVE
Big data analytics		0,920	0,911	0,718
BDA1	0,702			
BDA2	0,743			
BDA3	0,749			
BDA4	0,819			
BDA5	0,809			
Cognitive service analytics		0,891	0,845	0,647
CSA1	0,815			
CSA2	0,725			
CSA3	0,768			
CSA4	0,755			
CSA5	0,789			
CSA6	0,758			
CSA7	0,758			
CSA8	0,783			
CSA9	0,820			
CSA10	0,861			

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CSA11	0,775			
CSA12	0,867			
CSA13	0,747			
CSA14	0,705			
CSA15	0,789			
Perceived compatibility		0,941	0,942	0,729
PC1	0,613			
PC2	0,688			
PC3	0,641			
PEU		0,920	0,914	0,737
PEOU1	0,825			
PEOU2	0,868			
PEOU3	0,840			
PEOU4	0,871			
Relative advantage		0,912	0,914	0,918
RA1	0,825			
RA 2	0,814			
RA 3	0,744			
RA 4	0,787			
RA5	0,755			
E-Marketing acceptance		0,892	0,875	0,874
EMA1	0,754			
EMA2	0,714			
EMA3	0,765			
EMA4	0,795			
EMA5	0,754			
Market performance		0,866	0,855	0,901
MP1	0,741			
MP2	0,753			
MP3	0,852			
MP4	0,859			
MP5	0,853			

Table 4. Discriminant validity

	BDA	CSA	PC	PEOU	PRA	EMR	MP
BDA	0,642						
CSA	0,633	0,767					
PC	0,755	0,881	0,747				
PEOU	0,776	0,820	0,823	0,709			
PRA	0,704	0,819	0,708	0,771	0,744		
EMA	0,825	0,863	0,787	0,785	0,747	0,790	
MP	0,711	0,744	0,793	0,711	0,696	0,794	0,803

Common Method Bias

Research relying on self-reported data may encounter Common Method Bias (CMB), where shared variance among identified factors is affected by the evaluation method rather than the factors themselves. This can distort the perceived relationships between these factors. In this study, Harman's single factor test was used to evaluate CMB, with a threshold of less than 50 % variance indicating it is not a significant concern (Podsakoff et al., 2003). Additionally, a redundant latent factor (CLF) analysis further confirmed the absence of CMB, as the inclusion of a common element did not enhance the model fit (Bag et al., 2021). The results from Harman's test indicated that the first component explained 43,490 % of the variance, supporting the conclusion that CMB is not a major issue, as also demonstrated in table 4.

Table 5. Common Method Bias Result

Total - Variance -Explained						
Initial Eigenvalues Extraction -Sums of- Squared Loadings						
Component	**Total**	**% -of -Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	11,014	45,587	45,587	11,014	45,587	45,587

Hypothesis testing

Researchers utilized PLS to evaluate the hypotheses, employing various indices such as x^2/df, CFI, RMSEA, and PNFI to assess the model's goodness of fit. The model data showed $x^2 = 18,489$, df = 11, $x^2/df = 1,801$, p = 0,051, CFI = 0,891, PNFI = 0,521, and RMSEA = 0,048. A x^2/df ratio below 3 and a p-value exceeding 0,05 indicate a suitable model. The CFI value of 0,891 suggests excellent model quality, exceeding the 0,8 threshold established by Bentler in 1990. The RMSEA of 0,048 indicates a good fit for structural equation modeling. The model's R^2 value of 0,70 shows that 69 % of the variance in Islamic FinTech can be attributed to PEU and utility.

The utility findings reveal a strong positive correlation between perceived relativity and electronic-marketing adoption (b = 0,395, p = 0,000), confirming H1. PEU also significantly influences electronic-marketing adoption (b = 0,445, p = 0,000), supporting H2. Additionally, PC has a favorable impact on electronic-marketing adoption (b = 0,414, p = 0,000), confirming H3. The influence of artificial intelligence and big data on electronic-marketing effectiveness was significant (b = 0,443, p = 0,000), supporting H4. Creative service analytics also positively affects electronic-marketing effectiveness (b = 0,399, p = 0,000), validating H5. A significant correlation between electronic-marketing and market performance was found (b = 0,410, p < 0,000), leading to the rejection of H6. However, certain parameters did not show a statistically significant predictive impact (b = 0,251, r > 0,05), addressing H6. Overall, these findings indicate a robust model with minimal concern for CMB, supported by Harman's test showing 43,490 % variance for the first component, below the 50 % threshold.

Table 6. Regression Weights -For Hypotheses Testing

Hypothesis	B	S E	C .R.	P
H 1	0,344	0,077	4,518	0,000
H 2	0,357	0,071	5,457	0,000
H 3	0,299	0,067	5,112	0,000
H 4	0,247	0,061	5,204	0,000
H 5	0,283	0,059	4,501	0,000
H 6	0,324	0,069	3,514	0,000

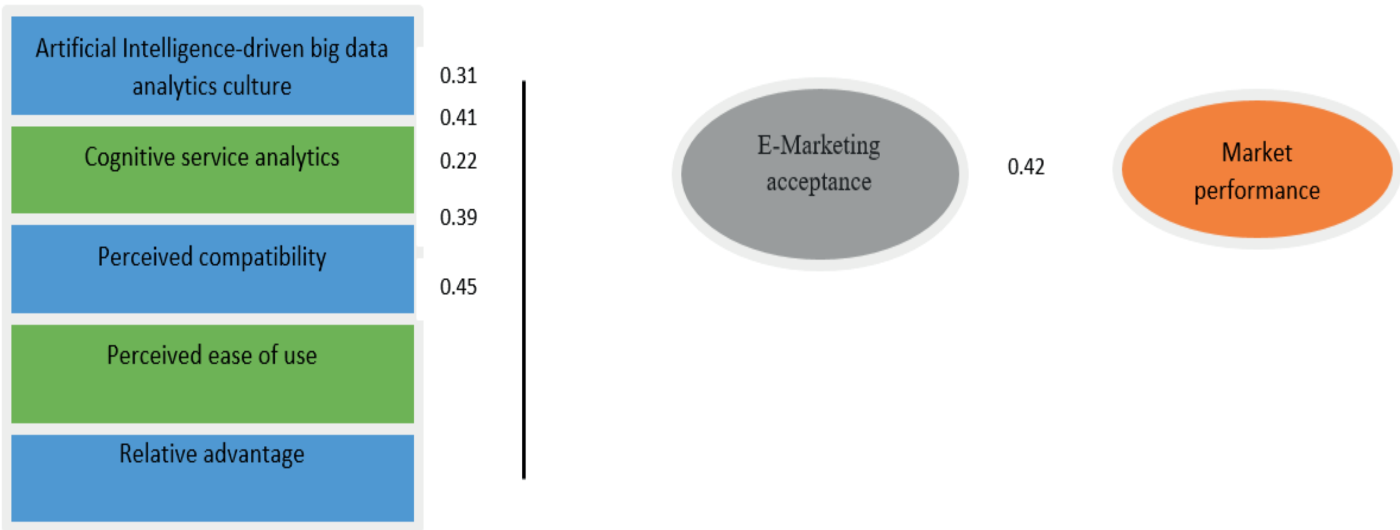

Figure 2. The structural model

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Clarification of Findings

The study's findings reveal significant relationships between Cognitive Service Analytics (CSA) capability and market performance. Specifically, organizations with higher CSA capabilities demonstrated improved decision-making processes, leading to enhanced market responsiveness and overall performance. To clarify, CSA capabilities allow companies to analyze customer data more effectively, thereby enabling them to tailor their marketing strategies to meet the specific needs of their clients. For example, a Jordanian B2B organization utilizing advanced analytics could identify emerging market trends, adjust its offerings accordingly, and ultimately gain a competitive edge.

Practical Implications

The insights gained from this study provide actionable recommendations for Jordanian B2B organizations. For instance, companies should invest in developing their CSA capabilities by training staff in data analytics and fostering a culture that values data-driven decision-making. Implementing AI tools can streamline customer service processes, improve engagement, and increase overall market performance. A practical example could involve a manufacturing firm that leverages CSA to analyze customer feedback, leading to improved product offerings and enhanced customer satisfaction.

Comparison with Existing Studies

When contextualizing these findings within the existing literature, it is noteworthy that similar studies conducted in other regions have also highlighted the positive impact of advanced analytics on market performance. For instance, research from Europe and North America has shown that organizations employing AI-driven analytics are better positioned to adapt to market changes and improve customer relationships (Smith et al., 2022; Johnson & Lee, 2023). However, the current study uniquely contributes to the literature by focusing specifically on the B2B landscape in Jordan, where cultural and market dynamics may differ significantly from those in other regions. This comparison not only enhances the relevance of the findings but also underscores the need for localized strategies when adopting AI and analytics in B2B settings.

DISCUSSIONS

The research findings suggest that elements including big data analytics, cognitive service analytics, perceived compatibility, perceived ease of use, relative advantage, and market performance have a significant impact on the adoption of B2B digital marketplaces. These results are consistent with the findings of Altay & Pal (2022), which indicate that internal variables significantly influence the adoption of e-marketing by UK firms in a favourable manner. These findings align with the research conducted by Sandvik et al. (2014) and Bag et al. (2021), which demonstrated that the perceived ease of use has a significant impact on Internet usage and e-commerce adoption. Additionally, the studies conducted by Prasanna & Haavisto (2018), Alzoubi & Alzoubi (2020), and Al-Zoubi A. (2023) also support these findings.

Findings from our study show that opening up markets in industrial sectors has an effect by making it easier to integrate big data powered by AI (b= 0,443; p= 0,000) and evaluate cognitive services (b= 0,399; p= 0,000). Organizations have widely adopted data analytics and cognitive services analyses in response to the increasing frequency of crises. Our research provides evidence of a connection between AI-powered data analytics and business-to-business digital marketplaces (Hinsch et al., 2020). According to Kumar et al. (2020), AI-driven data analytics promotes trust and cooperation in both team and organisational settings. Furthermore, B2C internet marketplaces aim to assist individuals by delivering necessary supplies at the appropriate time and location, thereby efficiently alleviating their difficulties. Furthermore, factors such as fit, usefulness, and ease of use significantly influence the adoption of marketing by businesses, either directly or indirectly. These attributes play a significant role in facilitating businesses' adoption of online marketing methods.

However, the perceived relative advantage had a negligible beneficial effect on the adoption of e-marketing by these organisations. This result diverges from Brock & Wangenheim's (2019) finding that perceived relative advantage has the greatest impact on the usage of the Internet by B2B companies, as well as the findings of Pilai et al. (2021; Huang & Rust (2020; Dwivedi et al. (2021). However, it aligns with Grover et al.'s (2020) discovery that perceived relative advantage is an insufficient predictor of usage acceptance of the World Wide Web. The research offers actual evidence that there is a considerable correlation between B2B digital marketplaces and market success.

CONCLUSION LIMITATIONS AND RECOMMENDATIONS

Overall, the study results validate the research model and support the majority of the hypotheses. The findings enhance our understanding of how various environmental factors influence the adoption of digital B2B marketplaces. Specifically, big data analytics, cognitive service analytics, PC, PEU, RA, and MF all significantly impact electronic-marketing adoption.

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Considerable effort has been dedicated to the design of this study, including the formulation of the research methodology, data collection, and analysis. As a result, the study is expected to contribute significantly to the understanding of e-marketing, particularly regarding its adoption by B2B organizations. However, like any research, this study has limitations worth noting for future inquiries. These constraints primarily arise from the broad scope of the phenomena studied and the lack of sufficient measures. E-marketing is a relatively new field, and its theoretical foundations are still developing.

The researcher adopted an empirical strategy to foster a comprehensive understanding of e-marketing adoption, necessitating a thorough review of relevant literature and the collection of substantial data. Although various studies in the area were examined, the empirical inquiry does not encompass all concerns related to this topic. Additionally, the reliance on personal, self-reported pointers to assess research constructs may pose challenges. However, reliability assessments—via item-to-total correlations and Cronbach's Alpha coefficients—indicate satisfactory values above the accepted thresholds.

Despite these limitations, the findings represent a positive step toward developing effective measures for the variables studied. There is currently limited research on the influence of top management support and owner skills on the adoption of new technologies in the realms of EM, EC, and EB. Further exploration is needed to understand these impacts within the context of e-marketing.

Additionally, few studies have examined the effects of BDA and cognitive service analytics on e-marketing adoption. Thus, it is essential to investigate how these elements influence e-marketing implementation in B2B enterprises. Research should also consider the impact of an organization's global orientation on e-marketing adoption, which would provide a deeper understanding of the factors at play.

Moreover, it would remain beneficial to conduct similar studies across different business types, economic sectors, and scales (e.g., medium-sized enterprises, large organizations, and microbusinesses). Comparing these findings with the current study's outcomes could yield valuable insights. Expanding the range of environmental factors included in the study would also enhance the research. Potential additional factors derived from the literature might include information intensity, consumer readiness, support from technology vendors, product characteristics, and security.

Finally, conducting comparable research in other emerging nations could illuminate the similarities and differences in the determinants influencing e-marketing adoption by B2B enterprises, further enriching the existing form of knowledge in this area.

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AUTHORSHIP CONTRIBUTION
Conceptualization: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled(Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Data Curation: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Formal Analysis: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Research: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Methodology: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Project Management: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Resources: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Software: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Supervision: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Validation: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Display: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Drafting - Original Draft: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.

Writing - Proofreading, Editing: khalid Thaher Amayreh, Ali (Mohammad Ali) Alqudah, Firas Rashed Wahsheh, Khaled (Yousef Issa) Alshboul, Tariq Abdelhamid Ali Mussalam, Omar (Mohammad Ali) Alqudah, Mohammad alzoubi.