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Leveraging Artificial Intelligence and Big Data to Enhance Efficiency and Customer Care: An Empirical Study

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الاستفادة من الذكاء الاصطناعي والبيانات الضخمة لتعزيز الكفاءة ورعاية العملاء : دراسة ميدانية

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ABSTRACT:
This research aims to explore the applications of Artificial Intelligence (AI) and big data in the service industry, assess their current usage, and examine prospects for further integration to enhance operational efficiency. Recent advancements in big data and AI have the potential to revolutionize customer service and experience across various industries, despite their current untapped potential in the service sector. A sample of 350 professionals from consulting, healthcare, and finance industries provides valuable insights into these technologies' applications, challenges, and impacts on customer satisfaction. The findings indicate that adopting AI and big data analytics significantly enhances customer care by improving service personalization and issue resolution speed, key drivers of customer satisfaction. Additionally, these technologies boost operational efficiency by automating routine tasks and optimizing processes. The research underscores the necessity of integrating AI and big data for operational advancements and elevating customer satisfaction. The study also highlights practical implications for harnessing these technologies more effectively and identifies areas for future research on related themes.

Keywords: Customer Service, Customer Experience, Operational Efficiency, Customer Satisfaction, Marketing.

الملخص:
تهدف هذه الدراسة إلى استكشاف تطبيقات الذكاء الاصطناعي والبيانات الضخمة في صناعة الخدمات وتقييم استخدامها الحالي، وكذلك النظر في المزيد من آفاق التكامل بينهم لتعزيز الكفاءة التشغيلية. إن التقدم الأخير في البيانات الضخمة والذكاء الاصطناعي لديه القدرة على إحداث ثورة في خدمة العملاء وتجربتهم عبر مختلف الصناعات، على الرغم من إمكاناتها غير المستغلة حالياً في قطاع الخدمات. عينة البحث تتكون من ٣٥٠ متخصصًا من قطاعات الاستشارات والرعاية الصحية والتمويل وتمثل رأيهم حول تطبيق وتحديات وتأثيرات هذه التقنيات على رضا العملاء. تشير النتائج إلى أن اعتماد الذكاء الاصطناعي وتحليلات البيانات الضخمة يعزز بشكل كبير رعاية العملاء من خلال تحسين تخصيص الخدمة وسرعة حل المشكلات، وهي المحركات الرئيسية لرضا العملاء. بالإضافة إلى ذلك، تعمل هذه التقنيات على تعزيز الكفاءة التشغيلية من خلال أتمتة المهام الروتينية وتحسين العمليات. يؤكد البحث على ضرورة دمج الذكاء الاصطناعي والبيانات الضخمة للتقدم التشغيلي ورفع مستوى رضا العملاء. وكذلك يسلط الضوء أيضًا على الآثار العملية لتسخير هذه التقنيات بشكل أكثر فعالية وتحدد مجالات البحث المستقبلية حول المواضيع ذات الصلة.

الكلمات المفتاحية: خدمة العملاء، تجربة العملاء، الكفاءة التشغيلية، رضا العملاء، التسويق.

1 Introduction

In an era when technology continually reshapes business landscapes, the service sector faces the imperative need for transformation to meet evolving customer demands and competitive pressures. Including diverse industries such as finance, healthcare, and retail, this sector contributes significantly to global economic activity. Most service providers operate with direct customer contact and contribute significantly to business development. Despite this, maintaining a high standard of efficiency and providing outstanding customer service, which are the primary objectives of every service provider, remains the top priority.

Recent advancements in AI and big data have emerged as game-changers for various industries, promising to revolutionize service delivery and experience. The potential of AI and big data in enhancing service sector performance is immense but still underexplored. While AI offers the benefits of advanced data processing, learning algorithms, and automation, big data allows companies to handle large, complex datasets and provides actionable insights. When combined, they provide a powerful toolkit for meeting the core challenges of the service sector (Hayajneh & Yousra, 2023).

Literature suggests that these technologies are being adopted incrementally in service-oriented businesses, with positive outcomes for customer engagement, operational efficiency, and decision-making processes. Studies have shown improved Customer Satisfaction (CS) through AI-enabled personalized services and enhanced operational efficiency through predictive analytics and automation (Sheikh et al., 2023). Though these developments are promising, a gap exists in the comprehensive understanding and application of these technologies across the service industry.

This study aims to delve into the nuances of leveraging AI and big data in the service sector, identifying the current scope of their application, and exploring the potential for further integration. Through operational improvement, it seeks to identify how these technologies can be harnessed more effectively to enhance efficiency and CS. It also examines the ethical considerations and challenges involved and identifies gaps in current applications of AI and big data by examining the existing literature and case studies. The objective of the study is to contribute to the body of knowledge in this field by making strategic recommendations for their optimal use in the service sector.

Technology and business analytics have been fundamentally reshaped by the interaction between big data and AI. The following review summarizes their evolution from the early days of operations research in the mid-twentieth century to the present day of cutting-edge AI applications in a wide range of fields (Miller, 2018). In addition to providing a comprehensive overview of these technologies' historical development, current importance, and challenges, it discusses their transformational potential. By examining the continuous adaptation and potential of big data and AI to drive future innovation and improve the operational performance of organizations, we intend to gain a better understanding of the continuous adaptation and potential of these technologies.

1.1 Research Questions

The main research questions for this study are:

1. To what extent does the adoption of Artificial Intelligence (AI)/Big data analysis (BDA) technologies affect customer care services?

2. To what extent does the adoption of AI/BDA technologies enhance efficiency and performance?

3. Does customer satisfaction improve with the adoption of AI/BDA technologies?

1.2. Research Objectives

This research aimed to study the relationship between the use of AI techniques and big data and their impact on the level of efficiency and Customer Care (CC) in companies and to reach a set of results and recommendations through the field study conducted by the researcher to achieve the optimal use of AI techniques and big data to increase the level of efficiency and customer care.

Hence, the research has been formulated with the following primary objectives:

1. Assess the current use of AI and big data in the service sector.
2. Identify challenges and barriers to implementation and develop strategies to overcome them.

2 Literature review

2.1 Background of Big Data and AI

Operations research and Management Science (OR/MS) played a key role in the development of business analytics during the 1940s when the world was at war and scarce resources needed to be allocated efficiently. This period was marked by the development of methodologies that laid the foundation for what would become business analytics (Delen & Ram, 2018), primarily focused on optimization and simulation. Data-driven decision-making was initiated through these early methods, which were instrumental in solving complex logistical and strategic problems (Delen & Ram, 2018). As the digital era started in the 1970s and 1980s, organizations saw the advent of Enterprise Resource Planning (ERP) systems and Relational Database Management Systems (RDBMS). Data was integrated and efficiently managed across various organization functions because of these technologies, marking a significant shift from manual data collection and expert-driven models. As a result of the introduction of RDBMS, in particular, a more structured approach to managing and retrieving data was provided. This became essential in the analysis of business data in the future (Delen & Ram, 2018).

The 1990s and early 2000s saw a significant emergence of business intelligence systems designed to support decision-making processes by leveraging data warehousing technologies. Executives were provided with insights into key performance indicators through these systems, equipped with dashboards and scorecards, allowing for more informed decision-making. The evolution of business intelligence marked a shift from traditional data processing to advanced analytical practices, paving the way for the era of analytics-driven business models (Delen & Ram, 2018).

A pivotal moment occurred in the technological landscape in the late 2000s when the exponential growth of data ushered in the age of big data. During this era, the existing analytics infrastructure was challenged by the large volume, velocity, and variety of data, requiring significant advancements in analytical techniques. Among these advancements, machine learning and network science emerged as critical tools to process and draw insights from large datasets. Consequently, business analytics expanded to include predictive and prescriptive analytics. This evolution reflected a continuous adaptation to the increasing complexity of business environments and technological advancements, providing not only insight into past and present performance but also foresight into future trends and decision-making strategies (Delen & Ram, 2018).

In anticipation of future innovation, the field leveraged emerging technologies to uncover deeper insights and make strategic business decisions, laying the groundwork for the ascent of AI. AI has elicited a range of viewpoints from prominent figures in the technological and scientific communities, suggesting that it can serve as both a force that augments human intellect and a source of apprehension regarding the implications of its adoption. International Business Machines Corporation (IBM) Chief Executive Officer (CEO) Ginni Rometty positions AI as a natural progression from using big data for analytics to employing AI for deeper, more complex problem-solving (Bean, 2018), enhancing human potential. Stephen Hawking and Bill Gates, on the other hand, have expressed concerns about the potential threats of AI, with Hawking suggesting that its full development could signal the extinction of humanity (Duan et al., 2019).

AI is typically defined as a machine's ability to learn, adapt, and perform tasks similarly to human intelligence. The introduction of big data and advances in computational power have enhanced AI, enabling its integration into leading corporations and used for predictive analytics and decision-making (Miller, 2018; Daugherty & Wilson, 2018). Based on a Gartner survey conducted in 2018, AI is regarded as one of the most important strategic technologies, with predictions extending into 2025 regarding its ability to enhance decision-making, innovate business models, and transform customer experiences. The novel and intricate nature of AI technologies presents challenges, even though early AI efforts provide important lessons for future implementation (Duan et al., 2019).

As a result of the development of AI, various techniques have been employed, notably rule-based inference. Initially, rules were derived from human experts, but recent methods have shifted towards automated techniques, such as classification trees, regression trees, and association rule mining. As a result of its continuous adaptations and integrations into a wide range of applications, AI is becoming increasingly significant in shaping the future of technology and human interaction (Duan et al., 2019). The field of AI lacks a universally accepted definition, reflecting the complexity of the field and the wide range of concepts that it encompasses. The definition of AI has evolved significantly throughout history, starting with early attempts equating it with algorithms and ending with strict interpretations framing it as the imitation of human intelligence. Some have adopted a broader approach, defining AI as a technology that enables machines to mimic human skills, but without specificity. The definitions provided by others include the capability of AI to function with foresight, perception, pursuing objectives, initiating actions, and learning from feedback, all of which are aimed at a task-based perspective. The challenge in defining AI mirrors the broader challenge of understanding human intelligence, a subject that has been studied extensively but is still underexplored. A further complicating factor is the intertwining evolution of human and AI research, which is exemplified by advances in the ability of AI to play chess, illustrating Moravec's paradox of the divergence between computational and human cognitive ease. An open definition advocates AI as a broad, evolving field aimed at understanding and simulating human intellectual capabilities to accommodate the diversity of current applications and anticipate future developments. It highlights the dynamic nature of AI, driven by technological advancements and increasing insights into human cognition while emphasizing the ambition of AI research and the complexity of attaining Artificial General Intelligence (AGI) (Sheikh et al., 2023).

2.2 The Multifaceted Roles of AI

AI can be conceptualized as a technology that simulates Human Intelligence (HI) by automating tasks across four distinct levels of intelligence (Huang and Rust, 2018): mechanical, analytical, intuitive, and empathic (Huang, 2018). Mechanical intelligence is the ability of AI to perform routine, repetitive tasks with a minimum of adaptation, such as those performed by service robots. The use of analytical intelligence enables AI to process information, solve problems, and learn from data, making it suitable for a wide range of tasks that require logical decisions based on structured data, such as those requiring logical decision-making. Intuitive intelligence is an advanced form of AI that uses deep learning techniques to understand and adapt to complex situations, thus handling tasks involving creative problem-solving and decision-making in less structured environments. Empathetic intelligence, the highest form of intelligence, is the ability of AI to recognize, understand, and respond to human emotions, so it is ideally suited to tasks that require a high degree of human interaction (Huang, 2018). As Huang and Rust (2021) explain, AI development occurs sequentially, beginning with mechanical and analytical tasks and progressing gradually to intuitive and empathetic ones. With increasing sophistication, AI is more capable of mimicking and eventually surpassing human capabilities in all areas, including the service sector (Huang and Rust, 2021).

AI can be implemented in a variety of ways, including through AI devices. Over the last few years, AI devices have been significantly accelerated and implemented in various industries, marking a transformation in the way tasks previously performed by humans are now performed by AI technologies (Duan et al., 2019; Dwivedi et al., 2021). The trend is evident across a wide range of applications, such as robotic assistants in hotels and AI-based customer service solutions (Tavakoli & Mura, 2018). Based on the superior data processing and personalization capabilities of AI, its integration into service delivery processes reflects a broader trend toward greater operational efficiency and improved service quality (West et al., 2018). Despite this, the adoption of AI in the context of services also raises complex issues regarding customer acceptance and the integration of technology (Huang & Rust, 2018; West et al., 2018). Models of technology acceptance include the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which is a framework developed to explain and predict how people accept and use technology within organizations. It synthesizes elements from various existing theories into four core determinants of usage intentions and behavior: performance expectancy (the belief that using the technology will provide benefits in job performance), effort expectancy (the ease of use of the technology), social influence (the degree to which an individual perceives that important others believe they should use the technology), and facilitating conditions (the degree to which an individual believes that an organizational and technical infrastructure supports the use of the system). These factors are influenced by individual characteristics, such as age, gender, experience, and voluntariness of use, making UTAUT a comprehensive model that accounts for significant variance in technology acceptance and UB (Venkatesh & Xu, 2012). These models, however, may not fully capture the unique aspects of AI technologies, given their focus on non-intelligent systems (Sundar et al., 2016; Fritz et al., 2016). Considering the unique nature of AI devices, such as their ability to mimic Hello and interaction, new frameworks are needed to better understand customer acceptance (Gursoy et al., 2019).

A key component of implementing AI in employee management, as outlined by Hughes et al. (2019), is to use the capabilities of AI to improve decision-making, employee engagement, and workplace fairness. To facilitate a more engaged workforce, AI systems analyze vast amounts of data to inform management decisions and personalize employee experiences. A critical component of the successful deployment of AI in this context is making sure that the systems are perceived as fair and trustworthy, which involves transparent decision-making processes and protecting employee privacy (Hughes et al., 2019). The technology must also be easy to use and perceived as useful by employees so that it is accepted by them. In addition, organizations must continuously monitor the impact of AI on employee satisfaction and retention, adjusting strategies as necessary to ensure positive outcomes for both the organization and its employees (Hughes et al., 2019).

2.3 The Impact of Big Data on Business

The role of big data in business analytics is marked by its evolution from traditional analytics practices to modern, advanced approaches. Analytics have transitioned from descriptive methods, which focus on interpreting past and present data, to predictive and prescriptive analytics, which attempt to forecast future trends and determine optimal decision-making paths (Sharda, 2017). This shift underscores the complexity and dynamism of today's data-driven business environment, where decision-making is enhanced by insights drawn from vast volumes of diverse data (big data) (Ram et al., 2015).

A big data challenge is generally defined by three characteristics: volume, variety, and velocity. Businesses are now facing the challenge of managing and making sense of large amounts of unstructured data that are generated at high speeds from a multitude of different sources at the same time. To achieve this, innovative data management strategies must be developed that go beyond conventional databases and analytical methods, necessitating the development of algorithms, software, and hardware that can efficiently handle a situation of such complexity (Delen & Ram, 2018).

Technological advances are crucial to navigate the challenges posed by big data. To analyze and process large datasets, mathematical, statistical, machine learning, and network science methodologies have been developed. The use of these technologies facilitates the transformation of raw data into actionable insights, which facilitates the process of making decisions in a timely and informed manner. Moreover, to effectively leverage big data, businesses must be able to extract meaningful, actionable information from big data that will help them gain a competitive edge in the marketplace. This includes the integrity and accuracy of data and the sophistication of analytical tools (Helo & Hao, 2021).

The use of data science has become imperative rather than merely a tool for any organization that wishes to remain competitive in the market today. To maximize the value of their data assets, companies must invest in the right people, tools such as AI, and strategies (Siddiqa et al., 2017). This applies to industries in which data is a core business asset, such as banking, healthcare, e-commerce, and the service sector (Emani et al., 2015; Gandomi & Haider, 2015). Companies in these fields require data science to generate valuable insights and increase operational efficiency. A company that does not have a comprehensive data science strategy to leverage its data more effectively is at risk of losing out to its competition.

2.4 Big Data Analysis

Further, Big Data Analysis (BDA) refers to analyzing and evaluating large data sets to highlight the firm's or organization's performance (Nicola et al., 2014). BDA refers to the application of statistical processing and analytics techniques to big data for advancing business and is widely used to gain competitive advantage, enhance firm performance, and foster sustainability (Gopalkrishnan et al., 2012). As a result of its capability to predict customer preferences, streamline decision-making, and innovate marketing processes, BDA plays an integral role in driving organizational growth in a globalized economy. Despite its recognized benefits, empirical studies on the direct impact of BDA on financial performance are limited (Thompson, 2019). The value of BDA is manifested in various ways, including operational efficiency, customer segmentation, decision automation, and the development of new business models, leading to improved financial indicators such as revenue, profits, and market share. In addition, the contribution of BDA to sustainability through the facilitation of Product-Service Systems (PSS) and Circular Economy (CE) initiatives illustrates its broader impact beyond financial performance (Martin et al., 2016). The integration of BDAs with the Internet of Things (IoT) and analytics is essential for sustainable decision-making and supply chain management, promoting a data-driven approach to environmental and social challenges. As the importance of BDA grows, future research must explore interdisciplinary strategies that maximize its financial and sustainable potential (Colicev, 2016).

2.5 AI and Big Data Implementation

In recent years, BDA and AI have become increasingly important in improving Operational Oerformance (OP) within organizations (Teece, 2012 & 2014). Their effectiveness is significantly influenced by the organization's strategic level of Entrepreneurial Orientation (EO) and the dynamism of the environment in which the organization works. When an organization is characterized by innovation, proactiveness, and risk-taking, it can fully exploit and explore the capabilities of BDA-AI, which increases its operational efficiency. Based on the assumption that firms possess dynamic capabilities, it argues that such capabilities are essential for them to adapt to and thrive in rapidly changing environments (Dalenogare et al. 2018; Aydiner et al. 2019; Dubey et al. 2020). In organizations, AI and big data interact with each other, resulting in the ability to process and analyze large datasets and identify patterns, trends, and insights that can assist in informed decision-making processes (Chen et al., 2015). As a result, this capability is essential for OP, as it allows firms to innovate, optimize processes, and respond more effectively to market conditions. Nevertheless, implementing BDA-AI technologies and realizing the benefits that can be derived from them requires the creation of a strategic alignment with the company's entrepreneurial capabilities and an understanding of the external conditions that could impact its effectiveness (Dubey et al. 2019; Daqar & Smoudy, 2019).

Essentially, this implies that managers should not only focus on the investment of BDA-AI technologies, but also cultivate an EO within the organization. As part of this process, innovation must be encouraged, risks must be tolerated, and market engagement must be proactive. Moreover, managers need to be adept at scanning the external environment to adjust their strategies accordingly, ensuring that their EO and BDA-AI capabilities are aligned with the current level of environmental dynamism to optimize performance outcomes (Dubey et al., 2020). BDA and AI implementation in manufacturing organizations involves more than just the technology itself; it requires strategic alignment with the firm's EO and an adaptable approach to varying environmental conditions to succeed. By using this comprehensive approach, organizations can harness the full potential of BDA-AI to enhance OP (Teece, 2012; Chen et al., 2021).

According to Dubey et al. (2020), an established EO significantly facilitates the adoption of BDA-AI technologies, thereby improving operational efficiency. Based on this, entrepreneurial organizations are well suited to leveraging BDA-AI to achieve superior operational results. In addition, the impact of EO on the adoption of BDA-AI and OP is modulated by environmental dynamism (ED). The results indicate that dynamic environments enhance entrepreneurial efforts' impacts on technology adoption and operational efficiency.

2.6 Implementation in The Service Sector

As AI advances within service industries, the interaction between AI and big data emerges as a pivotal element, particularly during the phase of analytical intelligence. During this phase, AI systems become capable of learning from and adapting based on extensive data analysis, which allows them to automate tasks that had previously required human analytical abilities. Integrating AI into service tasks leverages its ability to process and learn from large amounts of data, resulting in personalized and efficient service delivery. For instance, AI-driven customer service chatbots can quickly and accurately answer customer inquiries and provide personalized recommendations based on past interactions. Hence, BDA enhances AI systems' ability to undertake tasks traditionally requiring human analytical expertise (Huang, 2018). The combination of AI and big data not only accelerates the automation of analytical tasks, but also induces a strategic shift towards developing higher forms of intelligence, such as intuitive and empathetic skills among human employees (Davenport, 2015). This strategic orientation underscores the necessity for human workers to adapt by developing skills that AI is slower to replicate, thus maintaining their relevance in the workforce. The theory underscores the instrumental role of big data in enabling the learning process of AI, significantly influencing the AI implementation framework across service sectors. This dynamic interaction between AI and big data not only revolutionizes service delivery by enhancing efficiency and personalization but also reshapes the employment landscape by shifting skillset demands from analytical to more sophisticated, human-centric capabilities (Rust et al., 2014; Demirel, 2022).

Within service industries, organizations must invest in technologies and platforms that facilitate the effective harnessing of big data, allowing AI systems to learn, adapt, and evolve based on service demands. They must also reevaluate workforce development strategies, emphasizing the cultivation of intuitive and empathetic skills that complement the automated capabilities of AI. Businesses can achieve a balanced and innovative service delivery model that caters to their clients' complex and evolving needs by nurturing a symbiotic relationship between the analytical ability of AI and human employees' unique cognitive abilities (Huang, 2018).

As AI and big data transform public health and medical diagnostics, they provide unprecedented opportunities for enhancing disease detection, precision medicine, and epidemiological research. Using a combination of massive computational resources, cyber-physical systems, and advanced analytics, early epidemic detection can be achieved, genetic profiles can be used to target treatments, and deep learning algorithms can improve diagnostic accuracy (Benke, 2017; Beam, 2016). Despite these advances, ethical and privacy concerns and the possibility of marginalizing human diagnostic specialists are raised. To ensure responsible use of AI and big data in healthcare, robust regulatory frameworks and ethical standards are emphasized. Medical specialists may become integrators of AI-driven diagnostic information within clinical contexts in the future, highlighting the need for interdisciplinary dialogue and policy development to address the challenges associated with these technologies and harness their potential in public health and healthcare services (Benke & Benke, 2018).

2.7 *AI Applications in The Kingdom of Saudi Arabia*

As part of Saudi Arabia's ambitious Vision 2030 strategy, which aims to diversify the country's economy and reduce its dependence on oil, the implementation of big data and AI forms a cornerstone. Saudi government officials have recognized the transformative potential of these technologies across a variety of sectors, including health care, education, energy, and government services (Memish et al., 2021).

To promote a data-driven and AI-enabled future, the Kingdom has launched several initiatives. Among the most significant steps was the establishment of the Saudi Data and Artificial Intelligence Authority (SDAIA), which is responsible for driving the national data and AI agenda to transform Saudi Arabia into one of the world's leading data-driven economies. The SDAIA's initiatives, such as the National Data Management Office and the National Information Center, play a vital role in standardizing data and AI practices across government agencies and promoting innovation (Memish, 2021).

As a result of collaborations between the Ministry of Health and technology companies, AI and big data are transforming patient outcomes through diagnostics, disease prediction, and efficient resource management. As a result of this partnership, telemedicine services have been significantly enhanced, leading to improved accessibility and quality of health care (Memish, 2021). Additionally, companies such as Saudi Aramco use these technologies for operational efficiency, predictive maintenance, and sustainability, thereby optimizing oil extraction and minimizing environmental impact (Memish, 2021; Buhalis & Sinarta, 2019). The Kingdom's public health services also use AI to improve citizen engagement and streamline operations, as demonstrated by digital platforms, such as Absher for government services and Tawakkalna for COVID-19 management, demonstrating how AI and big data can contribute to better service delivery and health administration (Al Anezi, 2021; Alotaibi & Alshehri, 2023).

2.8 SDAIA AI Ethics Principles

The AI ethics principles established by SDAIA are intended for application across various sectors in the Kingdom of Saudi Arabia. This includes individuals from public, private, and non-profit entities, researchers, employees in both sectors and consumers. Notably, these principles are meant to be universally applicable to all AI tools, not limited to generative AI (SDAIA, 2023 & SDAIA, 2024a).

The seven core principles are:

1. Fairness: Eliminating bias and discrimination in AI systems.
2. Privacy and security: Protecting individual data privacy and ensuring robust security measures.
3. Humanity: Aligning AI systems with human rights and cultural values.
4. Social and environmental benefits: Promoting positive societal and environmental impacts.
5. Reliability and safety: Ensuring AI systems function as intended without posing risks.
6. Transparency and explainability: Making AI decisions clear and justifiable to stakeholders.
7. Accountability and responsibility: Establishing clear roles and responsibilities for AI system operators.

These principles aim to guide the ethical development and use of AI technologies, fostering innovation while safeguarding fundamental rights and values (SDAIA, 2024b).

2.9 Conceptual Framework and Hypotheses

Developed originally by Venkatesh et al. in 2003, the Unified Theory of Acceptance and Use of Technology (UTAUT) offers a comprehensive model for understanding the adoption and use of new technologies within organizations to boost performance. According to UTAUT, performance expectancy, effort expectancy, social influence, and facilitating conditions are the primary determinants of technology acceptance and usage. Performance expectancy is the degree to which an individual believes that using technology will help them achieve gains in job performance. This is somewhat analogous to the perceived usefulness of the Technology Acceptance Model (TAM) but is broader in its consideration of performance impacts. Effort expectancy is the ease of use associated with the technology, similar to the perceived ease of use of TAM, but it also encompasses a wider range of usability aspects. The UTAUT framework suggests that for the implementation of AI and BDA technologies, the decision-making process is significantly influenced not only by the anticipated benefits in operational efficiency and CS (akin to performance expectancy) but also by the influence of others (social influence) and the availability of necessary resources and support (facilitating conditions). This holistic approach provides a more detailed understanding of the factors influencing the adoption of AI and BDA technologies in organizational settings (Venkatesh & Xu, 2012). The conceptual framework integrates the core constructs of the UTAUT to examine the adoption and use of AI and BDA technologies within the service industry. It aims to understand the determinants of technology acceptance and subsequent UB, which are hypothesized to improve operational efficiency and CS, see Figure 1.

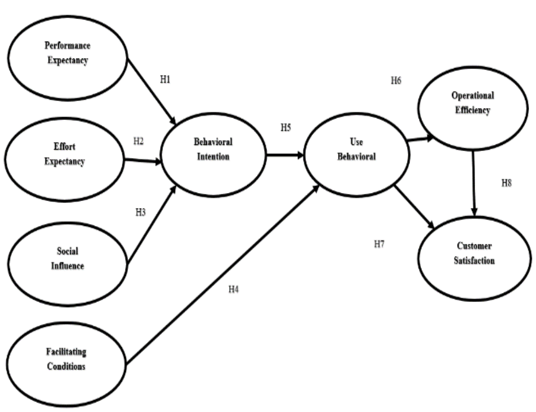

Figure 1: Research model and hypotheses

H1: Performance expectancy (PE) positively affects behavioral intention (BI) to adopt AI /BDA technologies.

H2: Effort expectancy (EE) positively affects behavioral intention (BI) to adopt AI/BDA technologies.

H3: Social influence (SI) positively affects behavioral intention (BI) to use AI/BDA technologies.

H4: Facilitating conditions (FC) positively affect use behavior (UB) of AI/BDA technologies.

H5: Behavioral intention (BI) positively affects use behavior (UB) of AI/BDA technologies.

H6: Use behavior (UB) of AI and BDA technologies positively affect operational efficiency (OE).

H7: Use behavior (UB) of AI/BDA technologies positively affects customer satisfaction (CS).

H8: Operational efficiency (OE) positively affects customer satisfaction (CS).

3 Methodology

The research design aims to investigate the use and impact of AI and big data technologies within the service sector through a quantitative approach. The primary objective is to quantify the adoption rates and assess the impact of these technologies on efficiency, productivity, and customer experiences. The methodology involves a non-probability sampling technique to ensure representation from various service industries, including banking, healthcare, retail, and consultancy (Creswell & Creswell, 2017). Hence, a positive approach that uses structured surveys to gather information is adopted to fulfill the study objectives.

3.1 Sample Size

The target population includes professionals in a variety of service industries, including the financial, healthcare, and consulting sectors. To ensure that the service industry is represented across a wide range of sectors, convenience sampling was adopted as a sampling technique, and 350 respondents participated in the study.

3.2 *Questionnaire Development*

The questionnaire was chosen as the primary data collection tool due to its simplicity and brief time requirement, typically taking between five to seven minutes to complete. Scales were adopted from previous studies, as shown in Table 1.

Table 1: Scales Adopted

Variable	Items	Cronbach's alpha	Sources
Effort Expectancy	4	0.900	Alshehri et al. (2020)
Performance Expectancy	4	0.840	Alshehri et al. (2020)
Social Influence	4	0.770	Alshehri et al. (2020)
Facilities Conditions	5	0.790	Alshehri et al. (2020)
Customer Satisfaction	4	0.930	Agag et al. (2024)
Behavioral Intention	4	0.920	Alshehri et al. (2020)
Use Behavior	3	0.922	Zhan, et al. (2021)
Operational Efficiency	10	0.896	Hosain, et al. (2020)

3.3 Data Collection

Responses to an online survey were gathered from professionals in various service sectors, including banking, healthcare, retail, and consultancy. Participants were invited via email, asking them to complete the questionnaire developed on Google Forms. The survey link was distributed through referral groups and social networking platforms such as WhatsApp and email.

3.4 Data Analysis

To achieve the study objectives, the collected data was systematically arranged, tabulated, and analyzed using SPSS version 22. Descriptive statistics were used to summarize the data, including measures of central tendency, variability, and test hypotheses.

3.5 Reliability and Validity

Cronbach's alpha coefficient was used to measure the reliability of the study, as shown in Table 2.

Table 2: Cronbach's alpha reliability test

Main Axis	Abbreviation	Items	Reliability
Effort Expectancy	EE	4	0.803
Performance Expectancy	PE	4	0.827
Social Influence	SI	4	0.866
Facilities Conditions	FC	5	0.897
Customer Satisfaction	CS	4	0.793
Behavioral Intention	BI	4	0.845
Use Behavior	UB	3	0.846
Operational Efficiency	OE	10	0.929

It is clear from Table 2 that Cronbach's alpha coefficient for scales adopted was not less than 0.7, which is an acceptable level (Peterson, 1994).

3.6 Ethical Considerations

The study was guided by ethical considerations to ensure that the scientific investigations were done responsibly and ethically to safeguard the well-being and rights of participants. One of the ethical considerations was voluntary participation. Participants chose to participate willingly without pressure or coercion. Another ethical consideration was informed consent, which was obtained from participants before data collection. The procedures, purpose, benefits, and risks of the study were explained to participants before they were asked to make an informed decision. Anonymity was also maintained to protect the participants' privacy and keep their identities confidential. Ethical approval was sought from the institutional review board before commencing the study.

4 Results

4.1 Demographic Characteristics of Respondents

The demographic characteristics of the respondents reveal a balanced representation of gender, with 54.3% male and 45.7% female. The age distribution shows that the majority of respondents fall within the 25-34 age group (33.1%), followed by those aged 35-44 (28.0%), 45-55 (18.3%), 55 and above (12.6%), and 18-24 (8.0%). Educational attainment among the respondents is high, with a significant proportion holding a master's degree (48.9%), followed by bachelor's degree holders (26.9%), those with a high diploma (18.3%), high school education (3.1%), and associate degree (1.7%).

In terms of experience, a substantial portion of respondents have over ten years of experience (40.6%), followed by those with seven to ten years (33.4%), four to six years (10.0%), one to three years (9.7%), and less than one year (6.3%). The distribution of sectors shows a notable representation from the private sector (31.4%), semi-government (29.7%), government (23.1%), self-employed individuals (13.4%), and other sectors (2.3%). The service sectors represented include healthcare (24.0%), consultation (25.7%), financial (25.4%), hospitality (18.9%), and other services (6.0%).

4.2 Coefficient Analysis

The coefficient analysis demonstrated that AI adoption has a significant positive impact on efficiency and customer service, with a t-value of 11.112 and a significance level of 0.000. This finding implies that as AI adoption increases, the improvement in efficiency and quality of customer service is notable.

4.3 One-sample t-test Results

The one-sample t-test for the first axis of the questionnaire showed that all statements had a significance level of 0.000, indicating that the responses were statistically significant. The lowest t-value recorded was 59.4, further underscoring the robustness of the responses.

4.4 Hypothesis Testing

Table 3: Summary of hypotheses

Hypothesis	path	P. value	Comment
H1	Performance Expectancy → Behavioral Intention	0.000	Accepted
H2	Effort Expectancy → Behavioral Intention	0.000	Accepted
H3	Social Influence → Behavioral Intention	0.000	Accepted
H4	Facilitating Conditions → Use Behavioral	0.000	Accepted
H5	Behavioral Intention → Use Behavioral	0.000	Accepted
H6	Use Behavioral → Operational Efficiency	0.000	Accepted
H7	Use Behavioral → Customer Satisfaction	0.000	Accepted
H8	Operational Efficiency → Customer Satisfaction	0.000	Accepted

In Table 3, all the statements of the axis related to the independent variable and the statements of the axis related to the dependent variable were tested using a t-test. The calculated t-values for each of them are greater than the tabulated t-value, and the significance level for all the statements was less than 0.05. This means the relationship between AI technologies and big data has a positive strong correlation (Pallant, 2020; Hair et al., 2021), as follows:

The value of Sig. (2-tailed) and the value of P is <= 0.05. This means that the researcher accepts the first hypothesis, which postulates a positive relationship between PE and BI to the adoption of AI technologies in the service sector.

The value of Sig. (2-tailed) and the value of P is <= 0.05. This means that the researcher accepts the second hypothesis, which postulates a positive relationship between EE and BI to the adoption of big data technologies in the service sector.

The value of Sig. (2-tailed) and the value of P is <= 0.05. This means that the researcher accepts the third hypothesis, which postulates a positive relationship between SI and BI to the adoption of AI technologies in the service sector.

The value of Sig. (2-tailed) and the value of P is <= 0.05. This means that the researcher accepts the fourth hypothesis, which postulates a positive relationship between FC and UB to the adoption of big data technologies in the service sector.

The value of Sig. (2-tailed) and the value of P is <= 0.05. This means that the researcher accepts the fifth hypothesis, which postulates a positive relationship between BI and UB to the adoption of big data technologies in the service sector.

The value of Sig. (2-tailed) and the value of P is <= 0.05. This means that the researcher accepts the sixth hypothesis, which postulates a positive relationship between UB and OE.

The value of Sig. (2-tailed) and the value of P is <= 0.05. This means that the researcher accepts the seventh hypothesis, which postulates a positive relationship between UB and CS.

The value of Sig. (2-tailed) and the value of P is <= 0.05. This means that the researcher accepts the eighth hypothesis, which postulates a positive relationship between UB and CS.

5. Discussion

The impact of the use of AI and big data technologies on enhancing efficiency and customer care in service companies in Saudi Arabia is significant, as shown by studies such as Delen and Ram (2018), Memish (2021), and Sheikh et al. (2023).

The correlation analysis of the relationship between the independent variable and the dependent variable makes clear that the value of the coefficient is between medium and high in most of the statements of the questionnaire axes, indicating the existence of a relationship between the two variables.

Further, the data reviewed for the ANOVA analysis evidence the relationship between AI technologies and big data in terms of efficiency and customer care. All the expressions on the axis of the independent variable and the expressions on the axis of the dependent variable had calculated f-values greater than the tabulated f-value, and the probability value of each expression was less than 0.05.

After applying this research, the researcher concluded that most service companies aim to develop and employ information technology, especially AI, and big data technologies to provide greater market opportunities to achieve higher levels of efficiency and to increase customer care.

This adds to the company’s capabilities that help them overcome many challenges facing various departments, divisions, and sectors, and thanks to the ability of AI techniques to make qualitative shifts in the way of dealing with administrative problems and completing all required tasks and routine work efficiently and effectively. The company's goals exceed human capabilities.

Thus, relying on AI technology gives corporate management greater administrative capabilities in dealing with problems, and also the possibility of storing large amounts of data, which the company can benefit from in dealing with customers, as these technologies can simply be used to store historical data for customer transactions.

All study variables related to AI and big data technologies demonstrate a Cronbach's alpha value above 0.70, signifying that each measure used in the study maintains internal consistency within Saudi Arabian service organizations.

- **To what extent does the adoption of AI/BDA technologies affect customer care services?**

The behavior of using AI/BDA technologies had a positive impact on CS, significantly enhancing the quality of service and the overall customer experience. In addition to the improvements noted in communication and after-sales support and the availability of detailed product information, this resulted in a better level of customer service (Benke & Benke, 2018).

- **To what extent does the adoption of AI/BDA technologies enhance efficiency and performance?**

PE and EE were found to positively affect BI toward adopting AI/BDA technologies. This suggests that beliefs in the potential to enhance work performance and the perceived ease of use of these technologies contribute to a stronger intention to adopt and use them, which in turn leads to increased actual usage (Delen & Ram, 2018; Duan et al., 2019; Grewal et al., 2017).

The actual use of AI/BDA technologies significantly improves OE and performance. This is observed through better resource management and optimized operational processes, indicating a direct correlation between technology use and enhanced operational outcomes (Aydiner et al., 2019; Memish, 2021).

- **Does CS improve with the adoption of AI/BDA technologies?**

The adoption of AI/BDA technologies directly enhances CS by improving service operations. Indirectly, improvements in OP fostered by these technologies also contribute to elevated levels of CS. Both pathways demonstrate the crucial role of AI/BDA in improving the quality of customer interactions and overall satisfaction (Benke & Benke, 2018; Memish, 2021).

- **SI and Facilitation Conditions**

SI from peers and superiors also positively affects the intention to use AI/BDA technologies. Additionally, the presence of necessary organizational and technical support (facilitation conditions) has been identified as a critical factor in increasing the actual usage of these technologies, underscoring the importance of supportive management practices in successful technology adoption (Sheikh et al., 2023; Huang & Rust, 2021).

- **BI and Operational Efficiency**

The study further validates that a strong intention to use AI/BDA technologies due to PE, EE, and SI translates into higher actual usage, which in turn positively impacts OE and CS (Hughes et al., 2019).

6 Conclusion

Optimal investment in AI and big data technologies in the services sector will not only provide companies with the opportunity to benefit from important technologies, but will also make them accessible to officials who use these technologies to give new dimensions to the future and increase levels of efficiency by providing more comprehensive data collection or predictions to automate tasks that are more complex than usual.

Considering the research findings, the following recommendations are made to service organizations in the Kingdom of Saudi Arabia to improve productivity and customer care:

- Enhance interest in efficiency processes based on the use of AI technology or big data by providing information in the appropriate form and manner in the company and providing appropriate alternatives for making various administrative decisions to enhance the level of efficiency, and also through planning to determine the appropriate goals and strategies for the company to make effective decisions, follow-up, and audit. Various activities increase the effectiveness and efficiency of operations.

- Enhance the BI dimension based on the use of effort prediction by providing appropriate information at the right time while maintaining the provision and securing of the required information and working to collect information to deepen the efficiency process.
- Strengthen the UB dimension based on the use of SI by overcoming the basic challenges that managers face to complete the process of addressing the problems that hinder increasing the level of efficiency and also overcoming uncertainty in the surrounding environment and the complexity or ambiguity of the surrounding environment. This is also evident by identifying all opportunities and risks coming from the surrounding environment.

- Enhance the OE dimension based on the use of FC through the speed of completion of administrative work in the company and the adequacy of the correct administrative processes within specific dimensions in the company. The prompt arrival of information to managers helps to speed up the completion of the work entrusted to them and maintains accurate information. Also, the information must be up-to-date, comprehensive, and of high quality, all of which are in the interest of speed of work and OE.

- To attain efficiency and speed in performance and deliver the best possible services, service companies need to dive more deeply and take digital transformation and information technology more seriously.

- Strengthen companies with the competencies and human cadres necessary to monitor the level of OP and evaluate it from time to time. This will strengthen the company's competitive position in the market, especially in light of successive rapid technological changes, which impose on companies' management the necessity of first knowing about these changes and then keeping up with them so that customers always feel sure these companies keep pace with everything new in the business environment.

6.1 Theoretical Implications

From a scientific perspective, this research is important because it looks at how AI and big data may be used to increase productivity and customer service. To ascertain how these technologies should be employed, the researcher conducted a field study on businesses. The findings are intended to offer conclusions and suggestions that elevate the standard for client assistance and boost productivity.

6.2 Managerial Implications

The study provides implications that would help and can be used to improve productivity and customer service. This study concludes and offers recommendations for how these technologies, AI and big data could be used to raise the bar for customer service and improve efficiency. The study provides managerial and practitioner insight into how AI and big data technologies can be implemented in practical situations. To enhance OE and CS, it is necessary to identify common challenges and formulate strategic recommendations so that they may make informed decisions and overcome barriers to technology adoption. The study would help policymakers, consultants, and technology providers gain a better understanding of AI and big data in the service sector. The information provided can help shape policy development, consulting approaches, and technological solutions to promote growth and innovation within the service industry. Benchmarking of technology use in different service sectors can be conducted using the outcomes of the study so businesses can strategize their technological advancements in alignment with industry trends and customer expectations by evaluating the potential benefits and risks associated with integrating AI and big data.

6.3 Limitations and Scope for Future Research

This study contributes to the academic discourse on technology integration into service industries. However, the nature of the adopted methodology has limitations and considerations. Researchers should be able to apply the findings to build on their understanding of AI and big data applications, challenges, and impacts. Additionally, this paper serves as a reference for future research exploring similar or related topics, providing a solid foundation for future research and identifying areas for further investigation.

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