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Identification and Hierarchical Structuring of Factors Influencing the Adoption of Artificial Intelligence for Customer Behavior Prediction in Electronic Businesses

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Abstract This paper focused on determining and ranking critical variables that influence the role of artificial intelligence (AI) in predicting consumer behavior in e-businesses. The statistical population consisted of 11 AI specialists in e-business, who were chosen on the basis of academic qualification, relevant experience, and knowledge of AI technologies. They were supposed to be familiar with technical infrastructure, employee skills and attitudes, data accessibility, organizational culture, ethics and trust, cost and resources, implementation issues, and organizational agility. The relationship among the factors was analyzed using Interpretive Structural Modeling (ISM) and the Matrix of Cross-Impact Multiplications Applied to a Classification (MICMAC) analysis. The results of the ISM suggested that technical infrastructure and resources are the most influential ones. The MICMAC analysis divided factors into independent, dependent, linkage, and autonomous categories. The findings are believed to guide e-businesses to make the best use of AI acceptance and optimize customer behavior forecasting.

Keywords: *Electronic business, Customer behavior prediction, Factor identification, Hierarchical structuring*

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1. Introduction

As digital technologies continue to spread widely and e-commerce continues to grow, understanding customer behavior has become one of the most crucial challenges that modern businesses are facing. Artificial Intelligence (AI) is one of the new technologies that has opened new directions of consumer behavior analysis and forecasting, as it has the ability to handle large amounts of data and identify patterns that were previously hidden. The introduction of AI in a company's operations allows individualizing services, streamlining marketing processes, and enhancing customer satisfaction. However, the successful deployment of AI in the said scenario requires a profound insight into what determines the adoption and implementation of AI. Alan Turing (1950), in his seminal article, "Machine

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Computation and Intelligence", asked the question, Can machines think? And laid out the theoretical foundations of this developing field by presenting the Turing test. Being one of the most revolutionary technological and scientific innovations of the modern world, AI has a significant impact on the optimization of organizational procedures and the provocation of innovation in business models (Wang, 2025). The present-day companies, especially in marketing and customer service spheres, use AI to simplify big data analysis, allow companies to understand customer needs more thoroughly, and provide them with individual recommendations. As an example, chatbots can interact with customers in an intelligent manner, reducing the customer care expenses due to automated interaction (Kaplan & Haenlein, 2019). The ability of AI to handle and analyse large volumes of data has made it a powerful competitor in the e-commerce sector, where sites like Amazon and Alibaba use advanced algorithms to create tailored product recommendations. Besides, AI helps in the optimization of pricing, detection of fraud, inventory, and optimization of digital advertisement; consequently, enhancing the efficiency of targeting and boosting the rate of conversion (McAfee & Brynjolfsson, 2017). The AI-based analytics allows marketing decision-making and strategic planning by identifying complex trends and patterns in data (Huang & Rust, 2020). Empirical research has shown that companies using AI to analyze customer behavior are better at customer retention and enhanced customer experiences (Davenport & Ronanki, 2018). Kumar and Reinartz (2012) also noted that predictive models that are run by AI can help reduce marketing expenses and increase the turnover of potential customers into devoted clients.

Although such positive results have been achieved, the use of AI is still uneven across industries. The determinants specified in previous studies include technological complexity, implementation expenses, user acceptance, model interpretability, and application and implementation of AI in the firms (Dora et al., 2020). A methodical classification of these factors can help enterprises to design better strategies to further enhance the use of AI in electronic business (e-business). With the current competitive landscape, the ability to accurately determine customer requirements, expectations, and behaviours may bring a good level of competitive advantage. Through the study of large amounts of data and the identification of hidden behavioural patterns, AI can enable companies to provide a personalised experience, boost conversion rates, and strengthen customer loyalty.

Even though several studies have investigated the application of AI in e-commerce, very few studies have specifically aimed at defining and hierarchically classifying the factors that determine the adoption of AI in predicting customer behaviour. An overview of the available literature shows that a major gap exists in the research related to a comprehensive framework that can combine these determinants. Although some studies have been done on variables like data quality, user trust, or organisational readiness, the variables have been treated as singular entities instead of being the components of a complex model. The given research, therefore, attempts to define and rank the main aspects of the adoption of AI to predict customer behaviour in e-businesses through Interpretive Structural Modelling (ISM) and the Matrix of Cross-Impact Multiplications Applied to a Classification (MICMAC) analysis. This study attempts to create a model structure that can shed light on the avenues of the successful application of AI in predicting consumer behaviour. Based on this, two main research questions can be formulated:

1. What factors affect the adoption of AI in e-business to predict customer behaviour?
2. How are these factors organized hierarchically to explain their interrelationships and strengths of influence?

2. Theoretical Framework

AI is generally defined as the ability of a system to accurately process external data, learn from the data, and apply the acquired knowledge to achieve goals and perform specific tasks through flexible adaptation. Since its inception in the 1950s, AI has faced numerous challenges; however, technological advances, particularly in the fields of machine learning and artificial neural networks, have made AI one of the most influential scientific and industrial fields. AI plays a fundamental role in natural language processing, computer vision, recommendation systems, and organizational decision-making, and its future developments are expected to raise significant ethical, legal, and social issues. Using advanced algorithms and modeling, AI is able to identify complex patterns and provide accurate predictions. Its main applications include information processing, process optimization, and improving the security of digital systems. The integration of AI into cloud environments and distributed computing systems has also increased operational accuracy and efficiency and paved the way for the development of new technologies in various sectors (Sharma & Singh, 2022).

To apply AI in e-business, understanding the various taxonomies of AI is of great importance. These taxonomies not only play a role in understanding the various dimensions and functions of AI but also provide a basis for policymaking, technology development, and practical applications in various industries. One of the most important of these classifications is the AI Use Framework developed by the National Institute of Standards and Technology (NIST) (NBS, 2021). The framework emphasizes human-AI interaction and provides researchers and businesses with a structured approach to understanding the functions of AI in organizational processes. Similarly, OECD's Artificial Intelligence Systems Taxonomy Framework (OECD, 2022) focuses on the technical and structural characteristics of AI systems, like data, models, and algorithms, the interaction of the system with the environment, and the level of human oversight. It is particularly well-adapted to policy and regulatory use. Similarly, the Sectoral Taxonomy of AI Intensity estimates the extent of AI use across the economy's sectors based on four key indicators: AI-related human capital, degree of innovativeness, sector exposure to AI technologies, and use of AI technologies in production processes. It designates e-commerce, banking, and healthcare as the most AI-intensive sectors (OECD, 2024). The Generative AI Taxonomy is specifically interested in the application of generative AI and categorizes it into five categories: content creators, content redesigners, synthesizers, assistants, and facilitators. This classification highlights the business operational strategic role of generative AI in digital marketing, advertising, and intelligent content creation (Suchikova et al., 2025). Finally, the Center for Security and Emerging Technology's AI Systems Classification Framework highlights levels of automation, effect, human interaction, and risks, and is used in policymaking, security requirements, and business risk management (Aiken, 2021). In general, all of the frameworks laid out in Table 1 have specific goals in consideration during their development.

Table 1

Selected AI Frameworks and Their Applications in Business

Framework	Provider / Year	Main Focus	Key Dimensions / Criteria	Application Areas	Business Examples
AI Use Taxonomy	NBS, 2021	Human–AI interaction	Content creation, analysis and synthesis, decision-making, human support	Operational understanding of AI roles	Recommender systems (Netflix, Amazon)
Framework for Classification of AI Systems	OECD, 2022	Technical structure and components of AI	Data, algorithms, environment interaction, human oversight	Policymaking, regulation, risk assessment	Legal frameworks for digital platforms
Sectoral Taxonomy of AI Intensity	OECD, 2024	AI intensity across sectors	Human capital, innovation, AI exposure, practical usage	Economic analysis, industry comparison	Identify sectors with the highest AI reliance (e.g., e-commerce)
Generative AI Taxonomy	Suchikova et al., 2025	Generative AI applications	Creator, re-designer, combiner, assistant, enabler	Digital marketing, advertising, content creation	Brand marketing and online ads (Amazon Ads, eBay)
Classifying AI Systems	Aiken, 2021	Automation, risk, human interaction	Automation, impact, human interaction, risks	Policy, safety standards, risk management	AI risk assessment in technology companies

In the case of e-business, the most relevant framework is the NIST (Laurie, 2023) framework due to its focus on real-world applications and capacity to forecast customer behavior. In addition, the OECD (2024) AI Intensity Framework emphasizes the e-commerce sector as utilizing the most AI. Similarly, the Generative AI Framework (Suchikova et al., 2025) supports applications towards digital marketing and smart content creation.

E-business describes the use of information and communications technology to carry out business activities, provide services, and sell goods and services electronically. It encompasses business-to-business (B2B), business-to-consumer (B2C) and some others like consumer-to-consumer (C2C) and government-to-business (G2B). The most important uses of e-business are the minimization of the cost of operation, improvement of efficiency, and increased customer interaction via the internet. The purchase and sale of products and services, management of supply chain, customer relations, and enhancement of processes in the companies through digital media is referred to as e-business. Accelerated and convenient access to global markets, lower operating expenses, and increased customer experiences are some of the biggest benefits of e-business. The behavior of the users in the e-commerce websites is observed to give them customized advice on search and purchases. Key success factors include maximization of user experience, security of transactions on the web, customized suggestions, and data-driven wisdom to optimize business operations. The other significant growth and expansion drivers include AI-specific personalization and customer trust. The use of AI in e-commerce is diverse and falls into a wide scope of applications, identified as recommender systems to ease the shopping experience, chatbots and virtual assistants as customer support, predictive analytics to manage demand, dynamic pricing, and more advanced applications such as augmented reality (AR) and virtual reality (VR). The given developments suggest that AI is not merely a new technology but a competitive power and an engine of enhanced customer satisfaction (Singh & Singh, 2024).

In e-commerce, the greatest AI applications are intelligent recommender systems, whereby AI analyzes user behavior and searches history, purchases, and preferences to propose suitable products to the user. This has been personalized, and it has been done in a bid to offer an enhanced user experience, enhance conversion rates, and boost loyalty (Wang, 2025). Smart customer support is another possible application where AI software-driven chatbots and virtual assistants answer the call of the customers in real-time, and the service is responsive, scalable, and inexpensive based on natural language processing (Agrawal et al., 2025). Another urgent sphere where AI predicts customer behavior and supply chain optimization is achieved through the analysis of past information, market dynamics, reduced wastes, automated inventory management, and quicker and more responsive reaction to demand fluctuations (Iseri et al., 2025). AI is also essential in dynamic pricing and optimization, which adjusts the prices of products dynamically based on supply, demand, competitive pricing, and market conditions with the aim of maximizing profit margins, remaining competitive, and ensuring customer satisfaction (Zhang et al., 2025). Moreover, when it comes to virtual and augmented reality applications, which, combined with AI, can change the process of online shopping, the experience is enhanced by interactive visualization and interactivity with the product (Saha, 2025).

Subsequent research placed more emphasis on AI-based models when it comes to predicting customer behavior. Gkikas and Theodoridis (2024) have presented the idea of using machine learning models to anticipate online shopping. Their research grouped and analyzed the levels of interaction of the user by applying Google Analytics algorithms and other models like Decision Trees, Naive Bayes, and k-Nearest Neighbors. The results revealed that the Decision Tree model was the most successful with an accuracy rate of 97.98 percent in online purchase behavior prediction. According to Patil (2024), the consumer experience can be improved with the help of AI-driven real-time personalization and recommendations, with higher conversion and loyalty due to the combination of purchase history, search behavior, and user interaction. Chenavaz and Dimitrov (2025) performed a systematic literature review of 95 peer-reviewed journals in order to investigate the role of AI in dynamic pricing. In their work, they have found four important clusters, namely, financial modeling, market dynamics, commodity markets, and behavioral decision-making, proving that it is important to include AI in the pricing strategy to enable businesses to stay competitive and adaptive to changing market conditions. Malmir et al. (2025) created a model based on the Gradient Boosting algorithm to forecast the relative price of initial public offerings (IPO) in the Iranian stock market. The researchers used the data of 42

Tehran Stock Exchange and 121 Iran Fara Bourse listed firms during 2013-2023. The results showed that the ensemble Gradient Boosting model was more precise than the individual models and had a good ability to fit complex interactions and non-linear relationships between variables. Comprehensively, the literature suggests that AI plays three fundamentally crucial roles in customer behavior forecasting: individual customer experience customization (with the help of intelligent recommender systems and real-time suggestions), inventory planning and demand forecasting (based on data-driven analytics), and customer loyalty reinforcement (with the assistance of sentiment analysis, churn probability, dynamic pricing, and marketing strategy).

Although this has been done, research still has a gap to determine and classify the factors influencing the use of AI to predict customer behavior. Such predictors are the quality of information, the comprehensibility of machine learning models, the level of user confidence, and the preparedness of organizations- the most important but insufficiently studied aspects. In order to fill this gap, the present study adopts ISM and MICMAC analysis to determine and categorize the influential variables in AI adoption in e-business customer behavior prediction. Due to the changes in customer behavior and the development of social networks and increased competition, the previous approaches to data analysis are insufficient. Firms are currently in need of a better understanding of customer requirements and behavioral patterns. This paper logically discusses these variables and provides a proper model of AI adoption in e-business systems.

3. Methodology

3.1. Participants

The present study was based on a descriptive research design, with questionnaires being the primary data collection instrument. The target audience was 11 professionals in the sphere of AI and e-business. The experts had technical expertise, familiarity with the emerging technologies, and experience with the application of AI in e-business. Consequently, they could deliver a comprehensive and authentic insight into what makes the adoption of AI. This group made the data scientific, practically valid, and reliable in terms of analysis and making meaningful conclusions. The purposive sampling method was chosen with the purpose of involving only those individuals who possess at least a master’s or a doctorate level of education, have over five years of professional experience in the field of digital business, have start-ups or AI and e-commerce-related firms, and have experience in the use of AI technologies and their implementation in e-business. Theoretical saturation was used to arrive at the sample size.

3.2. Procedure

To begin with, a literature review assisted in determining the factors affecting AI applications in predicting customer behaviour. A questionnaire was developed that was structured and sent to the experts and professionals in AI and e-business. The questionnaire was the main tool of the data collection, on the basis of which SM (Warfield, 1974) and MICMAC analysis (Godet, 1986) were conducted. ISM was applied after the data collection to classify the identified factors hierarchically, whereas MICMAC analysis was applied to define the effects and dependencies between the identified factors, which ultimately gave the final results.

3.2.1. Interpretive Structural Model (ISM)

The factors of customer behavior prediction that affect AI adoption were initially found through a thorough review of the literature. The views of the experts were utilized to guarantee the completeness and applicability of the factors. On these grounds, the Self-Interaction Matrix (SSIM) was developed, in which the professionals rated the comparative effect of the factors identified. The SSIM applied the VAXO notation to determine the type of relationships, where “V” is direct influence, “A” is reverse influence, “X” is mutual influence, and “O” is no influence. The SSIM was then transformed into an Original Reachability Matrix wherein 1 and 0 were binary measures of the existence or lack of relationships between the factors. Afterward, a Final Reachability Matrix was prepared by using the principle of transitivity in order to take into consideration indirect relationships between the factors. The last step was level partitioning to group the factors at the same level, in which factors with intersection and reachability sets that are symmetrical met. This repeated procedure was carried out until the factors were all categorized, and then a graphical representation of the ISM model was developed to explain the hierarchical relationships between the factors.

3.2.2. MICMAC

After the ISM, driving power and dependence of factors were studied using MICMAC. Factors have been ordered into four categories: (1) Independent Variables, which have low reliance and high impact. (2) Dependent Variables, which are under the influence of other factors to a great extent. (3) Variables of linkage that have high dependence and high influence and play a very crucial role in the system. (4) Autonomous variables that have low dependence and low influence are not as critical in the system. This approach enables a methodical interpretation of the most important drivers that influence the adoption of AI in predicting customer behavior and gives the e-businesses practical contributions that can be made towards improving their AI strategies.

4. Results

4.1. ISM Results

The identification of the factors that determine the adoption of AI in e-business started with the identification of the key factors using a massive literature review. A structured questionnaire was developed and sent to 11 experts in AI and e-business in order to collect the expert opinions on the causal interdependencies between these factors and to create an interpretive structural model. These professionals gave their advice, which was used to validate and refine the identified factors (see Table 2). Then, SSIM was developed, in which qualitative measures of relationships between the factors were transformed into a quantitative binary score so as to enable the analysis.

Table 2
Identified Factors Influencing the Adoption of AI in Predicting Customer Behavior

Factor	Definition	References
1. Technical Infrastructure and Resources	Adequate computational infrastructure, servers, databases, and advanced processing tools are foundational for AI adoption in e-business. These resources enable machine learning algorithms and real-time data analysis for accurate customer behavior prediction and decision-making.	Liang & Hongtao (2025); Chadaga et al. (2025); Kasemrat (2025); Chugh & Jain (2024); Bawack et al. (2022)
2. Accessibility and Quality of Customer Data	High-quality, comprehensive, and up-to-date customer data allow AI models to extract precise patterns of preferences, purchase habits, and future needs.	Chadaga et al. (2025); Kasemrat (2025); Stamkou et al. (2025); Awad (2024)
3. Implementation Challenges	Organizational ability to manage AI implementation processes affects successful adoption. Adequate knowledge and tools accelerate integration and improve customer experience.	Khamdamov et al. (2025); Liang & Hongtao (2025); Nugroho (2025); Chadaga et al. (2025); Awad (2024)
4. Customer-Centric Systems	Customer-centric systems facilitate AI-driven analysis of interactions, enabling personalized solutions and better engagement.	Khamdamov et al. (2025); Dixit et al. (2025); Raji et al. (2024)
5. Organizational Dynamic Capabilities	Organizational flexibility to adapt to technological and behavioral changes enhances AI model improvement and predictive accuracy.	Chadaga et al. (2025); Nugroho (2025); Awad (2024); Mikalef et al. (2021)
6. Perceived AI Effectiveness	Belief in AI effectiveness drives adoption; recognition of AI's impact on prediction accuracy and cost reduction encourages investment.	Dixit et al. (2025); Awad (2024); Nagy & Hajdu (2021)
7. Organizational Culture and Leadership	Open, innovative culture and supportive leadership promote AI adoption by encouraging experimentation and employee engagement.	Chadaga et al. (2025); Nugroho (2025); Awad (2024); Mikalef et al. (2021)

8. Ethical Concerns and Trust	Customer trust in ethical data usage is essential; transparency and data security improve AI model inputs and predictive outcomes.	Khamdamov et al. (2025); Dixit et al. (2025); Raji et al. (2024); Nagy & Hajdu (2021)
9. Costs and Resource Allocation	Adequate investment in software, tools, and skilled personnel ensures effective AI implementation and maximizes benefits.	Khamdamov et al. (2025; Liang & Hongtao (2025); Mikalef et al. (2021)
10. Employee Attitudes and Skills	Positive attitude and technical expertise in AI and data analysis facilitate the effective deployment of predictive models.	Liang & Hongtao (2025); Chadaga et al. (2025); Kasemrat (2025)

The symbols V, A, and X were set to 1 to represent the existence of a relationship, whereas O was set to 0 to represent the non-existence of a relationship. These binary values were then utilized to build the Starting Reachability Matrix (Table 3), which was the result of the direct impact of the identified factors.

Table 3
Initial Reachability Matrix

10. Employee Attitudes and Skills	9. Costs and Resource Allocation	8. Ethical Concerns and Trust	7. Organizational Culture and Leadership	6. Perceived AI Effectiveness	5. Organizational Dynamic Capabilities	4. Customer-Centric Systems	3. Implementation Challenges	2. Accessibility and Quality of Customer Data	1. Technical Infrastructure and Resources	
1	1	0	0	1	1	1	1	1	1	1. Technical Infrastructure and Resources
1	0	0	0	1	1	1	1	1	0	2. Accessibility and Quality of Customer Data
1	1	0	0	1	1	1	1	1	0	3. Implementation Challenges
1	1	1	0	1	1	1	0	1	0	4. Customer-Centric Systems
1	1	0	0	1	1	1	1	0	0	5. Organizational Dynamic Capabilities
1	1	1	1	1	1	1	1	0	0	6. Perceived AI Effectiveness
1	1	1	1	1	1	1	1	1	0	7. Organizational Culture and Leadership
1	0	1	1	1	1	1	1	1	0	8. Ethical Concerns and Trust
1	1	0	1	1	1	1	1	1	1	9. Costs and Resource Allocation
1	0	0	0	1	1	1	1	1	0	10. Employee Attitudes and Skills

Transitivity principles were used to incorporate the indirect relationships between the factors in the Final Reachability Matrix (Table 4). The indirect associations were represented by the symbol 1*, which implied the chains of influence that were not based on direct relationships but on intermediate factors.

Table 4
Final Reachability Matrix

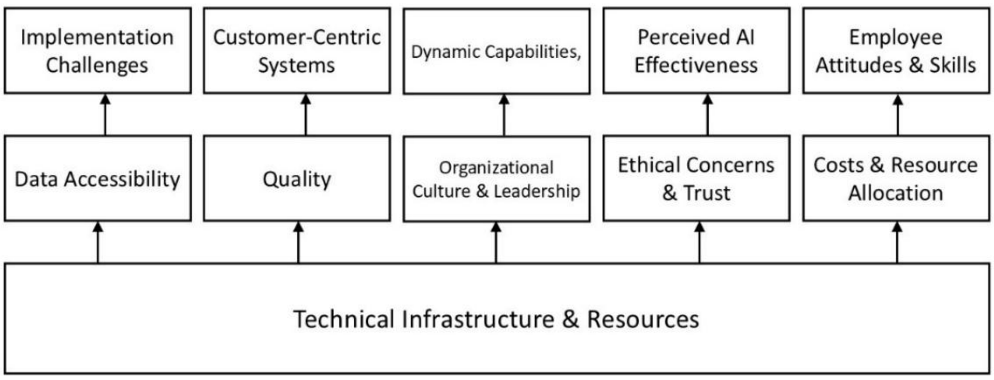
10. Employee Attitudes and Skills	9. Costs and Resource Allocation	8. Ethical Concerns and Trust	7. Organizational Culture and Leadership	6. Perceived AI Effectiveness	5. Organizational Dynamic Capabilities	4. Customer-Centric Systems	3. Implementation Challenges	2. Accessibility and Quality of Customer Data	1. Technical Infrastructure and Resources	
1	1	1*	1*	1	1	1	1	1	1	1. Technical Infrastructure and Resources
1	1*	1*	1*	1	1	1	1	1	0	2. Accessibility and Quality of Customer Data
1	1	1*	1*	1	1	1	1	1	0	3. Implementation Challenges
1	1	1	1*	1	1	1	1*	1	0	4. Customer-Centric Systems
1	1	1*	1*	1	1	1	1	0	0	5. Organizational Dynamic Capabilities
1	1	1	1	1	1	1	1	0	0	6. Perceived AI Effectiveness
1	1	1	1	1	1	1	1	1	0	7. Organizational Culture and Leadership
1	0	1	1	1	1	1	1	1	0	8. Ethical Concerns and Trust
1	1	0	1	1	1	1	1	1	1	9. Costs and Resource Allocation
1	0	0	0	1	1	1	1	1	0	10. Employee Attitudes and Skills

The factors were arranged in a hierarchy using the final reachability matrix, in a level partitioning. Level 1 (Top) was made up of influential factors that had a strong influence on others, such as factors 3, 4, 5, 6, and 10. Level 2 indicated moderately dependent variables, i.e., factors 2, 7, 8, and 9. The bottom (Level 3) consisted of the factor that had the most total impact on the system, and this was factor 1. Figure 1, which is the ISM, was created to demonstrate the causal relationships between these factors, as shown in Table 5.

Table 5
ISM Hierarchical Levels

Level	Factors
1	3. Implementation Challenges, 4. Customer-Centric Systems, 5. Dynamic Capabilities, 6. Perceived AI Effectiveness, 10. Employee Attitudes & Skills
2	2. Data Accessibility & Quality, 7. Organizational Culture & Leadership, 8. Ethical Concerns & Trust, 9. Costs & Resource Allocation
3	1. Technical Infrastructure & Resources

Figure 1
Final ISM Model



4.2. MICMAC Analysis

The MICMAC also divided the factors further into sub-classifications in terms of their power of influence (driving power) and dependency (Table 6). Key drivers (KDs) are independent factors that are less dependent and highly influential. Dependent factors are highly dependent, and they are characterized by other factors. Connection factors are highly influential and dependable as well as critical factors in system stability. The factors that are uncontrollable do not make any difference because they lack influence and dependency.

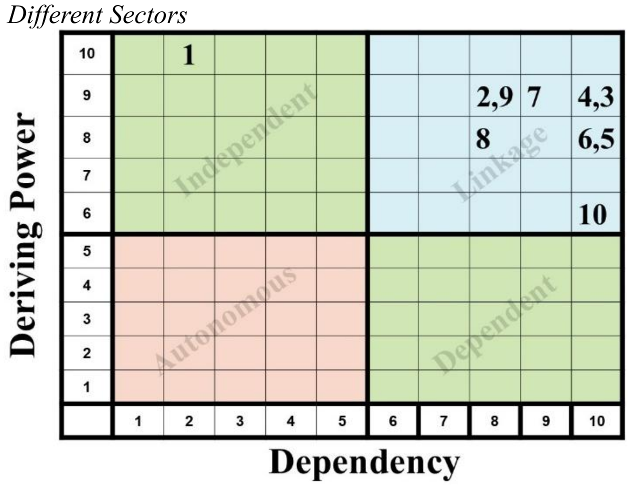
Table 6

The Degree of Dependence and Influence of the Factors

Influence	10. Employee Attitudes and Skills	9. Costs and Resource Allocation	8. Ethical Concerns and Trust	7. Organizational Culture and Leadership	6. Perceived AI Effectiveness	5. Organizational Dynamic Capabilities	4. Customer-Centric Systems	3. Implementation Challenges	2. Accessibility and Quality of Customer Data	1. Technical Infrastructure and Resources	
10	1	1	1*	1*	1	1	1	1	1	1	1. Technical Infrastructure and Resources
9	1	1*	1*	1*	1	1	1	1	1	0	2. Accessibility and Quality of Customer Data
9	1	1	1*	1*	1	1	1	1	1	0	3. Implementation Challenges
9	1	1	1	1*	1	1	1	1*	1	0	4. Customer-Centric Systems
8	1	1	1*	1*	1	1	1	1	0	0	5. Organizational Dynamic Capabilities
8	1	1	1	1	1	1	1	1	0	0	6. Perceived AI Effectiveness
9	1	1	1	1	1	1	1	1	1	0	7. Organizational Culture and Leadership
8	1	0	1	1	1	1	1	1	1	0	8. Ethical Concerns and Trust
9	1	1	0	1	1	1	1	1	1	1	9. Costs and Resource Allocation
6	1	0	0	0	1	1	1	1	1	0	10. Employee Attitudes and Skills
	10	8	8	9	10	10	10	10	8	2	**Dependence**

Figure 2

Classification of Variables in Different Sectors



The findings gave a strategic view of the aspects that need to be given priority to succeed in implementing AI and allocating resources in e-business conditions (Figure 2).

5. Discussion

Overall, the primary goal of the research was to select and rank the variables affecting the use of AI in predicting customer behaviour in electronic companies. The study was conducted on the basis of two research questions. The first research question was as follows: What are the determinants of the use of AI in predicting customer behavior in e-businesses? The results found that a number of interconnected factors, such as technical infrastructure and resources, staff skills and attitudes, data access and quality, organizational culture and leadership, ethics and trust, cost and resource allocation, implementation hurdles, customer-centric systems, organizational agility, and perceived effectiveness and efficiency of AI, played a role. The second research question was as follows: How are these factors hierarchically arranged? They were divided into three levels in the study. Technical infrastructure and resources constituted Level 3, which formed the fundamental foundation of the rest of the factors. The intermediate level (Level 2) discussed some organizational and managerial aspects, including data quality, leadership, ethics, trust, and resource allocation, that enabled/hindered higher-level functions. Level 1 (Level of operation) entailed implementation issues, customer-focused systems, organizational flexibility, perceived AI efficacy, and employee abilities and attitudes- aspects that become evident when the base and the management setting are fulfilled. This hierarchical organization shows that AI implementation in e-businesses is a gradual process, beginning with the infrastructural preparation and moving to the organizational alignment and lastly to the successful deployment of operations.

According to the results, some useful recommendations were provided to business leaders and policymakers. To begin with, the emphasis should be made by organizations in terms of investment in strong technical infrastructure and adequate resources, as these are the basis of any other activity aimed at AI integration. Sustainable implementation requires developing scalable digital systems, implementing secure cloud-based architectures, and providing high levels of cybersecurity. Second, the strategic focus should be on data quality and accessibility, with the quality and availability of accurate and reliable customer data being the fuel of AI-driven insights. To improve the overall quality of decision-making, it can be recommended to establish clear data governance frameworks and apply sophisticated technologies, including machine learning to clean data or blockchain to make decisions more transparent. Moreover, the innovation-oriented organizational culture and transformational leadership should be promoted in order to minimize change resistance. The managers are encouraged to be participatory, reward innovation, and encourage an open dialogue on the concerns of the employees as a way of building trust and engagement. The aspect of ethics should also be embedded into AI strategies so that customer trust can be reinforced, clear policies on the use of data, and explainable AI algorithms can help to increase legitimacy and trust. Also, the financial planning must shift to long-term strategic investment instead of short-term cost control, which will guarantee the sustainability and expansion of AI projects. Lastly, the organization needs to have ongoing employee training programs that deal with both technical and ethical aspects of AI, which can build competence and commitment within the organization.

To enhance the validity and applicability of the findings, it is also suggested that future studies should be done using a mixed-methodology that should involve the integration of qualitative understanding with quantitative analyses. The statistical methodologies and more extensive surveys might be considered to clarify causal relationships between the factors that influence the adoption of AI.

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