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How AI Tools Affect the Customer Experience: a case study

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ABSTRACT

Using an integrative review, this study provides a hypothetical-deductive approach of the effects of adopting AI tools on enhancing customer experience. The study was motivated by the observation that, in today's competitive business environment, organizations often struggle to fully leverage AI technologies to understand and address customer needs, which can limit the effectiveness of customer experience strategies. To address this issue, this study employed an integrative review as a qualitative research method, structured around literature search, data extraction, and thematic analysis. From the analysis of relevant literature, findings suggest that the effective implementation of AI tools including chatbots, recommendation systems, and predictive analytics is closely linked with the personalization and efficiency of customer interactions. Proper integration of AI enables organizations to anticipate customer needs, optimize service processes, and foster stronger relationships. However, insufficient adoption or misalignment of AI strategies may hinder customer engagement and satisfaction. By examining the role of AI adoption in enhancing customer experience, this study sheds light on the mechanisms through which intelligent technologies bridge the gap between businesses and clients. Future research could employ exploratory empirical methods to develop a structured model that further elucidates how specific AI tools contribute to improved customer experiences across different industries.

Keywords: Artificial Intelligence, AI Tools, Customer Experience, Management Organizations

INTRODUCTION

In today's highly competitive and digitalized business environment, customer experience has become a critical determinant of organizational success. Companies are increasingly adopting innovative technologies to better understand customer expectations, enhance interactions, and build long-term relationships. In this context, Artificial Intelligence (AI) has emerged as a transformative tool that enables organizations to deliver more efficient, personalized, and responsive services.

AI tools, including machine learning algorithms, natural language processing, and predictive analytics, allow firms to process large volumes of customer data and extract valuable insights. AI-driven data analytics enhances customer engagement by enabling highly personalized marketing strategies tailored to individual preferences (Rini , 2024). Similarly, AI improves customer experience through key dimensions such as personalization, efficiency, and trust, particularly in online retail environments (Ali , Mahmoud , & Narjes , 2024).

Furthermore, AI-powered applications such as chatbots and virtual assistants have significantly transformed customer service operations by providing instant responses and continuous support. These technologies improve service quality and customer satisfaction by reducing response time and increasing interaction efficiency (Amitabh, 2025). In addition, advanced AI systems further enhance customer experience by delivering real-time

assistance and context-aware solutions (Agrawal, 2025).

Despite these advantages, the integration of AI into customer experience management raises important challenges related to transparency, ethics, and data privacy. The development of explainable and transparent AI systems is essential to building customer trust and ensuring sustainable engagement (Dezao, 2024).

Based on these perspectives, this study aims to examine how AI tools enhance customer experience by focusing on personalization, efficiency, and customer engagement, while also addressing the key challenges associated with their adoption.

Research Problem

With increasing competition in the telecommunications industry, enhancing customer experience has become a critical concern for companies such as Mobilis "Algérie Télécom Mobile". The utilization of Artificial Intelligence (AI) tools, including chatbots and Smart POS systems, is perceived as a fundamental strategy to elevate service quality and customer satisfaction. Nonetheless, the actual impact of these tools on customer experience remains insufficiently understood:

How Does the Adoption of AI Tools influence Customer Experience in Mobilis?

METHODOLOGY

This study adopts an inductive-deductive approach, grounded in initial hypotheses that are subsequently tested empirically. The research is predicated on the assumption that the adoption of AI tools directly influences the enhancement of customer experience, measured across four key dimensions: Cognitive, Emotional, Relational, and Pragmatic. These dimensions are assessed within the context of the Mobilis Firm as experienced by Algerian consumers during the purchase of various products or services. Data were gathered through a structured questionnaire, serving as the primary data collection instrument. The responses were analyzed using SPSS Version 23 for descriptive and inferential statistics, along with partial least squares structural equation modeling via SmartPLS4 software.

Study themes

The study is structured around the following thematic divisions:

- Introduction: encompassing the problem statement, sub-questions, hypotheses, significance, objectives, methodology, and tools;
- First axis: Literature Review and Hypotheses Development;
- Second axis: Methodological procedures of the empirical investigation;
- Third axis: Presentation and analysis of findings, including hypothesis testing;
- Conclusion: summarizing key results, recommendations, and future directions.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Multiple data scientists and market analysts have examined the influence of Artificial Intelligence (AI) within the field of marketing across various countries. In 2018, customer experience futurist Blake Morgan outlined three key ways in which AI enhances customer experience. The author indicated that consumers often favor communication with virtual assistants during or after the purchasing process. Personalized services have demonstrated efficacy in shaping customer purchasing decisions. Furthermore, AI facilitates behavioral insights, enabling organizations to design responsive strategies (Abu Daqar & Smoudy, 2019).

This section is dedicated to outlining the theoretical foundations of the study variables, beginning with AI tools and their role in digital transformation within a technologically evolving environment, followed by a focus on customer experience and its associated measurement dimensions.

ARTIFICIAL INTELLIGENCE TOOLS

Artificial Intelligence (AI) tools are computer programs designed to perform tasks that usually need human intelligence. These tasks include analyzing data, understanding language, recognizing images, and making decisions. AI tools use techniques like machine learning to find patterns in data and provide useful results.

The concept of Artificial intelligence

Artificial Intelligence (AI) does not have a single universally accepted definition. In November 2018, the OECD's AI Group of Experts (AIGO) established a subgroup to develop a comprehensive description of an AI system. This description was designed to be clear, technically accurate, and neutral with respect to specific technologies, while remaining applicable across both short- and long-term perspectives. It is sufficiently broad to cover the various definitions of AI used in scientific, business, and policy contexts, and it also contributed to shaping the OECD Council's Recommendation on Artificial Intelligence. (OECD, 2019, p. 22)

Artificial Intelligence (AI) refers to computational models integrated into complex systems that enable perception and decision-making, but which can be vulnerable to attacks affecting their integrity, availability, and confidentiality. (Kathrin & Alexandre , 2024, p. 2)

In more accessible terms, Artificial Intelligence constitutes a field of study and technological development aimed at constructing and analyzing intelligent systems—machines capable of executing tasks typically requiring human cognition by simulating thought processes, perception, and actions.

Artificial Intelligence properties

We need to delve further if we want to learn which kind of artificial intelligence is most commonly used in business: (Bharadiya, Thomas, & Farhan , 2023, p. 89)

Learning capability

Artificial Intelligence is characterized by its ability to learn from large datasets through machine learning techniques. It enables the analysis and interpretation of data to support informed and effective decision-making processes.

Security enhancement

AI possesses the capability to strengthen cyber security by detecting, analyzing, and preventing potential threats. It ensures continuous monitoring of systems and contributes to the protection of digital infrastructures.

Automation and performance improvement

AI facilitates the automation of processes, leading to increased productivity and operational efficiency. It also improves service quality and supports data-driven decision-making within organizations.

Artificial intelligence Tools

Chatbot: chatbots are described as computer applications powered by artificial intelligence that interact with customers using natural language through text or speech on online platforms. They have evolved from simple rule-based programs to advanced systems that use natural language processing (NLP) and natural language

understanding (NLU) to interpret a user's intent and respond appropriately. Chatbots aim to assist customers in tasks such as answering inquiries, guiding product choices, and routing conversations to the right service agent when necessary. They offer highly consistent and instantaneous responses, making them a valuable tool in customer service, especially for handling simple, repetitive requests. (Tran, Pallant, J. I, & L. W, 2021, p. 5)

A chatbot, also referred to as a digital human, is an AI system engineered to replicate human appearance, behaviour, and communicative functions through realistic visual and linguistic interaction. It integrates 3D modeling, natural language processing, and interactive design, allowing users to communicate with a virtual character in a natural, human-like manner (Simone, Bruno, Enrico, & Luca, 2025, p. 5).

Chatbots simulate human interaction by employing advanced natural language processing techniques and intelligent interface design. These features allow users to access desired information efficiently and engage across sectors in an ethical and inclusive manner.

Recommendation Systems (AI personalization): AI-based personalized recommendation systems are described as intelligent tools that analyze individual customer data and behavior to suggest products, services, or content that match each user's preferences. These systems use machine learning algorithms to learn from past interactions, such as browsing history, past purchases, and ratings, enabling them to generate relevant, tailored suggestions for each consumer. By delivering recommendations that align with a customer's interests, these systems aim to enhance engagement, improve satisfaction, and increase the likelihood of continued interaction with the platform or brand. (Yin, J, 2025, p. 21)

Sentiment Analysis (ML for customer insights): Sentiment analysis is an AI-driven approach that applies machine learning and natural language processing to automatically identify and interpret the emotions and opinions expressed in textual data, such as customer reviews, social media posts, and online feedback. By categorizing sentiments as positive, negative, or neutral, it provides organizations with valuable insights into customer preferences, satisfaction, and attitudes. When integrated with predictive modeling, sentiment analysis can help forecast customer behavior, guide marketing decisions, and enhance products and services, ultimately supporting more informed, data-driven strategies for improving the customer experience. (Gooljar, V, Issa, T, Hardin-Ramanan, S, & Abu-Salih, B, 2024, p. 07)

CRM and AI personalization: refers to AI-powered customer relationship management systems that analyze customer data to automate interactions, anticipate needs, and provide personalized recommendations, improving engagement, satisfaction, and loyalty. (Chiara, Alessandra , & Alfonso , 2022, pp. 49-50)

Predictive Analytics (AI forecasting customer behavior): Predictive Analytics in the context of AI refers to the use of machine learning and statistical models to analyze historical and real-time customer data in order to forecast future behavior, purchase patterns, and potential churn. These AI-driven systems identify trends and patterns that help organizations anticipate customer needs, optimize marketing strategies, and make data-driven decisions to improve engagement, retention, and overall business performance. By integrating predictive analytics into customer management, companies can proactively respond to market changes and enhance strategic planning. (Bujor & Bogdan Ene, 2025, pp. 981-984)

Mobilis Smart POS: Mobilis Smart POS is a free Android-based application developed by Innovate for IT Solutions. It functions as a modern barcode scanning and point-of-sale system, supporting businesses such as retail stores and restaurants in managing orders, monitoring sales, processing payments, and handling customer information with high efficiency (APK, 2025).

Mobilis effectively integrates advanced AI tools, including chatbots and the Smart POS system, to elevate both customer experience and operational performance. Chatbots powered by Large Language Models (LLMs) offer real-time assistance by responding to inquiries and guiding users through services in a manner that is human-like, ethical, and transparent. Concurrently, the Mobilis Smart POS application facilitates streamlined management of sales operations, payment processes, and customer data monitoring within retail branches or affiliated outlets. These AI tools collectively enable Mobilis to enhance its service delivery, optimize internal workflows, and solidify its standing as a leading telecommunications provider in Algeria.

Customer Experience and its dimensions

Given the crucial role that customers play in attaining organizational success, retaining and acquiring new

consumers is a major problem for well-established businesses. Improving customer satisfaction has a significant impact on reducing attrition and increasing client retention. Businesses' customer base becomes more varied as they grow. Targeted engagement tactics are necessary because every consumer has a unique profile and set of motives. Consequently, it becomes strategically necessary to comprehend each particular customer (Sujata, Aniket, & Mahasingh, 2019, p. 700).

Klein et al. (2017) looked at how providing a satisfying customer experience benefits a firm. According to survey data, 86% of consumers are willing to pay more for a product if they are brand loyal. Additionally, more than 70% of consumers tell others about their positive shopping experiences, and 43% are willing to purchase a lower-quality product if their previous contacts with the company were positive. These data confirm that better customer experiences lead to more word-of-mouth advocacy, stronger loyalty, and higher sales. Thus, providing exceptional service is a crucial differentiator in the marketplace (Abu Daqar & Smoudy, 2019, p. 25).

A new kind of competitive advantage has been introduced by customer experience (CX). A well-managed experience improves customer happiness, increases loyalty, aligns expectations, boosts confidence, strengthens brand perception, and creates emotional connections between clients and businesses. On the other hand, unpleasant experiences might cause long-term emotional damage (Da Silva, 2021, p. 21).

According to (Scibor-Rylski, Reducha, & Ochremiak, 2019, p. 15), Klaus and Maklan provide a thorough definition of customer experience in this context, characterizing it as "the cognitive and emotional evaluation of the consumer of various encounters, whether direct or indirect, with the organization related to their purchasing behavior." Customers' cognitive, emotional, sensory, and behavioral responses resulting from direct and indirect interactions with a business, its products, or its services are collectively referred to as customer experience (CX). Customers' interpretations of their engagement across various touch points and over time are reflected in this inclusive framework. Kuppelwieser and Klaus (2021) claim that customer experience (CX) is a cumulative psychological condition that develops as consumers evaluate their expectations against real events, including aspects of significance, emotion, and satisfaction (Hasan, Darna, & Yulia, 2025, p. 83).

Because customer experience is subjective by nature, evaluating it may be very challenging. Customer-specific utility-driven perceptions and emotional, cognitive, and behavioral aspects all influence the experience. Furthermore, it is difficult to fully measure the customer-organization connection since it involves multiple touch points and communication channels (Prakash & Padmakar, 2024, p. 2).

By highlighting the significance of customer-product interactions as a fundamental element in creating meaningful experiences, Gentile, Spiller, and Noci (2007) enhanced the idea of CX. Additionally, their approach incorporates human interaction in a variety of experiencing forms, such as intellectual, sensory, bodily, emotional, and spiritual engagement. One or more of these factors then influence how intense the consumer experience is (Da Silva, 2021, p. 22). These experiential dimensions align with terminology commonly used in the philosophy of mind literature—such as emotional, sensory, physical, and behavioral:

Table 1. The explanation of Customer Experience Dimensions

Dimension	Explanation
The Cognitive dimension	involves intellectual stimulation through curiosity, leading to knowledge formation
The relational dimension	focuses on consumers' perceptions of interactions with brands and their social connections
The sensorial dimension	engages the five senses, influencing emotional experiences and the overall quality of customer interactions
The symbolic dimension	Reflects customers' identities and values during interactions, serving as a cognitive mirror.
The physical dimension	Pertains to customers' bodily awareness during transactions. Finally
The pragmatic dimension	prioritizes practicality and monetary value, appealing to cost-conscious consumers through value-driven products and promotions

Source: Prepared by Researchers Based on (Gahler, Klein, & Paul, 2023; Hasan, Darna, & Yulia, 2025; Cachero-Martínez & Vázquez-Casielles, 2017).

To put it briefly, the notion of customer experience goes beyond the act of purchasing. It includes several connected components that come together to create a cohesive perception. The five main factors that affect

consumers' perceptions of value are sensory, emotional, cognitive, behavioral, and social, according to Wirtz et al. (2025). The sensory dimension involves stimuli, whether physical or digital, that shape impressions of aesthetics, comfort, and design. Affective reactions like happiness, trust, or enthusiasm are included in emotional aspects. Cognitive elements are linked to decision-making and problem-solving processes, which determine whether the experience meets expectations. Relationships and common experiences within the community are captured by the social dimension, whereas brand endorsement and repeat purchases represent behavioral consequences.

In this study, four dimensions have been selected as the most suitable to the research context: Cognitive Dimension, Emotional Dimension, Pragmatic Dimension, and Relational Dimension.

The Relationship between AI Tools and Customer Experience

Several studies have examined the relationship between Artificial Intelligence and Customer Experience. These studies indicate that AI technologies enhance personalization, service speed, and customer satisfaction.

Beginning with a study examining "AI-Powered Customer Service in Online Retail: Product-Type Differences, Information Asymmetry, and Seller Interventions" by (Shuyuan , Wang , & Xia, 2026) The study asks whether replacing human agents with AI-powered customer service reduces product information asymmetry and improves sales, and how this differs between search goods (objective, easily evaluated before purchase) and experience goods (subjective, only fully assessed after use). Using 6921 products from a large Chinese e-commerce platform in 2021, the authors exploit merchants' staggered adoption of a platform-standard AI chatbot to run a difference-in-differences (DID) analysis, with extensive fixed effects and Coarsened Exact Matching (CEM) to improve causal identification.

Another Study about "Artificial Intelligence Tools for Enhancing Customer Experience" by (Sujata, Aniket, & Mahasingh, 2019) addresses the challenge of customer retention and acquisition by improving customer experience using Artificial Intelligence (AI) tools. It proposes a conceptual model for how AI tools enhance customer experience through personalization, service quality, and hassle-free service, Implications are offered for practitioners, managers, academicians, and society to better understand and develop AI-driven customer engagement. Also the Study of intituled "The potential of Data-Driven Virtual Assistants to enhance Customer Experience in the Telecommunications Industry" by (Garcia, 2018) examine how artificial intelligence, especially virtual assistants and conversational agents, can improve customer experience, with one focused case in telecommunications and one broader literature review, Garcia's study explores how telecommunications firms can use data-driven virtual assistants (VAs), built on AI and Big Data, to improve how customers manage their telecom services.

The work is motivated by the contrast between people's everyday use of Siri/Google Assistant for simple tasks and their continued reliance on traditional channels (calls, shops) when dealing with service providers, which often produces poor customer experience and low satisfaction.

Previous studies have consistently shown that Artificial Intelligence plays a significant role in enhancing customer experience. Most researchers emphasize its impact on service quality, personalization, and responsiveness.

On the other hand, the researchers' paper (Gacanin & Wagner, 2019) discusses the role of artificial intelligence in enhancing customer experience management (CEM) in 5G and future networks. It argues that traditional rule-based network management is inadequate for managing dynamic traffic demands, necessitating a shift towards AI-driven decision-making for optimal CEM. To effectively enhance customer experience, CEM must integrate both network quality-of-service (QoS) and subjective quality-of-experience (QoE) metrics. The paper also outlines key future research areas, including service orchestration, standardized data collection across vendors, deeper QoS-QoE insights at radio access, and the application of AI/ML for proactive CEM and root-cause analysis.

However, these studies have primarily examined customer experience as a single construct, without addressing its multidimensional nature. In addition, limited research has explored the direct relationship between AI tools and the specific dimensions of customer experience.

Hypotheses Development and Theoretical Framework

Previous studies have highlighted the significant role of Artificial Intelligence tools in enhancing organizational performance and customer-related outcomes, such as service quality, responsiveness, and personalization. These improvements are closely associated with better customer experience.

However, most prior research has treated customer experience as a single construct and has not examined its multidimensional nature. In particular, limited attention has been given to how AI tools influence the different dimensions of customer experience.

Based on this reasoning, it is expected that AI tools contribute positively to customer experience improvement.

H1: Artificial Intelligence tools have a positive effect on Customer Experience Improvement.

Customer experience is a multidimensional construct that includes several dimensions such as emotional, cognitive, physical, and relational aspects. Since AI tools enhance interaction, personalization, and service efficiency, their impact is expected to extend to these different dimensions.

AI tools contribute to the cognitive dimension by providing accurate, relevant, and timely information, helping customers make better decisions.

H1a: Artificial Intelligence tools have a positive effect on the cognitive dimension of customer experience.

AI tools can improve the emotional dimension of customer experience by providing personalized interactions and quick responses, which enhance customer satisfaction and positive feelings.

H1b: Artificial Intelligence tools have a positive effect on the emotional dimension of customer experience.

AI tools enhance the pragmatic dimension by facilitating smoother and more efficient interactions during the service process.

H1c: Artificial Intelligence tools have a positive effect on the pragmatic dimension of customer experience.

AI tools support the relational dimension by enabling continuous interaction and engagement between the customer and the organization.

H1d: Artificial Intelligence tools have a positive effect on the relational dimension of customer experience.

Based on the prior cognitive efforts surrounding the research topic, and following the theoretical foundation established for the study variables (AI tools and customer experience), as well as the nature of the proposed research problem, the following framework is proposed.

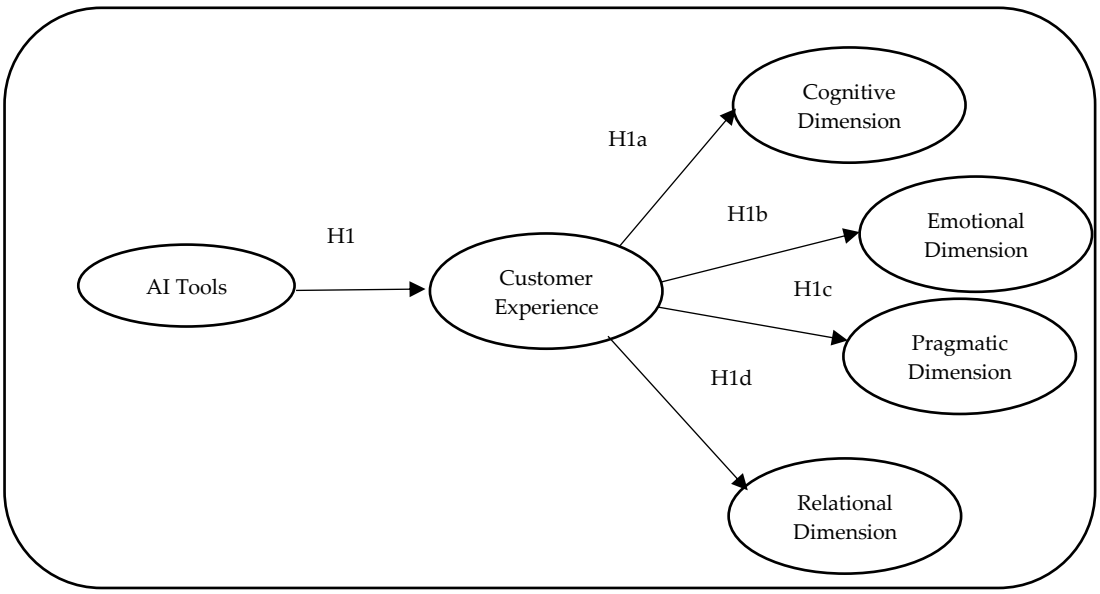

Figure 1. The theoretical Framework
Source: Prepared by Researchers.

Figure 1 presents the conceptual model with hypotheses (H1–H1d) linking AI Tools to Customer Experience and its dimensions (Cognitive, Emotional, Pragmatic, Relational).

Methodological procedures for the field study

This section addresses the procedures employed to determine the appropriate sample size and sampling technique, the primary data collection instrument and its distribution method, in addition to the statistical techniques applied to test the hypotheses under investigation. The study is grounded in a hypothetico-deductive approach, whereby hypotheses are developed based on theoretical foundations and subsequently tested empirically.

Sample and Study Tool

The empirical component of the study focuses on the Mobilis firm, which maintains a strong online presence and engages in marketing across various social media platforms. Given that the research variables—namely, AI adoption and customer experience—are qualitative in nature, an electronic questionnaire was selected as the primary instrument for data collection. This survey targeted Algerian consumers located throughout the national territory. A total sample of 350 respondents was successfully obtained between September 9, 2025, and October 12, 2025. A random sampling technique was deemed the most appropriate given the exploratory nature and the target population of the study.

As for the design of the questionnaire (in which we relied on the five-point Likart scale), it contained three main parts, one related to descriptive data (gender/educational level), A second part relates to the items of the artificial intelligence tools variable, the construction of which we relied on studying each of (Chiara, Alessandra , & Alfonso , 2022; Tran, Pallant, J. I, & L. W, 2021; Yin, J, 2025), A third part revolved around the customer experience variable, which was measured in four dimensions, the items of which were built based on a study (Cachero-Martínez & Vázquez-Casielles, 2017; Gahler, Klein, & Paul, 2023).

Statistical Methods Used

Descriptive statistical techniques, including measures of central tendency (mean) and dispersion (standard deviation), were employed to analyze the general trends and variability in the participants' responses to the questionnaire items. To evaluate the study's hypotheses and validate the proposed conceptual model, the Partial Least Squares Structural Equation Modeling (PLS-SEM) method was adopted. PLS-SEM serves as a suitable alternative under the following conditions (Kwong & Wong, 2013, p. 3):

- When the assumptions of multivariate normal distribution are not met;
- In cases involving small sample sizes (fewer than 100 participants);
- When the theoretical framework is underdeveloped, and uncertainty exists concerning model specification or variable relationships.

Most of these criteria are consistent with the characteristics of the present study, with the exception of the sample size, which exceeded the 100-participant threshold.

Presentation and Analysis of Study Results and Testing of Hypotheses

The first section of this chapter presents and analyzes the descriptive results of the study to identify patterns in the responses of the research sample, along with a profile of the demographic and contextual characteristics of the respondents. The second section details the results of structural equation modeling using the Partial Least Squares method to validate the study's hypothetical model and examine the statistical significance of the proposed hypotheses.

Presentation and Analysis of Study Results

This section is dedicated to describing the characteristics of the study sample using frequency distributions and percentage breakdowns. It further analyzes response trends through descriptive statistics (mean and standard deviation), thereby providing insight into how participants responded to various questionnaire items and dimensions.

Table 2. Descriptive characteristics of the study sample

Descriptive characteristics		Repetitions	Percentages(%)
Sex	male	183	52.3
	female	167	47.7
Educational level	PhD	84	24
	university level	217	62
	secondary level	49	14

Source: SmartPLS4 outputs.

Looking at the previous table, the following observations can be made:

- The majority of respondents were male (183), representing 52.3% of the total sample, while the remainder were female. These relatively similar percentages suggest that Mobilis provides competitive advantages to a diverse customer base—including business owners, students, and university graduates. Furthermore, the company demonstrates a strong ability to provide network coverage even in rural areas, which leads consumers to prefer Mobilis over competitors such as Ooredoo and Djezzy.

- A significant proportion of respondents (62%) held a university degree, followed by 24% holding postgraduate qualifications and only 14% having a secondary education level. This distribution confirms that the majority of participants belong to the educated demographic. It is likely that they are self-employed or employed by prominent companies, which often provide Mobilis SIM cards due to the exceptional service offers and reliable network coverage that the company is known for.

Table 3. Trends in the responses of the study sample

	N	Minimum value	Maximum value	Mean	STDV
AI Tools					
AI 1	350	2.0	4.0	3,450	0,613
AI2	350	2.0	4.0	3,415	0,655
AI 3	350	2.0	4.0	3,608	0,562
AI 4	350	2.0	4.0	3,444	0,628
AI 5	350	2.0	4.0	3,585	0,582
Cognitive Dimens					
CD1	350	2.0	4.0	3,450	0,586
CD2	350	2.0	4.0	3,717	0,535
CD3	350	2.0	4.0	3,421	0,616
Emotional Dimens					
ED1	350	2.0	4.0	3,640	0,555
ED2	350	2.0	4.0	3,633	0,545
ED3	350	2.0	4.0	3,540	0,598
ED4	350	2.0	4.0	3,508	0,620
Pragmatic Dimens					
PRD1	350	2.0	4.0	3,521	0,549
PRD2	350	2.0	4.0	3,524	0,554
PRD3	350	2.0	4.0	3,441	0,580
PRD4	350	2.0	4.0	3,688	0,516
Relational Dimens					
RD1	350	2.0	4.0	3,479	0,665
RD2	350	2.0	4.0	3,514	0,605
RD3	350	2.0	4.0	3,402	0,643

Source: Smartpls4 outputs.

Based on the results presented in **Table 2**, the following conclusions can be drawn:

- Regarding the items associated with the variable AI Tools, the data reveals that respondents largely expressed agreement. This is evidenced by the arithmetic mean values, which ranged between 3.444 and 3.585—falling within the agreement category.

- Similarly, for the items and dimensions related to the variable Customer Experience, most participants also tended to agree. The mean scores ranged from 3.373 to 3.688, indicating that participants positively perceived the questions and constructs within this variable.

- The standard deviation values across all items are relatively low, indicating that the responses were not widely dispersed. Instead, the sample's answers were concentrated around similar values. This can be attributed to the demographic composition of the sample, as most respondents are university graduates or postgraduates. Their advanced educational backgrounds likely contribute to their awareness and understanding of the company's initiatives aimed at customer satisfaction.

- The high levels of agreement among respondents confirm the presence of well-established study variables within the enterprise under investigation. Consequently, the following hypotheses are supported:

- The level of adoption of AI systems in the Mobilis enterprise, from the perspective of Algerian consumers, is high (achieved).
- The level of customer experience with the services and products offered by the enterprise is high, as perceived by Algerian consumers (achieved).

Structural equation modeling using partial least squares (PLS-SEM)

Following the presentation of the general characteristics of the study sample and the identification of trends in the respondents' answers to the questionnaire items and dimensions, the analysis proceeds to a crucial stage—structural equation modeling. This stage is vital as it tests the hypothetical model and the research hypotheses developed in response to the study problem. The testing process is conducted sequentially, beginning with convergent validity, followed by discriminant validity, and culminating in the extraction of the structural equation modeling results.

Convergent Validity Test

The convergent validity test evaluates the degree to which the measured indicators are consistent and compatible with the latent constructs they are intended to represent within the measurement model. The results of the convergent validity test are summarized in the following table:

Table 4. Convergent validity test results

Latent Variables	Measured indicators	Loading	Cronbach's alpha	CR	AVE	VIF
AI	AI1	0.714				1,796
	AI2	0.659				1,718
	AI 3	0.773	0.774	0.846	0.524	1,574
	AI 4	0 .708				1,458
	AI 5	0.761				1,607
CusExp	CD1	0.846				1,416
	CD2	0.664				1,939
	CD3	0.793				1,199
	ED1	0.822	0.909	0.924	0.505	1,343
	ED2	0.863				1,711
	ED3	0.885				2,110
	ED4	0.857				1,903
	PRD1	0.806				2,308
	PRD2	0.875				2,575

PRD3	0.790	2,626
PRD4	0.720	2,870
RD1	0.801	2,242
RD2	0.846	2,627
RD3	0.735	2,205

Source : Smartpls4 outputs.

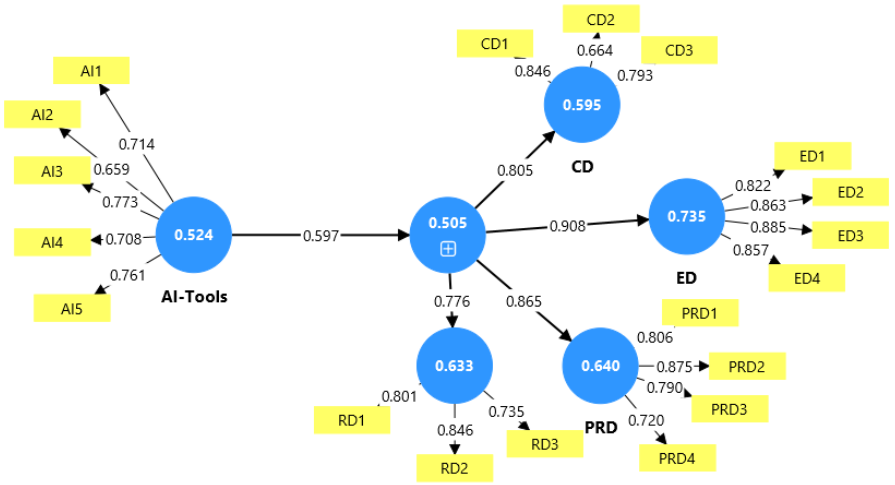

Figure 2. Convergent validity test results
Source: Smartpls4 outputs.

Upon reviewing the table and the figure above, the following observations can be made:

- Regarding the loading values, it is observed that most indicators exceed the acceptable threshold of 0.7. The only exceptions are two items—AI2 (0.659) and CD2 (0.664)—which fall slightly below the threshold but remain within an acceptable range for exploratory research.
- Cronbach's Alpha values are satisfactory, measuring 0.774 for the AI Tools variable and 0.909 for the Customer Experience variable, indicating a high degree of internal consistency.
- The composite reliability (CR) values are well above the recommended threshold of 0.7, confirming strong internal consistency across the indicators for both latent variables.
- The average variance extracted (AVE) for the AI Tools variable is 0.524, for the Customer Experience variable is 0.505 which meets the standard criterion of exceeding 0.5.
- All variance inflation factor (VIF) values are below 5, confirming the absence of multicollinearity among the indicators.

Based on these findings, the study tool and measurement model exhibit acceptable levels of reliability and construct validity. As such, it was determined that no indicator needed to be removed, including those with loading values below 0.7, as their presence did not adversely impact the reliability or AVE scores.

Discriminant Validity Test

Discriminant validity assesses the extent to which each indicator distinctly represents the latent variable it is associated with, rather than overlapping with other latent constructs. It ensures that the dimensions and indicators included in the measurement model are uniquely identified and conceptually independent. The following table presents the cross-loadings used to evaluate discriminant validity.

Table 5. Results of the discriminant validity test (cross loadings)

	AI-Tools	CD	CX	ED	PRD	RD
AI1	**0,714**	0,387	0,398	0,380	0,319	0,257
AI2	**0,659**	0,292	0,338	0,306	0,277	0,264
AI3	**0,773**	0,456	0,461	0,438	0,387	0,299
AI4	**0,708**	0,421	0,452	0,384	0,415	0,316
AI5	**0,761**	0,431	0,489	0,452	0,441	0,311
CD1	0,481	**0,846**	0,720	0,630	0,577	0,417
CD2	0,384	**0,664**	0,479	0,476	0,378	0,364
CD3	0,417	**0,793**	0,637	0,561	0,465	0,351
ED1	0,481	0,605	0,756	**0,822**	0,576	0,511
ED2	0,463	0,592	0,771	**0,863**	0,548	0,490
ED3	0,477	0,625	0,794	**0,885**	0,592	0,481
ED4	0,454	0,663	0,791	**0,857**	0,580	0,496
PRD1	0,485	0,596	0,752	0,591	**0,806**	0,495
PRD2	0,437	0,508	0,729	0,516	**0,875**	0,572
PRD3	0,397	0,421	0,693	0,534	**0,790**	0,551
PRD4	0,312	0,461	0,577	0,498	**0,720**	0,456
RD1	0,296	0,353	0,593	0,434	0,487	**0,801**
RD2	0,398	0,487	0,711	0,545	0,583	**0,846**
RD3	0,246	0,301	0,530	0,378	0,471	**0,735**

Source : Smartpls4 outputs.

From the above table, it is evident that each measured indicator has its highest loading on the latent variable it is intended to measure. For instance, the indicator "AI1" loads 0.714 on the AI Tools variable, compared to only 0.398 on the Customer Experience variable. Similar patterns are observed across all other indicators, confirming that the constructs are empirically distinct and that each item exhibits stronger affiliation with its respective latent variable than with others.

This confirms that the measurement model meets the requirement for discriminant validity. In the next stage, we proceed to examine linear overlap, the results of which are presented in the following table.

Table 6. Fornell and Larcker test

	AI- Tools Variable	Cog-Dim	CusExp Variable	Emot-Dim	PR-Dim	Relational-Dim
AI-Tools Variable	**0,724**					
Cog-Dim	0,555	**0,772**				
CusExp Variable	0,597	0,711	**0,805**			
Emot-Dim	0,547	0,725	0,857	**0,908**		
PR-Dim	0,515	0,623	0,800	0,670	**0,865**	
Relational-Dim	0,401	0,487	0,776	0,577	0,650	**0,795**

Source : Smartpls4 outputs.

The table above demonstrates that the correlation values between each variable and itself are the highest. For instance, the AI Tools variable correlates with itself at a value of 0.724, while its correlation with the Customer Experience variable is 0.597. Similar patterns are observed across the remaining variables and their indicators, indicating that the constructs are distinct from one another and that there is no significant linear overlap among them.

Structural equation modeling (PLS-SEM) results

After completing the convergent and discriminant validity assessments and confirming the accuracy of the measurement model, the following figure illustrates the proposed structural model, displaying the factor loadings between the latent variables and their respective observed indicators.

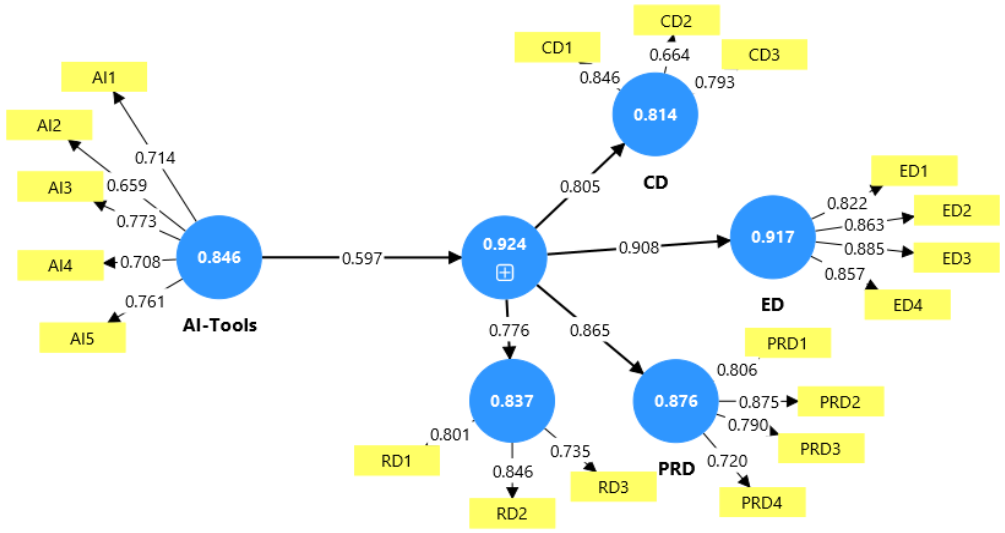

Figure 3. PLS-SEM results for the study model
Source: Smartpls4 outputs.

The figure above confirms that the proposed structural model is suitable for estimating the relationships between variables and for testing the research hypotheses. Both the measurement model and the structural model are validated, with all factor loadings exceeding the threshold of 0.7, except for the previously mentioned items which were retained as their exclusion was not warranted based on the reliability results.

More detailed insight into the model's predictive accuracy is presented in the following table:

Table 7. Predictive accuracy results for the study model

	R^2	R^2adjusted	F^2	Q^2
Cog-Dim	0.649	0.648	///	0.297
CusExp Variable	0.356	0.355	0.554	0.349
Emot-Dim	0.825	0.824	///	0.292
PR-Dim	0.749	0.748	///	0.260
Relational-Dim	0.603	0.601	///	0.151

Source: Smartpls4 outputs.

Key observations from **Table 7** include the following:

- The coefficient of determination (R^2) for the Customer Experience variable is 0.356, indicating that 35.6% of the variation in Customer Experience can be attributed to the AI Tools variable. The remaining 64.4% is explained by other factors not included in the model or by random error. This level of explained variance is considered acceptable within the context of human and administrative sciences, where numerous external factors often influence outcomes.
- The effect size of AI Tools on Customer Experience is measured at 0.554, signifying a strong and meaningful impact between the variables under investigation.
- The predictive relevance (Q^2) values for the Customer Experience variable are greater than zero, which supports the predictive capability and relevance of the proposed structural model.

The following table presents the direct path coefficients for the study hypotheses:

Table 8. Direct path coefficients for the study hypotheses

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI- Tools Variable -> CusExp Variable	0,599	0,599	0,041	14,729	0,000
AI –Tools Variable -> Cog-Dim	0,823	0,823	0,022	36,739	0,000
AI –Tools Variable -> Emot-Dim	0,904	0,905	0,011	84,192	0,000
AI –Tools Variable -> PR-Dim	0,877	0,877	0,018	48,709	0,000
AI –Tools Variable -> Relational-Dim	0,771	0,771	0,032	24,558	0,000

Source: Smartpls4 outputs.

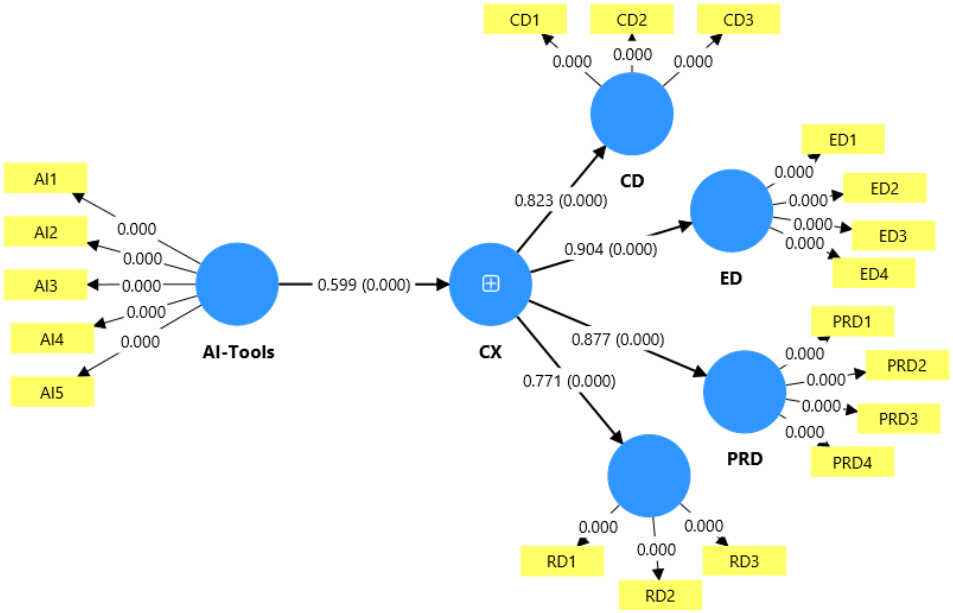

Figure 4. Direct path coefficients for the study hypotheses
Source: Smartpls4 outputs.

These results support the confirmation of all direct effect hypotheses, as each p-value equals 0.000, which is below the standard significance threshold of 0.05. Accordingly, the following conclusions are drawn:

H1: The AI tools have a positive effect on Customer Experience (Achieved).

H1a: The AI tools have a positive effect on Cognitive Dimension (Achieved).

H1b: The AI tools have a positive effect on Emotional Dimension (Achieved).

H1c: The AI tools have a positive effect on Pragmatic Dimension (Achieved).

H1d: The AI tools have a positive effect on Relational Dimension (Achieved).

RESULTS AND DISCUSSION

This study provides empirical evidence on the growing role of Artificial Intelligence (AI) in enhancing customer experience within the telecommunications sector, with a particular focus on Mobilis. The findings indicate that AI adoption is perceived at a high level by Algerian consumers, reflecting the increasing reliance on intelligent technologies in service delivery. In parallel, customers reported a high level of overall experience, suggesting that AI-enabled services are effectively meeting their expectations.

The statistical analysis further reveals that AI tools exert a significant positive influence on overall customer experience. This implies that the integration of AI applications contributes to improving customer interactions through greater efficiency, personalization, and responsiveness. Such results are consistent with prior research,

including the work of H. Gacanin and M. Wagner (2019), who emphasized the importance of AI-driven solutions in optimizing customer experience management in advanced network environments.

At the dimensional level, the results demonstrate that AI has a meaningful and statistically significant impact across all components of customer experience. In terms of the cognitive dimension, AI appears to facilitate better access to information and enhances customers' ability to evaluate services effectively, which supports the findings of M. P. Garcia (2018) regarding the role of intelligent virtual assistants in improving informational interactions.

Regarding the emotional dimension, the results suggest that AI contributes to more engaging and satisfying customer experiences, likely due to increased responsiveness and personalized communication. This observation aligns with the conclusions reported by J. Sujata et al. (2019), who highlighted the role of AI tools in strengthening emotional engagement.

In addition, the pragmatic dimension is positively influenced by AI adoption, indicating improvements in service usability, efficiency, and convenience. This finding is consistent with the study conducted by B. Shuyuan et al. (2026), which demonstrated that AI-powered systems enhance functional value and reduce customer effort in digital environments.

Finally, the relational dimension also shows a significant positive relationship with AI, suggesting that intelligent technologies contribute to building stronger and more sustainable relationships between customers and the enterprise. This highlights the broader strategic value of AI, not only as a tool for operational improvement but also as a driver of long-term customer engagement.

Overall, these findings confirm that AI adoption plays a comprehensive role in shaping customer experience across multiple dimensions. Moreover, this study extends the existing literature by providing empirical insights from the Algerian context, which remains relatively underexplored, thereby offering valuable implications for both researchers and practitioners.

CONCLUSION AND RECOMMENDATIONS

This study demonstrates that Artificial Intelligence plays a comprehensive and strategic role in enhancing customer experience across multiple dimensions. The findings highlight the importance of integrating AI technologies into service delivery systems to improve both functional and relational aspects of customer interactions.

Based on these results, it is recommended that organizations prioritize investment in digital transformation strategies through the adoption of advanced technologies such as Artificial Intelligence, the Internet of Things (IoT), and blockchain. These technologies can enhance transparency, speed, and accuracy in operational and logistical management. Furthermore, it is recommended to focus on deeply understanding customers' perceptions of value and to formally integrate customer satisfaction as a strategic performance indicator to guide continuous improvement initiatives.

Theoretical and Practical contributions (Added Value of the Study)

This study offers significant added value by providing an integrated perspective on the role of artificial intelligence tools in enhancing customer experience within the telecommunications sector. Unlike previous research that often examines these relationships in isolation or within developed economies, this study contextualizes the analysis within the Algerian market, thereby enriching the empirical understanding of AI adoption in emerging economies. Moreover, the study moves beyond a general assessment of customer experience by decomposing it into multiple dimensions—cognitive, emotional, pragmatic, and relational—allowing for a more nuanced and in-depth evaluation of how AI tools influence customer perceptions and interactions. The findings also generate actionable insights for decision-makers by linking technological adoption with practical improvements in service delivery and customer engagement. Consequently, this research bridges the gap between theory and practice, contributing both to academic discourse and to the development of more effective, AI-driven

business strategies.

Limitations

This study is limited spatially to Mobilis customers in Algeria and methodologically to survey data and PLS-SEM. Therefore, findings cannot be generalized to all Algerian companies.

Future Research Directions

Future research directions include the following:

- Test and validate models linking AI tools to customer experience improvements.
- Study AI adoption in specific sectors, such as retail, banking, and healthcare.
- Examine how customer trust and privacy concerns affect AI interactions.
- Explore combining AI tools with human service to balance efficiency and personal engagement.

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Conflict of interest

The authors declared no potential conflict of interest concerning this article's research, authorship, and/or publication.

REFERENCES

Abu Daqar, M., & Smoudy, A. (2019). The Role of Artificial Intelligence on Enhancing Customer Experience. International Review of Management and Marketing, 9(4), 22-31.

Agrawal, G. (2025). Redefining CX with Agentic AI: Minerva CQ Case Study. arXiv. doi:https://arxiv.org/abs/2509.12589

Ali , E., Mahmoud , E., & Narjes , E. (Éds.). (2024, 12 30). Analyzing the Relationship Between Artificial Intelligence and Customer Experience Improvement in the Online Retail Industry . Digital Transformation and Administration Innovation , 02(04), 73–81. doi:10.61838/dtai.2.4.9

Amitabh, A. (2025). Leveraging AI to Optimize Customer Experience. Journal of Information Systems Engineering and Management, 05(39), 245-251. Retrieved from https://jisem-journal.com/index.php/journal/article/view/7147

Bharadiya, J., Thomas, R., & Farhan , A. (2023, 06 05). Rise of Artificial Intelligence in Business and Industry. Journal of Engineering Research and Reports, 25(03), 85-103. doi:10.9734/JERR/2023/v25i3893

Bujor, D., & Bogdan Ene, A. (2025, 11 04). AI-Driven Predictive Customer Analytics for Forecasting Behavior, Churn and Future Buying Patterns. Conference: Proceedings of the International Conference on Business Excellence. Romania. Retrieved from https://www.researchgate.net/publication/394275375_AI-Driven_Predictive_Customer_Analytics_for_Forecasting_Behavior_Churn_and_Future_Buying_Patterns

Cachero-Martínez, S., & Vázquez-Casielles, R. (2017). Stimulating Curiosity and Consumer Experience in a Retailer. American Journal of Industrial and Business Management(7), pp. 473-486. doi:https://doi.org/10.4236/ajibm.2017.74034

Chiara, L., Alessandra , N., & Alfonso , V. (2022). Artificial intelligence in customer relationship management: Literature

review and future research directions. Journal of Business & Industrial Marketing, 37(13), 48–63. doi:https://doi.org/10.1108/JBIM%E2%80%9107%E2%80%912021%E2%80%910332

Da Silva, E. (2021). Customer Experience Project: A Framework to Create and Deliver Value to Customers. International Journal of Marketing Studies, 13(3), 21-32.

Dezao, t. (2024, 09 13). Enhancing Transparency in AI-Powered Customer Engagement. Journal of AI, Robotics & Workplace Automation, 05(03), 134-141.

Gacanin, H., & Wagner, M. (2019). Artificial Intelligence Paradigm for Customer Experience Management in Next-Generation Networks: Challenges and Perspectives. IEEE Network, 33(2), 188-194.

Gahler, M., Klein, J., & Paul, M. (2023). Customer Experience: Conceptualization, Measurement, and Application in Omnichannel Environments. Journal of Service Research, 26(2), 191–211.

Gahler, M., Klein, J., & Paul, M. (2023). Customer Experience: Conceptualization, Measurement, and Application in Omnichannel Environments. Journal of Service Research, 26(2), pp. 191-211. doi:DOI: 10.1177/10946705221126590

Garcia, M. P. (2018). The potential of Data-Driven Virtual Assistants to enhance Customer Experience in the Telecommunications Industry. Human Factors in Design, 7(13), 61-72.

Gooljar, V, Issa, T, Hardin-Ramanan, S, & Abu-Salih, B. (2024, 08). Sentiment-based predictive models for online purchases in the era of marketing. Journal of Big Data, 11(107). doi:https://doi.org/10.1186/s40537-024-00947-0

Hasan, A., Darna, N., & Yulia, L. (2025). The Influence of Customer Value and Customer Experience on Customer Loyalty at Soya Drink Ciamis. Journal of Economics Review, 5(2), 80-93.

Kathrin , G., & Alexandre , A. (2024, 09 16). Transportation Research Part C. ELSEVIER, 14, 1-30.

Kwong, K., & Wong, K. (2013). Partial Least Squares Structural Equation Modeling (PLS-SEM) Techniques Using SmartPLS. Marketing Bulletin, 24(1), 1-32.

OECD. (2019). Artificial Intelligence in Society. PARIS: OECD Publishing. Retrieved from https://doi.org/10.1787/eedfee77-en

Prakash, D., & Padmakar, S. (2024). Customer Experience Measurement: A critical review of literature. RGSA – Revista de Gestão Social e Ambiental, 18(8), pp. 1-13. doi:https://doi.org/10.24857/rgsa.v18n8-041

Rini , A. (2024, 10 28). journal of social science, 282-295. doi:10.59613/akx6j040

Scibor-Rylski, M., Reducha, M., & Ochremiak, J. (2019). Modern Reseach Methods In The Field Of Customer Experience. Journal of markiting and markt studies(XXVI). doi:DOI 10.33226/1231-7853.2019.10.2

Shuyuan , B., Wang , X., & Xia, J. (2026). AI-Powered Customer Service in Online Retail: Product-Type Differences, Information Asymmetry, and Seller Interventions. Journal of Theoretical and Applied Electronic Commerce Research, 1-27.

Sujata, J., Aniket, D., & Mahasingh, M. (2019). Artificial Intelligence Tools for Enhancing Customer Experience. International Journal of Recent Technology and Engineering, 8(2S3), 700-706.

Tran, A. D., Pallant, J. I, & Johnson, L. W. (2021, 11 30). Exploring the impact of chatbots on consumer sentiment and expectations in retail. Journal of Retailing and Consumer Services, 63(102718), 5. doi:https://doi.org/10.1016/j.jretconser.2021.102718

Yin, J. (2025, 01 24). The Impact of AI-Personalized Recommendations on Consumer Experience. Electronic Commerce Research, 20(01). doi:https://doi.org/10.3390/0718-1876/20/1/21