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A New Concept of Transforming Service: Impact of Generative Voice Chatbots on Customer Satisfaction and Banking Industry Productivity

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Abstract

This study examines the impact of implementing generative AI voice chatbots on customer expectations and satisfaction in the banking sectors of Kazakhstan, Russia, and Italy. To achieve this objective, this study conducted a survey of 253 customers from 35 commercial banks in Kazakhstan, Russia, and Italy from November 2023 to early April 2024. This study employed partial least squares structural equation modelling (PLS-SEM) to assess and validate the validity and reliability of the research model. The study integrates the Expectation Confirmation Model with AI components to analyze factors influencing customer satisfaction with AI-enabled digital banking services. Key findings indicate that expectation confirmation, perceived performance, visual attractiveness, problem-solving capabilities, and communication quality significantly affect customer satisfaction with AI chatbots. However, trendiness and customization features showed minimal impact. The research also explores how customer satisfaction and corporate reputation influence chatbot adoption. Additionally, the study investigates the relationship between chatbot adoption and productivity performance in banking operations. The study provides several policy recommendations, including enhancing perceived performance, expectation confirmation, communication quality, visual attractiveness, and corporate reputation, which can improve customer satisfaction and increase confidence in generative AI voice chatbots in the digital banking industry.

Keywords:

Generative Voice Chatbots;

Banks; Artificial Intelligence;

Productivity; Customer Satisfaction;

Bank Performance; Customer Expectation; Customer Focus;

Distant Bank Customer Support Service.

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1- Introduction

The global banking industry is experiencing a significant shift towards digitalization driven by rapid technological advancements and changing customer expectations. According to a 2021 survey of financial market participants, the most promising technologies for the digitalization of banking services include smartphone and tablet technology (73%

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of respondents), open APIs (64%), machine learning and AI (64%), cloud-based technologies (58%), and chatbots (54%) [1]. This digital transformation has been particularly evident in the rise of artificial intelligence (AI) and chatbots in financial services.

The introduction of generative AI (Gen AI) has unleashed opportunities in many industries, including banking. Generative AI (Gen AI) refers to artificial intelligence systems that can create new content, including text, images, or audio, based on patterns learned from existing data. Gen. AI chatbots can generate human-like responses to customer inquiries, adapt to various scenarios, and provide personalized assistance. Voice generative AI, a subset of this technology, focuses specifically on creating human-like speech. When applied to banking chatbots, voice-Gen AI enables natural conversational interactions between customers and AI systems, potentially enhancing the user experience by mimicking human-to-human communication. These advanced AI technologies represent a significant leap forward in digital banking capabilities, offering more sophisticated and interactive customer service solutions [2].

The adoption of AI in banking varies by country. In Kazakhstan, more than 30% of financial market stakeholders use AI in their activities, with banks being the most active in introducing AI [2]. Kazakhstan's financial institutions are transforming rapidly into information technology enterprises. Russia, with its already competitive banking and financial system, has an advanced technological infrastructure [3]. In 2024, almost 70% of the top 30 banks in Russia are using chatbots with different extents of automation. Italy, traditionally served by an established banking industry, has gradually but steadily converted into a digital form [4]. For instance, in May 2023, Intesa San Paolo announced the implementation of a series of artificial intelligence tools, including the Lisa project for analyzing Banking Supervision publications [5].

Despite the growing adoption of AI-driven chatbots in digital banking systems, significant challenges remain regarding their integration and implementation. Banks face technical hurdles in seamlessly incorporating advanced technologies into their existing infrastructure. Moreover, there is a notable gap in the understanding of customer expectations and satisfaction with AI chatbots in banking. As these technologies become more prevalent, it is crucial to assess how they align with customer needs and preferences, especially considering the diverse economic and cultural contexts of countries such as Kazakhstan, Russia, and Italy.

The adoption of AI chatbots in banking has significant economic implications. For example, VTB, a Russian bank, has saved 2.5 billion RUB in 2023 by cutting labor costs through the implementation of AI [6]. Beyond cost savings, AI chatbots have the potential to significantly enhance the customer experience and operational efficiency. The importance of customer satisfaction in digital banking cannot be overstated, as it directly impacts customer loyalty and, consequently, a bank's bottom line. Furthermore, the integration of AI into banking services has socially significant implications, such as improving customers' financial literacy and making banking services more accessible to a broader customer base [7].

Previous studies of AI in banking have explored various aspects of this technology. For instance, Kasilingam [8] investigated the attitude and intention to use smartphone chatbots for shopping, whereas Huang et al. [9] examined whether chatbot customer service can match human service agents in terms of customer satisfaction [9]. Theoretical frameworks, such as the Expectation Confirmation Theory, have been widely used to assess consumer satisfaction when utilizing Internet technologies [10]. However, there remains a significant gap in the literature regarding the comprehensive impact of AI-driven chatbots on customer satisfaction and adoption in the banking sector, particularly in the context of diverse economies, such as Kazakhstan, Russia, and Italy.

The primary aim of this study is to analyze how introducing generative AI (Gen. AI) voice chatbots into bank systems can shape attitudes towards customer expectations and satisfaction in Kazakhstan, Russia, and Italy. This research examines the factors influencing customer satisfaction with AI-enabled digital banking, investigates the relationship between customer satisfaction and adoption of AI-enabled banking, and assesses the impact of AI-driven banking on productivity performance. By focusing on these unique economic and technological ecosystems, this study aimed to provide valuable insights into the varying impacts of AI chatbot implementation across different cultural and economic contexts.

This study makes several important contributions to both theory and practice. From a theoretical perspective, it integrates the expectation-confirmation model with AI components to examine customer satisfaction with chatbots in AI-enabled digital banking. This integration enhances the existing knowledge on the subject and provides a more comprehensive framework for understanding customer behavior in the context of AI-driven banking services. This study's focus on three distinct countries—Kazakhstan, Russia, and Italy—offers a unique comparative perspective that can enrich our understanding of how cultural and economic factors influence AI adoption and customer satisfaction in banking.

From a practical standpoint, this study provides valuable insights for banks considering the implementation of AI-driven chatbots. This offers guidance on how to enhance customer satisfaction and increase the adoption of AI-enabled banking services, which can lead to improved operational efficiency and customer loyalty. The findings of this study can inform strategic decision-making in banks, helping them tailor their AI implementations to better meet customer expectations and improve overall service quality.

The remainder of this paper is organized as follows. The second section discusses the theory and literature review, as well as the development of hypotheses and a conceptual model for the research. Section 3 provides a detailed description of the methods employed in this study. In Section 4, an analysis of the results and discussion is presented. Finally, Section 5 concludes the paper by discussing the research implications, limitations, and future research prospects.

2- Literature Reviews and Hypothesis Development

A review of contemporary literature reveals a significant upsurge in research focused on conversational agents, particularly in the wake of the widespread adoption of generative artificial intelligence technologies. This burgeoning body of scholarship has identified numerous rationales for chatbot implementation in various domains. Upon critical analysis, these motivations can be systematically categorized into three overarching dimensions, each encompassing distinct, yet interrelated aspects of chatbot utility and impact: quality effects, transformational benefits, and economic advantages. These categories encompass a wide range of improvements that organizations can experience when integrating chatbots into their customer service operations.

Quality effects, also referred to as performance effects, have been documented extensively in recent studies. Paluch & Wittkop [11] highlighted the significant impact of chatbots on operator turnover, noting that, by alleviating repetitive tasks, chatbots contribute to higher job satisfaction and reduced burnout among customer service representatives. This aligns with the findings of Borges et al. [12], who observed increased employee engagement and skill development opportunities when operators transitioned to more complex chatbot-supported roles. Furthermore, chatbots have been shown to enhance service accessibility and availability. Hsu & Lin [13] reported that businesses leveraging chatbots across multiple channels, including websites, messaging platforms, and mobile applications, experience improved customer reach and satisfaction. The ability to provide 24/7 support across different time zones, as noted by Tamara et al. [14], contributes to forming an image of an innovative, digitalized brand and fostering customer loyalty.

The transformational benefits of chatbots in customer service operations have emerged as a crucial area of interest in recent literature. A key transformational aspect is the improvement of customer routing and inquiry handling. Priya et al. [15] demonstrated that chatbots significantly enhance the precision and speed of directing customers to appropriate specialized operators, resulting in reduced hold times and improved average handling times (AHT). This efficiency is further supported by chatbots' ability to gather pertinent information before transferring complex inquiries to human operators, as observed by Gamboa-Cruzado et al. [16]. These transformational benefits not only streamline the customer service process but also contribute to a more seamless and satisfying customer experience, potentially leading to increased customer retention and loyalty [17].

The economic benefits of chatbot implementation in customer service have been quantified in several recent studies, providing compelling evidence of their financial viability. A study by Fgaier & Zrubka [18] across major banks revealed that the introduction of chatbots alongside human operators led to a 50-66% reduction in the cost of processing individual customer inquiries. This significant cost reduction translates to substantial long-term savings, with Babatunde Adeyeri [19] estimating an average total economy for customer service expenses of 100-200 thousand USD over a three-year period for large financial institutions. However, it is important to note that these economic benefits are contingent upon certain operational thresholds. Key indicators for positive economic outcomes from chatbot implementation include a minimum of five operators, at least 1000 daily customer inquiries, and a self-service rate of 20% or higher. Together, these findings underscore the importance of strategic implementation and scale for realizing the full economic potential of chatbot technologies in customer service environments.

2-1- Expectation Confirmation (EXC), Satisfaction and Loyalty of Customers

Expectation confirmation theory is widely used to assess consumer satisfaction when utilizing Internet technology [10]. Huang et al. [9] asserted that customer happiness is the fundamental driver of customer loyalty and can be evaluated by examining the confirmation or disconfirmation of customer expectations and service execution. Customer expectation refers to the outcomes and benefits that customers anticipate and obtain when utilizing a certain service [20]. Perceived performance refers to how customers view the service attributes, advantages, and outcomes. Customers initially form expectations regarding AI performance in the banking context, and these expectations are either confirmed or disproven. Customers' expectations of AI-based banking align with their demands and effectively enhance their happiness. However, expectation disconfirmation leads to the development of negative attitudes and behaviors towards chatbots that utilize AI in the banking sector [21]. Positive confirmation enhances perceived performance, leading to increased customer happiness and acceptance of Gen. AI chatbots. Previous research has employed the EXC theory as a conceptual framework to examine how customers' expectations are either confirmed or disconfirmed and how this affects their perception of the usefulness of technology services. This was explored in a study by Alnaser et al. [22]. Thus, the following possibilities are proposed.

H1: Expectation confirmation positively affects the bank customer satisfaction.

H2: Expectation confirmation positively affects the bank customers' perceived performance.

H3: Perceived performance positively affects the bank customer satisfaction.

2-2- AI Features and Customer Satisfaction

Chatbots equipped with AI capabilities such as trend analysis, aesthetic appeal, and problem-solving abilities have enhanced the attractiveness, appeal, and innovation of banking operations. For example, Kaur et al. [23] asserted that customers prefer to utilize fashionable services rather than traditional services. One significant shift in the corporate sector is the diminished significance of salespeople as clients now depend on online systems to enhance their lifestyles. Prior research has demonstrated that chatbots utilizing AI in digital banking effectively cater to consumer needs and modern lifestyles, thereby increasing customer satisfaction [24]. In addition to being trendy, digital financial services should possess qualities that are visually pleasing and captivating [17, 25]. Visual attractiveness refers to the subjective sense of an online interface, characterized by vivid colors, brightness, cleanliness, clarity, creativity, expressiveness, and the ability to capture customers. According to Hariguna & Ruangkanjanases [26], visual appeal in a banking setting can create a sense of arousal and excitement, thereby reducing the likelihood of banking customers moving to another service. Multiple studies have consistently shown that effective visual design has a positive impact on customer happiness and enhances the customer experience. Another crucial component of this technology is its ability to solve problems [19, 27]. Thus, the implementation of chatbots equipped with AI in digital financial services has allowed providers to address client issues effectively, leading to increased levels of customer satisfaction [28]. Therefore, the following theories are proposed.

H4: Trendiness of chatbots with AI positively affects customer satisfaction.

H5: Visual attractiveness of chatbots with AI positively affects customer satisfaction.

H6: Problem-solving of chatbots with AI positively affects customer satisfaction.

It is crucial to measure the needs of e-commerce customers using a single parameter; thus, customization is necessary for e-services [29]. Customization refers to the extent to which an e-service can be adjusted, personalized, and adapted to meet customers' specific needs and preferences. Sachdeva & Dhingra [30] argued that personalization in e-services fosters a strong connection between service providers and clients, leading to increased happiness and loyalty towards the product. Previous research has established that chatbots equipped with AI applications effectively support clients in obtaining personalized services through chat interactions, thereby meeting their requirements [31]. In the context of digital banking, it has been observed that the use of AI in banking includes personalized features that help customers meet their financial needs and improve their satisfaction with digital banking. Effective communication is a crucial aspect of banking systems that utilize AI. The term "communication quality" refers to the extent to which a service agent delivers precise, reliable, efficient, solution-oriented, and time-saving information to clients [32]. Makudza et al. [33] argue that the presence of abundant and pertinent information decreases uncertainty and improves customer satisfaction. Furthermore, research confirms that e-service agents effectively provide information about products and services, cultivate positive relationships, and enhance customer satisfaction with digital banking services. Research has shown that when customers perceive effective communication of satisfactory quality from e-service agents, they are more likely to appreciate and engage in AI-driven digital banking [34]. Based on the aforementioned debate and supported by Naqvi et al. [35], the following assumptions were made.

H7: Customization feature of chatbots with generative AI positively affects customer satisfaction.

H8: The communication quality of chatbots with generative AI positively affects customer satisfaction.

2-3- Corporate Reputation (CR)

Corporate reputation is a crucial factor in e-commerce and has a significant impact on a company's value. Research conducted by Yoganathan & Osburg [36] provides compelling evidence that company reputation has a favorable impact on customer attitude and loyalty, effectively reducing anxiety and uncertainty about digital banking solutions. This study defines CR as a comprehensive assessment made by customers regarding digital banking services, including their interactions with stakeholders, credibility, trustworthiness, reliability, communication activities, and continuous corporate activities with the service provider. Pillai et al. [24] argue that CR is a comprehensive portrayal of a company's services. According to research conducted by Humairoh et al. [37], customers with limited knowledge about e-services tend to depend on the company's reputation. Research has established that a business reputation improves customer satisfaction and increases customer confidence in e-banking. According to Humairoh et al. [37], in the field of AI, it has been established that business reputation positively impacts customer pleasure. Thus, this study expands existing information by examining the causal association between customer pleasure and acceptance of Chatbots with AI in the context of digital banking. Consequently, the following hypothesis was formulated:

H9: Customer satisfaction positively affects customer acceptance of banking with Gen. AI chatbots.

H10: Corporate reputation positively affects customer acceptance of banking with Gen. AI chatbots.

2-4- Impact of Chatbot with AI in Banking Sector on Employee Productivity

Labor productivity in the service sector is quantified by measuring value added. Selwin et al. [38] discovered a direct correlation between innovation output and employee productivity and found that product innovation has a substantial impact on staff productivity. Process innovation has a positive effect on employee productivity. However, the effect of process innovation on productivity surpasses that of product innovation. Innovation has a positive impact on productivity in environments where individuals receive training and are given the authority to engage in creative ideas [39]. Enhancing the quality of creative output in the banking business positively impacts employee satisfaction, leading to increased productivity. The efficient utilization of information technologies enhances labor productivity [40]. Combining artificial technology with innovative activities has the potential to yield greater enhancements in employee productivity than using them alone. This is because technology can only contribute to increased productivity when appropriately utilized in conjunction with other resources [38]. Rezvani et al. [41] elucidated the role of technological advancements in fostering economic growth while also raising concerns about the potential displacement of human workers, as computer algorithms may surpass human capabilities. Al Naqbi et al. [42] contended that the impact of AI on worker displacement can be counterbalanced by its positive influence on productivity, particularly when labor demand is increased through efficient production methods. Chatbots possess the capacity to comprehend intricate and refined human discourse along with their aptitude for natural language processing and voice recognition. This enabled them to engage in empathic, compassionate, and hilarious conversations. In contrast to the prevailing assumptions in macroeconomics and labor economics, which suggest that areas with high labor demand will inevitably see the development of productivity-increasing technologies, the displacement effect can reduce labor demand, decrease wages, and result in fewer job opportunities [43, 44].

Furthermore, Shekshueva & Tatyanin [45] studied the combined impact of AI and chatbots on the competitiveness of commercial banks in Russia, and the results show that there is a positive impact on remote commercial services.

H11: Chatbots with AI-driven banks have a positive effect on productivity performance.

2-5- Proposed Conceptual Model of the Study

Based on a comprehensive literature review and the developed hypotheses, we propose a conceptual model to illustrate the relationships between various factors influencing customer satisfaction, chatbot adoption, and productivity performance in the context of AI-enabled banking services. Figure 1 illustrates the conceptual model.

The model posits that customer satisfaction is a central construct that is influenced by multiple factors. Expectation Confirmation directly affects Perceived Performance (H2) and Customer Satisfaction (H1). Perceived Performance influences Customer Satisfaction (H3). Several chatbot-specific features have been hypothesized to directly affect Customer Satisfaction. These include the Trendiness of Chatbots (H4), Visual Attractiveness (H5), problem-solving capabilities (H6), Customization Features (H7), and Communication Quality (H8). These factors represent various aspects of user experience and interactions with AI chatbots in banking services. The model further proposes that Customer Satisfaction leads to Chatbot Adoption (H9), suggesting that satisfied customers are more likely to embrace and continue to use AI chatbot services. Additionally, Corporate Reputation was hypothesized to have a direct effect on Chatbot Adoption (H10), indicating that a bank's reputation may influence customers' willingness to adopt new technologies. Finally, the model suggests that Chatbot Adoption positively impacts Productivity Performance (H11), implying that successful implementation and adoption of AI chatbots in banking can lead to improved operational efficiency and productivity.

This conceptual model provides a holistic view of the interrelationships between various factors in AI-enabled banking services, from user experience elements to broader organizational impacts. This serves as a framework for our empirical investigation and guides the subsequent analysis of data collected from Kazakhstan, Russia, and Italy.

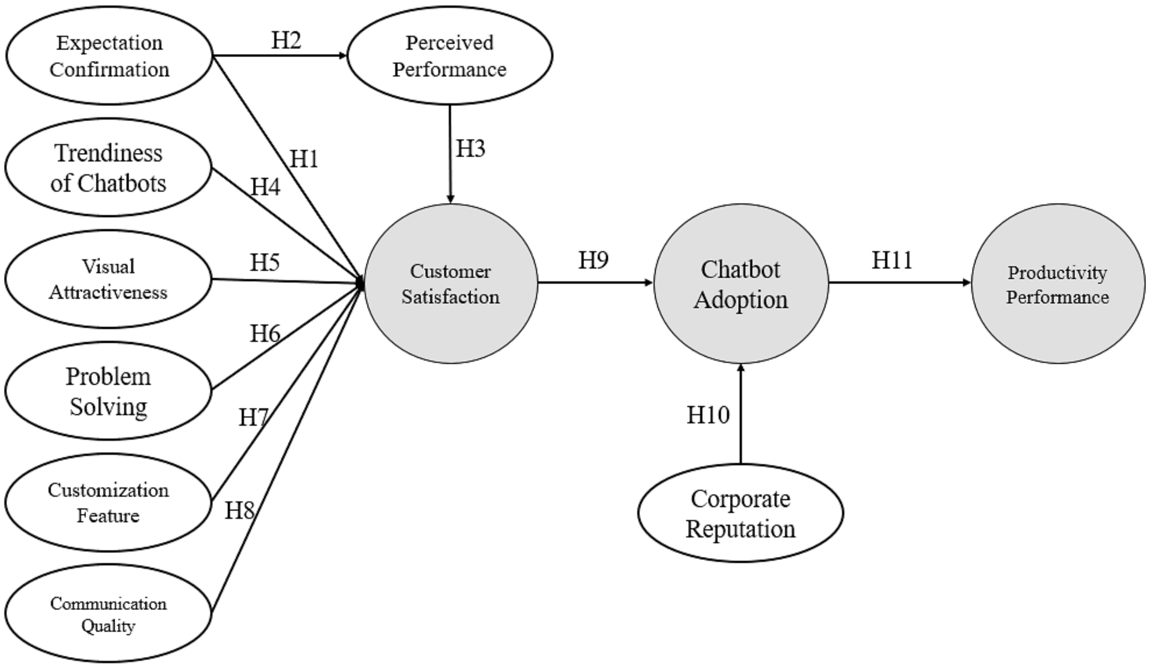

Figure 1. Proposed conceptual model of the study

3- Research Methodology

3-1- Research Design

Figure 2 illustrates the research method flowchart outlining the systematic approach used to investigate the impact of AI chatbots on customer satisfaction and banking performance in Kazakhstan, Russia, and Italy. The choice of countries for the study was driven by the authors' research interests and their priorities for international scientific collaboration. This study employed a quantitative, cross-sectional survey design targeting customers with experience in chatbot-enabled banking services. Data collection was facilitated through a web-based platform utilizing social media and bank fan pages to reach a diverse respondent pool. The survey instrument, based on validated scales refined through expert review and pilot testing, yielded 253 valid responses from an initial distribution of 400 questionnaires.

The analytical phase of the study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM), which was chosen for its predictive capability and ability to handle complex models. Hypothesis testing involved a rigorous assessment of the structural model, employing bootstrapping procedures with 5000 subsamples to ensure statistical robustness. Model fit was evaluated using a comprehensive set of indices, including SRMR, RMSEA, NFI, CFI, and TLI. As depicted in Figure 2, this methodological approach underscores the study's commitment to scientific rigor, providing reliable insights into the factors influencing customer satisfaction with AI chatbots in banking and their impact on adoption and productivity across the three countries.

Customers of banks that have used chatbot services from different banks in Kazakhstan, Russia, and Italy constituted the target sample for this study. Participants were asked to list the key benefits they believe technological innovation has brought to their everyday work as professionals, how AI has affected their productivity as employees, and how certain sectors or activities of their banks have been affected by technological innovation. The EXC and perceived performance constructs and the concepts of trendiness, issue resolution, and personalization are derived from the works of [46, 47]. Furthermore, satisfaction and communication items were derived from studies conducted by Wahbi et al. [48]. Additionally, things were incorporated from the study by Jaiwant [49], which added to visual appeal. The scale used to measure AI-enabled banking adoption was adapted from [50]. Hence, corporate reputation elements and productivity performance were taken from Bellini et al. [51]. Regarding the Likert scale, comprehensive research has consistently shown that a five-point Likert scale is preferred over a seven-point one [35]. An online survey tool was used to collect data. The questionnaire (available in the Appendix) was disseminated through various social networking platforms, including Facebook, LinkedIn, and Zalo. Additionally, we reached potential participants via the official social media pages and discussion boards of banking institutions.

This approach was chosen to maximize our reach and increase the awareness of our research among the target demographics. Five professionals with specialized knowledge of AI technology and mobile banking services assessed the questionnaire to guarantee face and content validity, ensuring that the survey items were comprehensible, straightforward, and meaningful. Subsequently, 30 mobile banking customers received the questionnaire for pretesting to ensure that the phrasing followed their native tongue usage patterns. To create a high-quality and trustworthy online survey, we followed Chen & Huo's [43] recommendation to limit the length of the questionnaire. We also stated that the questionnaire was anonymous and that the data would only be used for academic purposes in order to encourage responders to complete it honestly. Consequently, stable banking market leaders in Kazakhstan, Russia, and Italy are typical, all of which are foreign-capitalized banks. At the same time, the largest state-owned bank, Privat Bank, which is regarded as fairly advanced and inventive in terms of delivering client-oriented financial services based on cutting-edge technologies, falls short of credit. To ensure the authenticity of our participants' experiences with banking chatbots, we incorporated two key screening questions into our survey. These were: “Have you ever used the bank's chatbot service?” “Please write the name of the bank or chatbot with which you had experience”. The data collection phase spanned from November 2023 to early April 2024. Out of 400 questionnaires distributed to carefully selected bank managers, 305 responses were received, yielding a 76.25% return rate. After applying our screening criteria, we identified 253 valid respondents who genuinely used bank chatbot services. We excluded 52 participants owing to incomplete or inaccurate answers to the second screening question. Consequently, our final analysis was based on 253 cases, representing 63.25% of the total responses. This refined dataset formed the foundation for testing the proposed framework. Table 1 provides a comprehensive overview of the survey instruments.

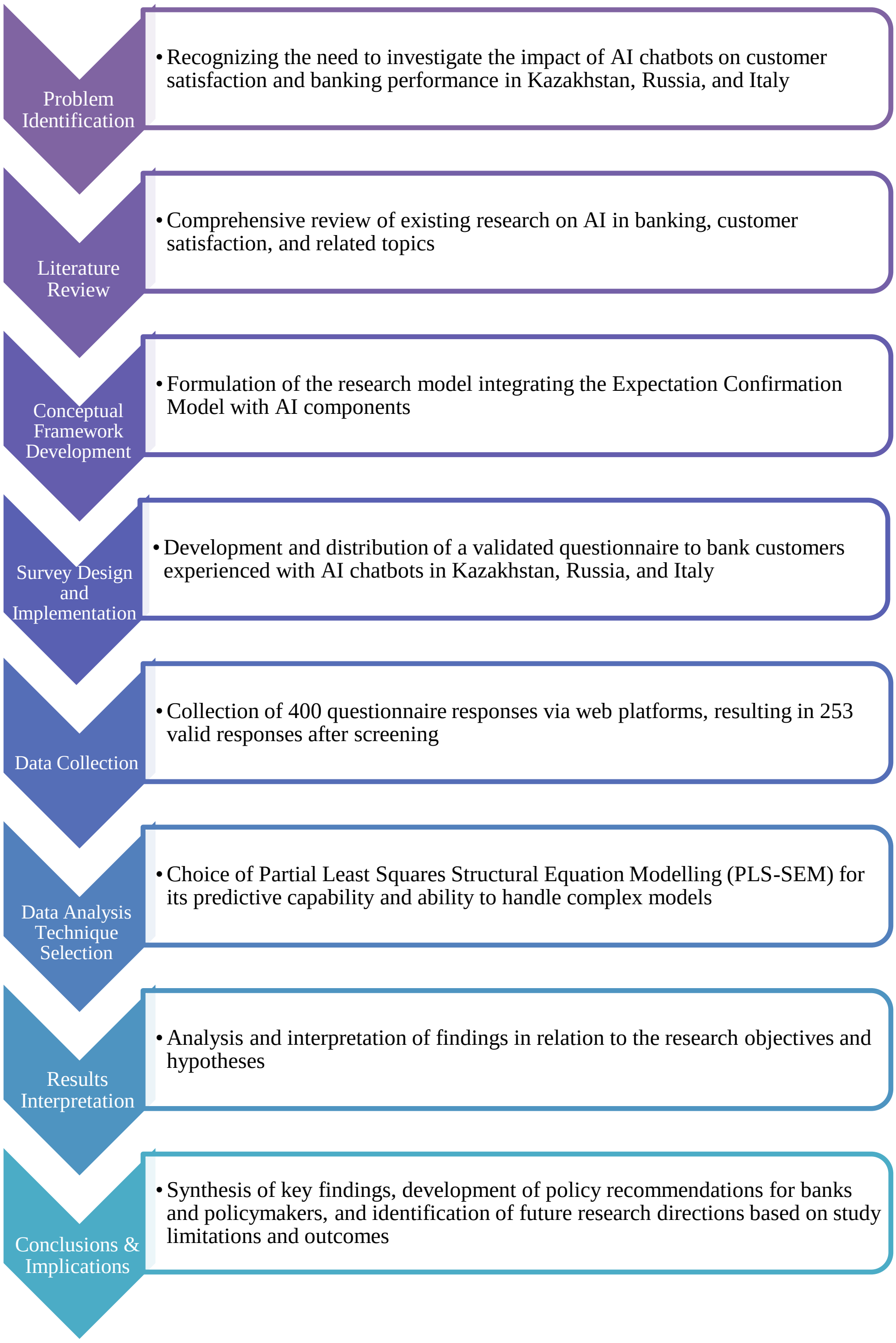

Figure 2. The research design flowchart of the study

Table 1. Instrument statements.

Instrument	Items	Statement
Expectation Confirmation (EXC)	EXC 1	I am pleasantly surprised by the performance of AI- driven digital banking, which has exceeded my initial expectations.
	EXC 2	The advantages of AI- driven digital banking surpass my first expectations.
	EXC 3	The AI- driven digital banking exceeded my expectations in terms of service quality.
	EXC 4	I have found that my expectations for AI- driven digital banking have been met.
Trendiness (TRN)	TRN1	The AI-powered digital banking platform provides updated information about digital banking services.
	TRN2	The most recent data regarding digital banking services is provided by AI- driven digital banking.
	TRN3	The most up-to-date details regarding digital banking services are provided by AI-driven digital banking.
Visual Attractiveness (VA)	VA1	AI-driven digital banking software is aesthetically pleasing.
	VA2	The AI-driven digital banking application has a visually appealing design.
	VA3	The AI- driven digital banking application has a well-designed user interface.
Problem Solving (PS)	PS1	I am confident that AI-driven digital banking possesses the capability to successfully accomplish the task.
	PS2	AI- driven digital banking enables direct and immediate resolution of client complaints.
	PS3	AI- driven digital banking possesses the capability to effectively address intricate issues.
Customization (CSN)	CSN1	This AI-powered digital banking aligns perfectly with my individual requirements.
	CSN2	I believe that the ability to customize enhances my transaction experience when comparing non-customizable digital banking applications.
	CSN3	The AI-powered digital banking platform provides unique and valuable capabilities that are not available in traditional digital banking systems.
	CSN4	The digital banking system, powered by AI, enables me to carry out transactions based on my personal preferences.
Communication Quality (COMQ)	COMQ1	AI-powered digital banking offers reliable information to customers.
	COMQ2	Utilizing AI in digital banking enhances communication, making it more efficient and beneficial.
	COMQ3	AI-powered digital banking significantly reduces time consumption.
Satisfaction Towards AI Banking (STAIB)	STAIB1	I am content with the AI- driven digital banking services.
	STAIB2	The AI-powered digital banking meets my expectations.
	STAIB3	Overall, I am content with the digital banking system driven by AI.
Perceived Performance (PP)	PP1	The employment of AI in digital banking has significantly enhanced my productivity.
	PP2	The employment of AI in digital banking enables me to expedite chores with greater efficiency.
	PP3	Utilizing AI-powered digital banking simplifies financial tasks for me.
	PP4	Utilizing AI technology in digital banking improves efficiency and effectiveness.
Chatbot Adoption (CA)	CA1	The integration of AI chatbots in banking services strongly motivates me to use them.
	CA2	I am eager to use AI-powered chatbots for conducting my banking operations.
	CA3	Using AI chatbots for banking services gives me a sense of satisfaction.
Corporate Reputation (CR)	CR1	I believe that banks offering AI-driven digital banking have a commendable reputation.
	CR2	I strongly believe that the integration of AI in digital banking offers excellent cost-effectiveness.
	CR3	I greatly appreciate and have a sense of satisfaction over the provision of AI- driven digital banking services by banks.
	CR4	I have confidence in the credibility and fulfilment of claims of AI- driven digital banking services.
Productivity Performance (PRP)	PRP1	AI will increase the innovation in products.
	PRP2	AI driven banking promotes technical process in productivity performance.
	PRP3	AI driven banking will make efficient service delivery time.
	PRP4	AI driven will control risk management.

3-2- Sampling and Data Collection

This study examines the elements that influence the economic impact of customer inclination to adopt AI in the digital banking context. Assessing the behavior of technology customers is an intricate phenomenon; hence, it is important to exercise caution when choosing appropriate respondents [52]. Thus, in this article, a digital priori power analysis was used to calculate the required sample size [53].

In Kazakhstan, there were more male (86.16%) than female respondents (13.84%). Half of the respondents were aged 29–35 years (75.49%), and more than one-third were between 46 and 55 years (11.85%). Regarding the highest educational level, most respondents held a master's degree (64.43%). Additionally, 81.42% of respondents had a monthly income of USD 1001–2000. Respondents' demographic information is presented in Table 2. In Russia, there were more male respondents (66.0%) than female (44.0%). The majority of the respondents were aged 29–35 years (57.31%), and the second-largest group of respondents was between 46 and 55 years (11.85%). Many of the respondents had a master's degree (69.96%). Additionally, 58.10% of respondents had a monthly income of USD 1001–2000. In Italy, most respondents were male respondents (77.86%). The majority of the respondents aged 29-35 years old and with master's degrees were (41.89%) and (70.75%). Finally, 85.77% of respondents had a monthly income of USD 1001–2000.

Table 2. Sample demographic profile; participants' details (n = 253)

	Kazakhstan		
		Frequency	**Percentage**
Gender	Male	72	85.71%
	Female	12	14.29%
Age	>22	00	0.0%
	23 – 28	9	3.55%
	29 – 35	191	75.49%
	36 – 45	19	7.50%
	46 – 55	30	11.85%
	>55	04	1.58%
Educational level	Bachelor	90	35.57%
	Master education	163	64.43%
Income	less than $1,500 per month	206	81.42%
	Greater than $1,500 per month	47	18.58%
	Russia		
		Frequency	**Percentage**
Gender	Male	56	66.67%
	Female	28	33.33%
Age	>22	22	8.69%
	23 – 28	15	5.92%
	29 – 35	145	57.31%
	36 – 45	32	12.64%
	46 – 55	30	11.85%
	>55	09	3.55%
Educational level	Bachelor	75	29.64%
	Master education	177	69.96%
Income	less than $1,500 per month	147	58.10%
	Greater than $1,500 per month	106	41.90%
	Italy		
		Frequency	**Percentage**
Gender	Male	66	77.65%
	Female	19	22.35%
Age	>22	42	16.60%
	23 – 28	10	3.95%
	29 – 35	106	41.89%
	36 – 45	26	10.27%
	46 – 55	18	7.11%
	>55	51	20.16%
Educational level	Bachelor	74	29.25%
	Master education	179	70.75%
Income	less than $1,500 per month	217	85.77%
	Greater than $1,500 per month	36	14.23%

3-3- Reasons for Using Partial Least Square Structural Equation Model (PLS-SEM)

PLS-SEM was employed to assess the instrument's validity and reliability as well as the study methodology, which is justified by its significant predictive capability, capacity to work with non-normal datasets, ability to handle small sample sizes, and complex processing techniques. Identifying unexplained heterogeneity (UH) is an additional advantage of PLS-SEM. Ramli et al. [54] asserted that PLS-SEM route analysis, when correctly utilized, is an effective method for evaluating cause-and-effect relationships. When using CB-SEM, certain parameters are intentionally excluded to provide a more accurate measure of the model's goodness of fit, as opposed to PLS-SEM. When employing PLS-SEM, the quality of dependability, consistency, and validity tends to be more robust. We used SmartPLS3.2.9 to conduct the PLS data analyses. Construct validity was assessed using the conventional PLS technique, which involves evaluating the reliability, convergent validity, and discriminant validity. Composite reliability (CR) and Cronbach's alpha (α) were calculated for each construct to ensure internal consistency. Table 3 demonstrates that all the values of CR and α exceeded the criterion of 0.70.

Table 3. Validity and reliability scores

Kazakhstan							
Instrument	**Items**	**Loadings**	**Significance**	**Cronbach's Alpha**	**Dijkstra–Henseler's Rho(r_A)**	**CRI**	**AVE**
Chatbot Adoption (CA)	CA1	0.736	0.000	0.912	0.935	0.975	0.735
	CA2	0.782	0.000				
	CA3	0.837	0.000				
Communication quality (COMQ)	COMQ1	0.716	0.000	0.812	0.840	0.890	0.784
	COMQ2	0.892	0.000				
	COMQ3	0.846	0.000				
Corporate Reputation (CR)	CR1	0.782	0.000	0.820	0.856	0.896	0.672
	CR2	0.774	0.000				
	CR3	0.856	0.000				
	CR4	0.745	0.000				
Customization (CSN)	CUS1	0.725	0.000	0.867	0.925	0.957	0.725
	CUS2	0.810	0.000				
	CUS3	0.885	0.000				
	CUS4	0.923	0.000				
Expectation confirmation (EXC)	EXC1	0.741	0.000	0.830	0.891	0.907	0.685
	EXC2	0.750	0.000				
	EXC3	0.782	0.000				
	EXC4	0.840	0.000				
Perceived performance (PP)	PP1	0.735	0.000	0.835	0.850	0.867	0.746
	PP2	0.847	0.000				
	PP3	0.865	0.000				
	PP4	0.882	0.000				
Problem solving (PS)	PRS1	0.895	0.000	0.902	0.942	0.966	0.694
	PRS2	0.839	0.000				
	PRS3	0.935	0.000				
Satisfaction towards AI Banking (STAIB)	STAIB1	0.842	0.000	0.821	0.856	0.885	0.690
	STAIB2	0.946	0.000				
	STAIB3	0.972	0.000				
Trendiness (TRN)	TRN1	0.946	0.000	0.831	0.962	0.892	0.780
	TRN2	0.857	0.000				
	TRN3	0.863	0.000				
Visual attractiveness (VA)	VA1	0.738	0.000	0.806	0.845	0.874	0.570
	VA2	0.879	0.000				
	VA3	0.892	0.000				
Productivity performance (PRP)	PRP1	0.734	0.000	0.825	0.860	0.896	0.645
	PRP2	0.896	0.000				
	PRP3	0.823	0.000				
	PRP4	0.857	0.000				

Russia							
Instrument	**Items**	**Loadings**	**Significance**	**Cronbach's Alpha**	**Dijkstra–Henseler's Rho(r_A)**	**CRI**	**AVE**
	CA1	0.782	0.000				
Chatbot Adoption (CA)	CA2	0.714	0.000	0.921	0.953	0.990	0.741
	CA3	0.890	0.000				
	COMQ1	0.724	0.000				
Communication quality (COMQ)	COMQ2	0.856	0.000	0.841	0.876	0.902	0.790
	COMQ3	0.841	0.000				
	CR1	0.787	0.000				
Corporate Reputation (CR)	CR2	0.724	0.000	0.854	0.875	0.896	0.672
	CR3	0.816	0.000				
	CR4	0.790	0.000				
	CUS1	0.721	0.000				
Customization (CSN)	CUS2	0.834	0.000	0.890	0.914	0.960	0.726
	CUS3	0.867	0.000				
	CUS4	0.945	0.000				
	EXC1	0.710	0.000				
Expectation confirmation (EXC)	EXC2	0.755	0.000	0.832	0.896	0.924	0.694
	EXC3	0.790	0.000				
	EXC4	0.843	0.000				
	PP1	0.736	0.000				
Perceived performance (PP)	PP2	0.812	0.000	0.832	0.869	0.872	0.755
	PP3	0.886	0.000				
	PP4	0.825	0.000				
	PRS1	0.892	0.000				
Problem solving (PS)	PRS2	0.835	0.000	0.912	0.956	0.975	0.692
	PRS3	0.953	0.000				
	STAIB1	0.878	0.000				
Satisfaction towards AI Banking (STAIB)	STAIB2	0.981	0.000	0.835	0.843	0.886	0.687
	STAIB3	0.934	0.000				
	TRN1	0.910	0.000				
Trendiness (TRN)	TRN2	0.876	0.000	0.815	0.849	0.895	0.789
	TRN3	0.831	0.000				
	VA1	0.735	0.000				
Visual attractiveness (VA)	VA2	0.897	0.000	0.802	0.851	0.894	0.590
	VA3	0.895	0.000				
	PRP1	0.713	0.000				
Productivity performance (PRP)	PRP2	0.860	0.000	0.822	0.865	0.880	0.654
	PRP3	0.825	0.000				
	PRP4	0.852	0.000				

Italy							
Instrument	**Items**	**Loadings**	**Significance**	**Cronbach's Alpha**	**Dijkstra–Henseler's Rho(r_A)**	**CRI**	**AVE**
Chatbot Adoption (CA)	CA1	0.790	0.000	0.924	0.937	0.976	0.730
	CA2	0.775	0.000				
	CA3	0.823	0.000				
Communication quality (COMQ)	COMQ1	0.762	0.000	0.809	0.845	0.892	0.785
	COMQ2	0.896	0.000				
	COMQ3	0.860	0.000				
Corporate Reputation (CR)	CR1	0.723	0.000	0.815	0.836	0.881	0.724
	CR2	0.795	0.000				
	CR3	0.863	0.000				
	CR4	0.724	0.000				
Customization (CSN)	CUS1	0.732	0.000	0.896	0.926	0.954	0.790
	CUS2	0.815	0.000				
	CUS3	0.890	0.000				
	CUS4	0.921	0.000				
Expectation confirmation (EXC)	EXC1	0.775	0.000	0.825	0.896	0.917	0.665
	EXC2	0.724	0.000				
	EXC3	0.706	0.000				
	EXC4	0.827	0.000				
Perceived performance (PP)	PP1	0.745	0.000	0.809	0.842	0.870	0.726
	PP2	0.886	0.000				
	PP3	0.823	0.000				
	PP4	0.887	0.000				
Problem solving (PS)	PRS1	0.834	0.000	0.917	0.935	0.986	0.656
	PRS2	0.825	0.000				
	PRS3	0.967	0.000				
Satisfaction towards AI Banking (STAIB)	STAIB1	0.814	0.000	0.806	0.849	0.886	0.693
	STAIB2	0.922	0.000				
	STAIB3	0.954	0.000				
Trendiness (TRN)	TRN1	0.913	0.000	0.905	0.942	0.990	0.752
	TRN2	0.875	0.000				
	TRN3	0.890	0.000				
Visual attractiveness (VA)	VA1	0.734	0.000	0.842	0.886	0.902	0.592
	VA2	0.872	0.000				
	VA3	0.812	0.000				
Productivity performance (PRP)	PRP1	0.787	0.000	0.820	0.834	0.876	0.675
	PRP2	0.824	0.000				
	PRP3	0.857	0.000				
	PRP4	0.886	0.000				

To assess the convergent validity of the constructs, we examined the outer loadings of the items and calculated the average variance extracted (AVE) [55]. Based on Cheung et al. [56], an item with a value less than 0.6 was excluded (see Table 3). Similarly, all constructs had AVE values exceeding the minimum threshold of 0.50, as shown in Table 3. Discriminant validity was initially assessed using the Fornell-Larcker criterion (Table 4).

Table 4. Discriminant validity (Fornell and Larcker Criterion)

Constructs	CA	COMQ	CR	CSN	EXC	PP	PS	STAIB	TRN	VA	PRP
Kazakhstan											
CA	0.880										
COMQ	0.625	0.745									
CR	0.672	0.617	0.723								
CSN	0.624	0.782	0.678	0.785							
EXC	0.590	0.586	0.623	0.523	0.715						
PP	0.567	0.637	0.642	0.578	0.612	0.845					
PS	0.525	0.692	0.530	0.554	0.646	0.457	0.892				
STAIB	0.559	0.620	0.679	0.519	0.690	0.548	0.524	0.764			
TRN	0.429	0.592	0.572	0.540	0.574	0.650	0.687	0.734	0.720		
VA	0.726	0.535	0.621	0.576	0.571	0.742	0.746	0.709	0.635	0.874	
PRP	0.456	0.523	0.497	0.643	0.657	0.540	0.674	0.732	0.745	0.690	0.890
Russia											
CA	0.876										
COMQ	0.641	0.754									
CR	0.686	0.642	0.745								
CSN	0.645	0.776	0.522	0.790							
EXC	0.542	0.524	0.451	0.575	0.725						
PP	0.590	0.675	0.526	0.580	0.621	0.835					
PS	0.531	0.690	0.409	0.521	0.523	0.420	0.891				
STAIB	0.437	0.625	0.567	0.634	0.756	0.521	0.612	0.721			
TRN	0.486	0.543	0.421	0.620	0.432	0.687	0.595	0.630	0.770		
VA	0.721	0.556	0.587	0.598	0.590	0.604	0.652	0.578	0.545	0.895	
PRP	0.497	0.514	0.452	0.654	0.621	0.520	0.587	0.510	0.657	0.670	0.870
Italy											
CA	0.764										
COMQ	0.451	0.720									
CR	0.592	0.676	0.790								
CSN	0.465	0.459	0.621	0.712							
EXC	0.427	0.591	0.582	0.456	0.751						
PP	0.592	0.423	0.345	0.392	0.562	0.893					
PS	0.486	0.540	0.590	0.532	0.476	0.425	0.895				
STAIB	0.592	0.590	0.621	0.450	0.695	0.541	0.545	0.726			
TRN	0.436	0.521	0.556	0.392	0.522	0.687	0.429	0.486	0.740		
VA	0.451	0.452	0.567	0.514	0.515	0.690	0.526	0.561	0.454	0.728	
PRP	0.390	0.592	0.490	0.636	0.527	0.621	0.312	0.629	0.529	0.429	0.792

According to Henseler [57], the square root of the average variance extracted (AVE) for each construct is larger than its highest correlation with any other construct. Furthermore, the HTMT values fell below the conservative criterion of 0.85, as determined by Franke & Sarstedt [58]. The cumulative data indicates that both constructs and items exhibit favorable measurement characteristics. Additionally, the VIF values of the items, which ranged from 1.127 to 2.9, were below the threshold value of 5. Therefore, there was no significant collinearity between any of the constructs.

4- Results

4-1- Model Fitness

Therefore, it is necessary to obtain an accurate estimate to assess the suitability of any model. This study initially computed the SRMR (standardized root mean square residual) to evaluate the adequacy of the model. A model can be considered fit if it has an SRMR value below 0.08, as stated by Sharma et al. [59]. Furthermore, the researchers utilized distinct fitness criteria to evaluate the study model in addition to SRMR. The normed fit index (NFI), Tucker-Lewis index (TLI), comparative fit index (CFI), and root mean square approximation error (RMSEA) are often employed as fit indicators. To verify the methodological strength of the model, it was necessary to analyze the chi-square value and its level of significance. According to Jain & Raj (2013) [60], the NFI, CFI, and TLI values must exceed 0.90; however, the RMSEA score should be less than 0.08. Ultimately, the chi-square p-value must be less than 0.05, as stated in James et al. (2024) [61] study. The fitness scores for NFI, CFI, and TLI are presented in Table 5 as 0.926, 0.954, and 0.967 in Kazakhstan; 0.921, 0.957, and 0.960 in Russia and 0.930, 0.955, and 0.972, respectively, in Italy. Similarly, the SRMR and RMSEA scores of 0.072 and 0.065 in Kazakhstan, 0.075 and 0.062 in Russia, and 0.079 and 0.067 in Italy indicated the adequacy of the model, with $\chi 2$ values of 1875.32, 1794.95, and 0.1826.12, respectively ($p < 0.05$).

Table 5. Model fitness report

	Kazakhstan		Russia		Italy		
Model Fit Criteria	**Fitness Value of the Study**	**Acceptance Criteria**	**Fitness Value of the Study**	**Acceptance Criteria**	**Fitness Value of the Study**	**Acceptance Criteria**	**Fitness Ensured**
SRMR	0.072	<0.08	0.075	<0.08	0.079	<0.08	Yes
RMSEA	0.065	<0.08	0.062	<0.08	0.067	<0.08	Yes
NFI	0.926	>0.90	0.921	>0.90	0.930	>0.90	Yes
CFI	0.954	>0.90	0.957	>0.90	0.955	>0.90	Yes
TLI	0.967	>0.90	0.960	>0.90	0.972	>0.90	Yes
χ^2	1875.32		1724.95		1826.12		Yes
χ^2 Significance	0.000	<0.05	0.000	<0.05	0.000	<0.05	Yes

4-2- Measurement Model

The Cronbach's alpha was used to assess the internal consistency of the measurement items. All results exceeded 0.7, which met the acceptable criterion defined by Cheung et al. [56]. Composite reliability (CR) is a measure of internal consistency reliability. Unlike Cronbach's alpha, this does not imply that indicator loadings are equally weighted. According to Bakshi et al. [62], in an exploratory study, the composite reliability should be higher than 0.60, and as a general guideline, it should be higher than 0.70. However, the value should not exceed 0.95.

We performed confirmatory factor analysis to establish the validity and dependability of the proposed model. The CR metric and Dijkstra-Henseler's rho (trA) were employed to assess the reliability of all structures. All components of this study had a CR Index (CRI) greater than 0.7, indicating that the parameters were suitable. Additionally, Cronbach's and rA values, both exceeding 0.7, were utilized to confirm the internal consistency and reliability of each case [63]. This study utilized three measures to assess convergent validity. We evaluated the magnitude of the loading, average variance extracted (AVE), and the statistical significance of the loadings. According to the cutoff value suggested by Wahab [64], all outer loadings should be equal to or greater than 0.5, provided that AVE is higher than 0.5.

Every external load in Table 3 exceeds 0.50. For each instance, the AVE was greater than 0.50. Therefore, the necessary criteria for fitness are guaranteed in all instances. An AVE higher than 0.5 for all parameters shows that the variation explains more than 50% of the variability in the indicators. This information is supported by the work of Makudza et al. [33]. The research shows that the Composite Reliability Index (CRI) for all constructs is over 0.70, which is higher than the Average Variance Extracted (AVE) as indicated in Table 3. Finally, a bootstrap resampling technique was employed to ascertain the statistical significance of loadings. All the study results were statistically significant at the 5% level. The convergent validity of the model was demonstrated by Yoganathan & Osburg [36].

4-3- Discriminant Validity

The Fornell-Larcker criterion is a widely used method in confirmatory factor analysis to assess the ability of a measurement model to distinguish between different constructs. The analysis examined the association between each concept and its accompanying indicators known as factor loadings. To establish discriminant validity, it is crucial that the square root of the AVE for each construct is greater than the correlation between that construct and other constructs in the model [65]. Table 4 presents the results of the Discriminant Validity assessment using the Fornell-Larcker criterion.

HTMT is a contemporary method used to assess discriminant validity. This analysis explored disparities between the correlations among several constructs (heterotrait correlations) and the average correlations within the same construct (monotrait correlations). Discriminant validity is considered good when correlations across distinct characteristics are lower than those within the same trait. Table 6 presents the results of the correlation analysis for the HTMT ratio.

Table 6. Discriminant validity (HTMT)

Constructs	CA	COMQ	CR	CSN	EXC	PP	PS	STAIB	TRN	VA	PRP
					Kazakhstan						
CA											
COMQ	0.720										
CR	0.516	0.715									
CSN	0.522	0.561	0.735								
EXC	0.426	0.574	0.672	0.673							
PP	0.265	0.325	0.452	0.578	0.624						
PS	0.391	0.216	0.476	0.542	0.607	0.639					
STAIB	0.427	0.423	0.318	0.462	0.429	0.325	0.762				
TRN	0.615	0.592	0.419	0.526	0.325	0.476	0.415	0.751			
VA	0.624	0.451	0.427	0.440	0.582	0.511	0.429	0.490	0.682		
PRP	0.564	0.497	0.523	0.656	0.442	0.425	0.670	0.543	0.550	0.570	
					Russia						
CA											
COMQ	0.724										
CR	0.519	0.753									
CSN	0.492	0.456	0.790								
EXC	0.514	0.592	0.535	0.642							
PP	0.390	0.365	0.489	0.456	0.620						
PS	0.451	0.427	0.423	0.426	0.538	0.635					
STAIB	0.476	0.531	0.354	0.497	0.432	0.413	0.724				
TRN	0.592	0.672	0.425	0.532	0.378	0.486	0.451	0.730			
VA	0.445	0.492	0.479	0.487	0.412	0.515	0.492	0.426	0.692		
PRP	0.590	0.465	0.542	0.415	0.481	0.496	0.609	0.534	0.590	0.543	
					Italy						
CA											
COMQ	0.723										
CR	0.427	0.712									
CSN	0.490	0.435	0.745								
EXC	0.326	0.594	0.690	0.670							
PP	0.472	0.427	0.243	0.586	0.642						
PS	0.492	0.592	0.476	0.512	0.547	0.695					
STAIB	0.416	0.476	0.390	0.396	0.495	0.423	0.724				
TRN	0.562	0.523	0.425	0.415	0.321	0.482	0.422	0.721			
VA	0.376	0.434	0.472	0.442	0.587	0.556	0.497	0.425	0.657		
PRP	0.610	0.490	0.534	0.687	0.412	0.565	0.694	0.539	0.576	0.592	

4-4- Structural Model

After ensuring reliability and validity, SEM was tested. This study assessed the presence of multicollinearity. To verify the absence of any correlations between the items, we assessed collinearity of the measures using the variance inflation factor (VIF) and weight significance. To confirm the absence of collinearity, the VIF must be less than 3.3, as stated by Ge et al. [66]. Weight ratings were subsequently assessed using bootstrapping technique with 5000 samples. All p-values in Table 7 indicate statistical significance for the weights. The considerable lack of connection between the variables and p-value ensures the absence of multicollinearity.

Table 7. VIF test

Constructs	Kazakhstan		Russia		Italy	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
CA	1.765	0.566	2.087	0.479	2.376	0.420
COMQ	1.286	0.778	1.209	0.827	1.286	0.778
CR	2.535	0.394	2.251	0.444	2.287	0.437
CSN	2.967	0.337	2.427	0.412	2.509	0.398
EXC	1.259	0.794	1.309	0.764	2.736	0.365
PP	1.645	0.607	1.526	0.655	2.165	0.462
PS	2.798	0.357	2.129	0.470	1.836	0.545
STAIB	2.543	0.393	1.992	0.502	2.287	0.437
TRN	2.070	0.482	2.173	0.460	2.760	0.362
VA	2.045	0.489	2.087	0.479	2.276	0.439
PRP	2.756	0.362	2.128	0.469	2.935	0.340

The R^2 values are crucial for evaluating the validity of the regression model and offer useful insights into the extent to which the independent variables collectively account for fluctuations in dependent variables. A statistical indicator in predictive modelling demonstrates an improved model accuracy and forecasting power. The R^2 and Q^2 values are presented in Table 8.

Table 8. Coefficient of determination

Constructs	Kazakhstan		Russia		Italy	
	R squared	Q squared	R squared	Q squared	R squared	Q squared
CA	0.45	0.60	0.40	0.65	0.47	0.64
PP	0.67	0.35	0.62	0.32	0.65	0.37
STAIB	0.49	0.26	0.45	0.29	0.46	0.28
PRP	0.75	0.64	0.76	0.65	0.72	0.68

4-5- Path Analysis

The research hypotheses were evaluated in the second stage of PLS-SEM, namely during the assessment of the structural model. A bootstrap procedure was conducted using a sample size of 5000, which aligns with previous studies by Rege [67]. Streukens & Leroi-Werelds [68] stated that the bootstrapping method is effective in addressing data normalcy issues, and should be included in the assessment of SEM models. The results of the SEM included β-values, standard errors, t-values, and p-values, which were used to determine whether the hypotheses were rejected or accepted. Table 9 presents the results of the hypotheses analysis. A structural model assessment was used to investigate the causal links among the hypotheses.

The results demonstrate a significant influence of EXC on customer satisfaction in all three countries studied. The path coefficient (β) was highest in Russia (0.519, $p = 0.005$), followed by Kazakhstan (0.436, $p = 0.000$) and Italy (0.256, $p = 0.000$). These results confirm **H1**, establishing EXC as a critical factor in customer satisfaction.

Similarly, EXC positively influenced perceived performance across the regions. The path coefficient (β) was 0.286 in Russia ($p = 0.012$), 0.257 in Kazakhstan ($p = 0.021$), and 0.194 in Italy ($p = 0.007$), confirming **H2**. These findings indicate a consistent positive relationship between EXC and perceived performance.

The observed performance had a strong favorable influence on customer happiness, confirming **H3**. The path coefficient (β) was 0.935 in Kazakhstan ($p = 0.009$), 0.932 in Russia ($p = 0.007$), and 0.516 in Italy ($p = 0.005$), highlighting its critical role in determining customer satisfaction.

In contrast, trendiness showed a negligible effect on customer satisfaction, leading to the rejection of **H4**. Path coefficients were 0.614 in Kazakhstan ($p = 0.176$), 0.645 in Russia ($p = 0.132$), and 0.487 in Italy ($p = 0.186$), failing to reach statistical significance in any region.

Visual appeal demonstrated a substantial positive influence on customer satisfaction, supporting **H5**. The path coefficient (β) was 0.276 in Kazakhstan ($p = 0.005$), 0.123 in Russia ($p = 0.000$), and 0.562 in Italy ($p = 0.000$). These results underscore the importance of visual factors in enhancing customer satisfaction.

The problem-solving capabilities of AI were found to have a verifiable positive impact on customer satisfaction, confirming **H6**. Path coefficients were 0.067 in Kazakhstan ($p = 0.007$), 0.090 in Russia ($p = 0.006$), and 0.129 in Italy ($p = 0.003$), indicating consistent benefits.

Customization, however, had a negligible effect on customer happiness, resulting in the rejection of **H7**. Path coefficients were 0.193 in Kazakhstan (p = 0.153), 0.176 in Russia (p = 0.190), and 0.310 in Italy (p = 0.125), showing no significant influence in any country.

Communication emerged as a crucial factor, with a significant positive effect on customer happiness, as evidenced by **H8**. Path coefficients were 0.425 in Kazakhstan (p = 0.012), 0.410 in Russia (p = 0.025), and 0.129 in Italy (p = 0.003), highlighting its universal importance.

Customer happiness had a strong favorable influence on customer adoption of AI-enabled banking, as shown by **H9**. The path coefficient (β) was 0.627 (p = 0.000), underscoring its significance.

Finally, business reputation positively influenced customer satisfaction, confirming **H10**. The path coefficient (β) was 0.556 in Kazakhstan (p = 0.000), 0.526 in Russia (p = 0.001), and 0.427 in Italy (p = 0.005). Similarly, hypothesis **H11** was supported in Russia (β = 0.412, p = 0.006) and Italy (β = 0.329, p = 0.007), further validating the importance of reputation in fostering customer satisfaction.

Table 9. Hypothesis test results

Path	B	S.E.	t-statistic	p-values	Results
Kazakhstan					
H1: EXC → STAIB	0.436***	0.116	3.750	0.000	Accepted
H2: EXC→ PP	0.257**	0.026	9.624	0.021	Accepted
H3: PP→ STAIB	0.935***	0.147	6.360	0.009	Accepted
H4: TRN→ STAIB	0.614	0.255	2.405	0.176	Not Accepted
H5: VA→ STAIB	0.276***	0.058	4.719	0.005	Accepted
H6: PS→ STAIB	0.067***	0.005	12.376	0.007	Accepted
H7: CSN→ STAIB	0.193	0.045	4.287	0.153	Not Accepted
H8: COMQ→ STAIB	0.425**	0.137	3.085	0.012	Accepted
H9: STAIB→ CA	0.627***	0.086	7.276	0.000	Accepted
H10: CR→ CA	0.556***	0.044	12.601	0.000	Accepted
H11: CA→ PRP	0.490**	0.065	7.534	0.005	Accepted
Russia					
Path	**B**	**S.E.**	**t-statistic**	**p-values**	**Results**
H1: EXC → STAIB	0.519***	0.120	4.297	0.005	Accepted
H2: EXC → PP	0.286**	0.056	5.089	0.012	Accepted
H3: PP → STAIB	0.932***	0.101	9.254	0.007	Accepted
H4: TRN → STAIB	0.645	0.052	12.394	0.132	Not Accepted
H5: VA → STAIB	0.123***	0.024	5.209	0.000	Accepted
H6: PS → STAIB	0.090***	0.012	7.239	0.006	Accepted
H7: CSN → STAIB	0.176	0.042	4.187	0.190	Not Accepted
H8: COMQ → STAIB	0.410**	0.110	3.695	0.025	Accepted
H9: STAIB → CA	0.656***	0.303	2.164	0.005	Accepted
H10: CR → CA	0.526***	0.169	3.095	0.001	Accepted
H11: CA→ PRP	0.412***	0.056	7.275	0.006	Accepted
Italy					
Path	**B**	**S.E.**	**t-statistic**	**p-values**	**Results**
H1: EXC → STAIB	0.256***	0.060	4.203	0.000	Accepted
H2: EXC → PP	0.194***	0.034	5.849	0.007	Accepted
H3: PP → STAIB	0.516***	0.062	8.275	0.005	Accepted
H4: TRN → STAIB	0.487	0.379	1.283	0.186	Not Accepted
H5: VA → STAIB	0.562***	0.130	4.309	0.000	Accepted
H6: PS → STAIB	0.129***	0.025	5.038	0.003	Accepted
H7: CSN → STAIB	0.310	0.052	5.906	0.125	Not Accepted
H8: COMQ → STAIB	0.451**	0.072	6.239	0.015	Accepted
H9: STAIB → CA	0.751***	0.061	12.348	0.001	Accepted
H10: CR → CA	0.427***	0.076	5.509	0.005	Accepted
H11: CA→ PRP	0.329***	0.060	5.397	0.007	Accepted

4-6- Results of the Conceptual Model Testing

Figure 3 presents the results of the testing of the conceptual model proposed in this study. This model illustrates the relationships between various factors influencing customer satisfaction, chatbot adoption, and productivity performance in AI-enabled banking services.

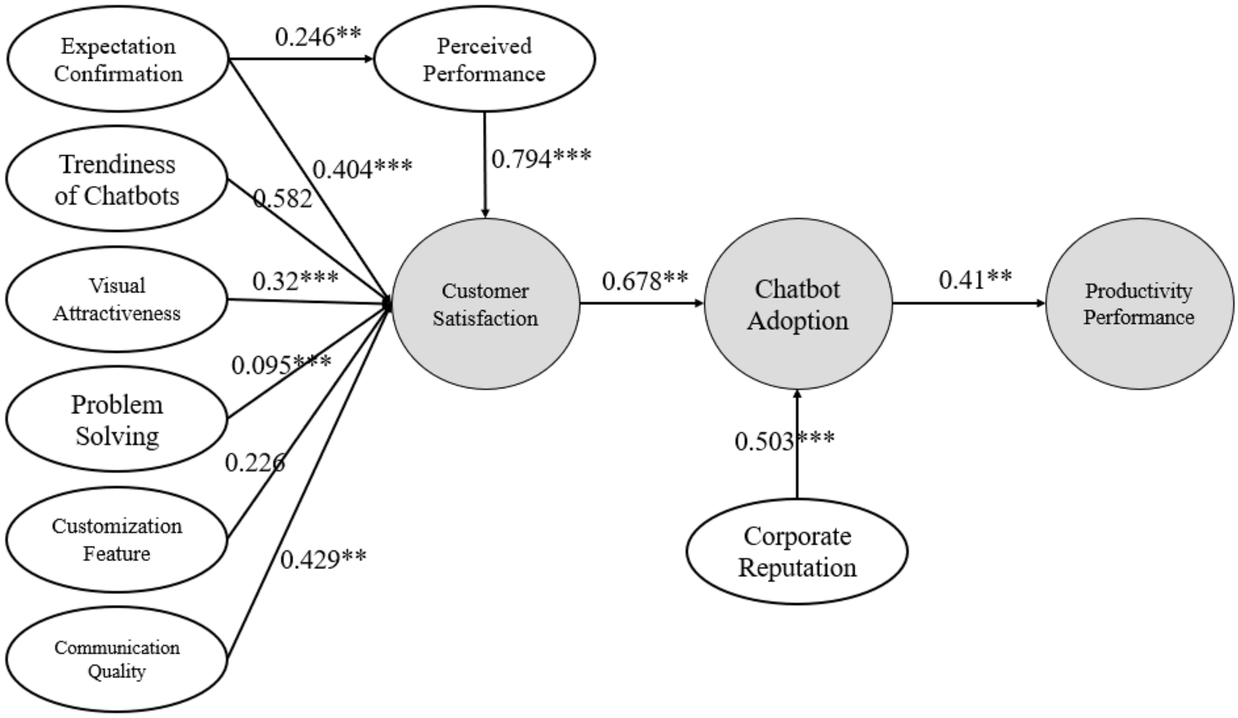

Figure 3. Structural model results with path coefficients

This model reveals several significant relationships. Expectation Confirmation emerged as a crucial factor that directly influenced both Perceived Performance ($\beta = 0.246$, $p < 0.01$) and Customer Satisfaction ($\beta = 0.404$, $p < 0.001$). This suggests that when customers' expectations of AI chatbots are met or exceeded, they positively affect their perception of chatbot performance and overall satisfaction. The strong relationship between Perceived Performance and Customer Satisfaction ($\beta = 0.794$, $p < 0.001$) underscores the importance of meeting customer expectations in AI-enabled banking services.

Among chatbot-specific features, Communication Quality had the strongest influence on Customer Satisfaction ($\beta = 0.429$, $p < 0.01$), followed by Visual Attractiveness ($\beta = 0.32$, $p < 0.001$). This implies that chatbots' ability to communicate effectively and their aesthetic appeal play a significant role in shaping customer satisfaction. Interestingly, while the trend of chatbots appears to have a substantial impact ($\beta = 0.582$), its statistical significance has not been reported, suggesting potential variability across the studied countries.

Problem-solving capabilities, although statistically significant ($p < 0.001$), show a relatively smaller impact on Customer Satisfaction ($\beta = 0.095$). This unexpected finding might indicate that while problem solving is essential, it may be viewed as a basic expectation rather than a differentiator in customer satisfaction. The Customization Feature also shows a modest but significant influence on satisfaction ($\beta = 0.226$, $p < 0.001$), highlighting the importance of personalized interactions in AI-enabled banking services.

The model demonstrates a strong relationship between Customer Satisfaction and Chatbot Adoption ($\beta = 0.678$, $p < 0.01$), indicating that satisfied customers are more likely to adopt and continue using AI chatbots to meet their banking needs. Corporate Reputation also played a significant role in Chatbot Adoption ($\beta = 0.503$, $p < 0.001$), suggesting that a bank's overall reputation influences customers' willingness to embrace new technologies.

Finally, the model confirmed a positive relationship between Chatbot Adoption and Productivity Performance ($\beta = 0.41$, $p < 0.01$). This finding supports the notion that the successful implementation and adoption of AI chatbots in banking can lead to improved operational efficiency and productivity.

The rejection of H4 and H7, concerning the effects of the trendiness and customization features of AI chatbots on customer satisfaction, presents an intriguing finding. This unexpected result can be attributed to several factors. First, in the rapidly evolving landscape of digital banking, customers might view trendiness as a fleeting attribute, prioritizing more enduring qualities, such as reliability and efficiency. The novelty of AI chatbots may have been worn off, with users focusing more on practical benefits. Regarding customization, the complexity of financial services and the need for standardized processes in banking might limit the perceived value of personalized interactions. Additionally, concerns about data privacy and security could make customers wary of extensive personalization in the financial context. It is also possible that current AI chatbot implementations in these banks have not yet achieved a level of customization that significantly enhances user experience, leading to its minimal impact on overall satisfaction.

These results provide valuable insights for banks and financial institutions seeking to implement and improve AI chatbot services. They highlighted the importance of managing customer expectations, ensuring effective communication, and maintaining an attractive and user-friendly interface. Moreover, the findings emphasize the role of corporate reputation in technology adoption and potential productivity gains from successful chatbot implementation. Future research could explore these relationships in more depth, particularly examining why some factors, such as problem-solving capabilities, show lower-than-expected impacts on customer satisfaction.

5- Discussion

In an age of technological progress and disruptive innovation, AI has emerged as an alternative technology for managing online banking services, channels, and solutions. Although the introduction of AI-powered Chatbots into digital banking has enhanced the quality of digital banking services, the challenges of integrating AI-driven chatbots into digital banking systems and achieving customer expectations remain unresolved. Hence, this study proposes a comprehensive methodology for examining customer happiness and adoption of chatbots equipped with AI in the context of digital banking. This study combines the EXC model with AI components to examine customer satisfaction with Chatbots in AI-enabled digital banking. The research framework is validated through empirical testing using observations collected from digital banking customers. The study's empirical findings have demonstrated a significant relationship between EXC and customer happiness and perceived performance, which aligns with previous research [69, 70].

Empirical evidence has verified that the implementation of AI in digital banking fulfills customer expectations and enhances customer satisfaction. These results suggest that trendiness has a negligible effect on customer happiness. This finding contradicts the notion proposed by Bialkova [31]. Consequently, visual appeal has demonstrated a favorable influence on customer happiness, aligning with Dewasiri et al. [71]. Additionally, research conducted by Chizoba Ekechi et al. [72] found that improved problem-solving abilities and communication quality had a beneficial impact on customer satisfaction. This study found that the association between personalization and pleasure was not substantial, contradicting the reasons proposed by Kaur et al. [32]. This occurred because of the disruptive nature of Chatbots with AI, which causes consumers to experience difficulties in customizing, leading to negative feedback. This study also validated that customer happiness and business reputation have a beneficial influence on customer behavior in accepting digital banking and overall loyalty, which aligns with the findings of Hsu & Lin [13] and Niu et al. [73]. Thus, Rahman et al. [1] argued that the accuracy of AI algorithms is a major factor in the application of AI. This is particularly evident in chatbots, where a high accuracy decreases the need for human input. Ullah & Pizzichini [74] suggested that these bots could take over services provided by humans in the banking sector.

However, although this result aligns with existing research suggesting that the accuracy of AI algorithms is crucial for chatbot adoption in Kazakhstan, there are critical points to consider. First, while high accuracy may reduce the need for human input in chatbots, there may still be concerns about the complexity of interactions and the effort required by customers to effectively engage with these systems [48, 75]. Second, while chatbots may indeed take over certain services provided by humans in the banking sector, there are potential drawbacks such as reduced personalization and inability to handle complex queries. They argue that Chatbots' simplicity and effectiveness, particularly in multitasking scenarios, may redirect customers' attention to more pertinent concerns such as trust and confidentiality, which are crucial factors in the sensitive banking sector [76]. This departure from expected behavior underscores the complexity of technology adoption and highlights the need for a deeper exploration of contextual influences on customer attitudes and behaviors in Kazakhstan. Sachdeva & Dhingra [30] observed that people prefer self-service when it is enjoyable. The researchers indicated that pleasure derived from using self-service encourages customers to spend more time engaging in it. Park et al. [77] also find that this factor has a notable impact on the acceptance and usage of banking services.

In addition, Rane [78] notes that virtual banking agents provide an entertaining experience when customers request banking services. In our study, usefulness seems to be a determining element affecting the intention to use AI in banking. According to our customer survey, 77% of the responses ranged from "somewhat agree" to "strongly agree." While these findings align with the notion that enjoyment from using technology can drive acceptance, critical considerations need to be made. First, although perceived usefulness may encourage initial use, it remains unclear whether it sustains long-term engagement or leads to tangible benefits for banking customers. Second, while studies indicate the pleasurable nature of interacting with AI in Russia, the specific context of banking introduces unique considerations such as trust, security, and the seriousness of financial transactions [79]. In light of this idea, this study confirms that customer perception influences AI-enabled customer experience, specifically AI-hedonic and AI-recognition customer experiences, in Russian banking environments. These findings lend support to the concept that, in these research contexts, comfort of use, personalization, trust, loyalty, and satisfaction are nested within the customer perception construct. The results also showed that fulfilling information needs was a significant benefit for the chatbot services. Chatbots are valuable business information tools that serve utilitarian objectives such as conveying company news, making product or service suggestions, and offering information that aids in purchase decisions.

The implementation of AI-powered chatbots in banking institutions has demonstrated a significant potential for enhancing workforce efficiency. This study reveals that financial institutions harness their AI innovation capabilities as strategic assets to produce innovative solutions. These advancements not only streamline operations, but also boost employee morale, elevate productivity, and improve financial performance. Bank executives are increasingly incorporating AI-centric initiatives into their core business strategies to leverage the latest technological developments for continuous innovation.

Our research is particularly noteworthy as it delves into the specific ways in which AI technology impacts bank employee productivity, exploring various factors that contribute to this effect. Although the findings represent subjective perceptions rather than objective facts, the substantial response rate of 59.39% lends credibility to the results. These opinions offer valuable insights into employee sentiments [80]. Furthermore, despite the diverse predictions surrounding AI's impact, Turnadžić et al. [29] emphasize the importance of empirical studies, such as ours, in providing concrete evidence of the influence of AI and robotics on workplace productivity in the banking sector.

6- Conclusion and Policy Implications

The primary objective of this study is to examine the influence of Chatbots with AI on the quality of service rendered in the banking sector in Kazakhstan, Russia, and Italy. Hypothesis testing revealed that Gen. AI chatbots have a statistically significant influence on service quality. While chatbots equipped with generative AI enhance data interpretation and can address consumer inquiries and intricate issues, the adoption of AI-enabled chatbots in digital banking is now in its early phases. Hence, this study constructs an integrated research framework that combines the EXC model and investigates customer behavior in relation to the acceptability of Chatbots with AI-enabled digital banking. We selected a positivist research paradigm for this study. Data were gathered from digital banking customers using a well-organized questionnaire. The data were analyzed using structural equation modeling, which identifies the fundamental factors that contribute to the development of Chatbots with AI, including trendiness, communication quality, customization, problem-solving ability, and visual appeal. Furthermore, it aims to examine the level of satisfaction among digital banking customers. The findings suggest that happiness in digital banking customers is influenced by several factors, including EXC, trendiness, perceived performance, problem-solving, customization, visual appeal, and communication quality. These factors account for a significant amount of the variation in customer satisfaction. While all external elements had a favorable influence on customer satisfaction, the impact of trendiness and personalization was deemed minor when assessing customer satisfaction with digital banking.

It is important to note that the quality, quantity, and economic effects of chatbot introduction are most pronounced in major banks that handle a high volume of customer inquiries. This study utilizes the average values for the banking industry in each country, providing a comprehensive overview of chatbot implementation outcomes. The efficiency of chatbot integration varied significantly among the countries studied. Russian banks are expected to experience the fastest adoption and integration of chatbot technology. For instance, the VTB Bank in Russia reported that generative chatbots contributed to a cost reduction of 2.5 billion rubles in contact center operations in 2023, while also improving customer experience and loyalty. This rapid integration in Russia can be attributed to factors such as a tech-savvy customer base, a supportive regulatory environment, and significant investments in AI technologies by major banks. Italy demonstrated a moderate pace of chatbot integration in its banking sector. Italian banks such as UniCredit have implemented chatbots to enhance customer service and operational efficiency. However, the adoption rate is not as rapid as that in Russia, possibly because of a more conservative approach to technological changes in the banking sector and varying customer preferences across different regions of the country. By contrast, Kazakhstan is anticipated to have the slowest integration process among the three countries studied. This slower pace can be attributed to factors such as the development of technological infrastructure, evolving regulatory frameworks, and a customer base that may be less familiar with AI-driven banking solutions. Despite this, banks such as Kaspi Bank began introducing chatbots, indicating a growing recognition of their potential benefits in the Kazakh banking sector. To increase the quality of its services, the banking industries in Kazakhstan, Russia, and Italy should provide a range of options to ensure safety and convenience, while also considering the varying speeds of chatbot integration and adoption in their respective markets. Future research should focus on the long-term impacts of chatbot adoption, including its effects on employee roles and skills, customer behavior, and the overall banking industry dynamics across these diverse markets.

6-1- Policy Implications

The findings of this study offer several practical implications for banks, considering the implementation of voice chatbots powered by artificial intelligence.

- Implementing generative AI-driven voice chatbots can significantly enhance the customer experience by providing 24/7 support and faster response times. This improvement in service delivery can lead to increased customer satisfaction across cultural contexts, as evidenced in Russia, Kazakhstan, and Italy. Banks should leverage this technology to offer consistent and reliable customer support, reduce wait times, and improve the overall service quality.
- Voice chatbots can help banks reduce operational costs associated with human customer service agents. Banks can allocate human resources to complex value-added tasks by automating routine inquiries and transactions. This cost efficiency is particularly beneficial in competitive markets where operational expenses must be carefully managed to maintain profitability.
- Given the varying cultural expectations and preferences in Russia, Kazakhstan, and Italy, banks should invest in customizing their voice chatbots to cater to local languages, dialects, and cultural nuances. Personalizing interactions to align with regional expectations can enhance customer satisfaction and acceptance of technology, thereby fostering a more positive customer experience.
- Voice chatbots can collect and analyze data from customer interactions, providing banks with valuable insights into customer behavior, preferences, and pain points. This data can inform strategic decisions, enabling banks to tailor their services more effectively and promptly to address emerging trends and issues.
- The transition to AI-driven voice chatbots requires a strategic approach to change the management and staff training. Banks must ensure that their employees are well-prepared to work alongside AI systems and adapt to new workflows. Providing adequate training and clear communication on the role of chatbots can mitigate resistance and enhance the overall effectiveness of technology.
- Banks should be mindful of regulatory and ethical considerations related to the use of AI in customer interactions. Ensuring compliance with data protection regulations and addressing ethical concerns regarding AI transparency and accountability are crucial for maintaining trust and protecting customer privacy.
- In summary, the integration of voice chatbots into banking can lead to improved customer satisfaction and operational efficiency, provided banks tailor their implementation strategies to local contexts, invest in employee training, and adhere to regulatory standards. By effectively leveraging AI technology, banks can enhance their service offerings and maintain a competitive edge in the evolving financial landscape.

6-2- Theoretical Implications

This study offers several significant theoretical implications.

- This research extends the existing technology acceptance models (TAM) by integrating the role of AI-driven voice chatbots in the banking sector. This suggests that customer acceptance of AI technologies is influenced by their expectations of service quality, perceived ease of use, and perceived usefulness. This extension emphasizes the need to consider contextual factors such as cultural differences when applying TAM frameworks in diverse geographic settings.
- These results highlight the importance of cultural context in shaping customer perceptions and expectations of AI technologies. The findings indicate that cultural differences can significantly affect how customers from different countries view and interact with voice chatbots. This study contributes to a broader understanding of how culture affects technology adoption and satisfaction, and suggests that theoretical models should incorporate cultural dimensions to provide more accurate predictions of technology acceptance and usage.
- By demonstrating how AI-driven voice chatbots influence customer satisfaction and expectation management, this article provides theoretical insights into the service quality dynamics in AI-mediated interactions. This suggests that traditional theories of service quality and customer satisfaction must be adapted to account for the unique attributes of AI technologies, such as their ability to handle large volumes of interaction and their potential for personalization.
- This study contributes to economic impact theories related to technology adoption by illustrating how AI chatbots can affect both operational costs and customer satisfaction. It offers empirical evidence that supports the notion that investing in advanced technologies can lead to economic benefits for banks, challenging earlier models that may have underestimated the potential economic advantages of AI in service industries.

- This research advances theoretical frameworks related to human-AI interaction by providing evidence of how AI-driven voice chatbots affect customer expectations and satisfaction. This suggests that theories of human-computer interaction (HCI) need to evolve to better accommodate the complexities of AI systems, including their ability to simulate human-like interactions and their impact on customer satisfaction and loyalty.
- These findings imply the need for customer-centric theoretical models that account for the evolving nature of customer expectations in the age of AI. They underscored the importance of integrating customer feedback into theoretical models to better understand how AI technologies can meet or exceed customer expectations and enhance satisfaction.

In summary, this research advances theoretical understanding in several areas, including technology acceptance, cultural influences on technology perception, service quality management in AI interactions, economic impact of technology adoption, human-AI interaction, and customer-centric model development. These contributions help refine existing theories and provide a more nuanced perspective on the role of AI in customer service environments.

6-3- Research Limitations and Future Directions

Examining the connections and consequences between the impact of artificial intelligence, the level of satisfaction with technological innovation, and staff productivity in banking organizations is intellectually intriguing. Future studies should incorporate a wider range of comprehensive factors that specifically address artificial intelligence, satisfaction levels related to artificial intelligence, and staff productivity inside banking organizations. Therefore, future studies could employ alternative data collection methods such as interviews and open-ended questions. The study is centered on the banking sector, and we can consider other organizations, such as the textile industry.

A notable limitation of this study is its lack of consideration of the economic differences between Kazakhstan, Russia, and Italy, which could significantly influence the adoption and perception of AI chatbots in banking. The varying levels of economic development, technological infrastructure, and financial regulations in these countries may have impacted the results in ways that were not accounted for in the current analysis. Future research should incorporate a comparative economic analysis of the countries involved and examine how factors such as GDP, technological readiness, and financial sector maturity affect the implementation and customer reception of AI chatbots in banking. This approach provides a more nuanced understanding of the role of the economic context in shaping customer satisfaction and AI adoption in diverse markets.

7- Declarations

7-1- Author Contributions

Conceptualization, S.K. and V.P.; methodology, O.S. and M.D.; software, E.M. and L.V.; validation, R.F., S.A., and G.S.; formal analysis, M.D., R.F., and G.S.; investigation, E.M., S.A., and L.V.; resources, I.N. and O.S.; data curation for Kazakhstan, S.K. and M.D.; data curation for Russian Federation, O.S. and V.P.; data curation for Italy, R.F.; writing—original draft preparation, all authors; writing—review and editing, all authors; visualization, I.N. and G.S.; supervision, M.D.; project administration, O.S. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available in the article. Additional data may be required from the corresponding author through a reasonable request.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

Ethical review and approval were waived for this study due to the reason human interaction being limited by anonymous survey.

7-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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Appendix I: Research Questionnaire

Thank you for participating in this survey! Your feedback is invaluable in helping us understand the economic effects and customer satisfaction related to the use of AI voice chatbots in banking. The questionnaire is anonymous and the data will only be used for academic purposes.

Demographic:

1. Age:
   - Under 18
   - 18-24
   - 25-34
   - 35-44
   - 45-54
   - 55-64
   - 65 and above
2. Gender:
   - Male
   - Female
   - Non-binary/Other
   - Prefer not to say
3. Employment Status:
   - Employed
   - Self-employed
   - Unemployed
   - Student
   - Retired
   - Other
4. Educational Level
   - High school or less
   - Diploma
   - Bachelor
   - Higher School
5. Banking Experience:
   - Less than 1 year
   - 1-3 years
   - 4-6 years
   - 7-10 years
   - More than 10 years

Artificial intelligence banking adoption:

6. The integration of AI chatbots in banking services strongly motivates me to use them.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

7. I am eager to use AI-powered chatbots for conducting my banking operations.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

8. Using AI chatbots for banking services gives me a sense of satisfaction.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Communication quality (COMQ):

9. AI-powered digital banking offers reliable information to users.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

10. Utilizing AI in digital banking enhances communication, making it more efficient and beneficial.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

11. AI-powered digital banking significantly reduces time consumption.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Corporate Reputation (CR):

12. I believe that banks offering AI-driven digital banking have a commendable reputation.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree
13. I strongly believe that integrating AI into digital banking offers excellent cost-effectiveness.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree
14. I greatly appreciate and feel a sense of satisfaction with banks' provision of AI-based digital banking services.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree
15. I have confidence in the credibility and fulfilment of claims for AI-driven digital banking services.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree

Customization (CSN):

16. This AI-powered digital banking aligns perfectly with my individual requirements.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree
17. I believe that the ability to customize enhances my transaction experience compared with non-customizable digital banking applications.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree

18. The AI-powered digital banking platform provides unique and valuable capabilities unavailable in traditional digital banking systems.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree

19. The digital banking system, powered by AI, enabled me to conduct transactions based on my personal preferences.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree

<u>Performance Expectancy:</u>

20. I am pleasantly surprised by the performance of AI-driven digital banking, which exceeded my initial expectations.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree

21. The advantages of AI- driven digital banking surpass my first expectations.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree

22. The AI- driven digital banking exceeded my expectations in terms of service quality.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree

23. I have found that my expectations for AI- driven digital banking have been met.
    - Strongly agree
    - Agree
    - Neutral
    - Disagree
    - Strongly disagree

Perceived performance (PP):

24. The employment of AI in digital banking has significantly enhanced my productivity.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

25. The employment of AI in digital banking has enabled me to expedite my chores with greater efficiency.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

26. Utilizing AI-powered digital banking simplifies financial tasks for me.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

27. Utilizing AI technology in digital banking improves efficiency and effectiveness.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Problem solving (PS):

28. I am confident that AI-driven digital banking can accomplish this task successfully.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

29. AI- driven digital banking enables direct and immediate resolution of client complaints.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

30. AI- driven digital banking possesses the capability to effectively address intricate issues.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

<u>Satisfaction towards AI Banking (STAIB):</u>

31. I am content with the AI- driven digital banking services.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

32. The AI-powered digital banking meets my expectations.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

33. Overall, I am content with the digital banking system driven by AI.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

<u>Trendiness (TRN):</u>

34. The AI-powered digital banking platform provides updated information about digital banking services.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

35. The most recent data on digital banking services is provided by AI-driven digital banking.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

36. Most up-to-date details of digital banking services are provided by AI-driven digital banking.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Visual attractiveness (VA):

37. AI-driven digital banking software is aesthetically pleasing.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

38. The AI-driven digital banking application has a visually appealing design.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

39. The AI- driven digital banking application has a well-designed user interface.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Productivity performance (PRP):

40. AI driven banking promotes technical process in productivity performance.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

41. AI driven banking will make efficient service delivery time.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

42. AI driven will control risk management.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree