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Article

The Impact of Explainable AI on Customer Trust and Satisfaction in Banking

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Abstract: This study employed a structured questionnaire to gather data from bank customers, focusing on customer perceptions of Explainable AI, Customer Trust (CT), and Customer Satisfaction (CS) in the banking sector. A total of 180 questionnaires were distributed, with 169 valid responses analyzed. The study selected various indicators such as Customer Age, Education Level, Risk Appetite, Previous Internet Experience, Previous AI Experience, Engagement, Post-Use Feedback, Personalized Service, Prediction Accuracy, Data Privacy, System Reliability, Service Efficiency, and Information Push to assess their impact on customer trust and satisfaction. Reliability and validity analyses ensured the robustness of the collected data. Ordered probit analysis revealed significant influences of variables like Customer Risk Preference, Perceived Innovation, and Perceived Accuracy on customer trust and satisfaction.

Keywords: explainable AI; customer trust; customer satisfaction

1. Introduction

In recent years, the banking industry has witnessed a significant shift towards incorporating Artificial Intelligence (AI) technologies to enhance customer services. One crucial aspect of AI adoption is the transparency and interpretability of AI algorithms, known as Explainable AI. urgt's study explores the application of Explainable AI specifically in the banking sector, shedding light on how transparency and interpretability can enhance AI systems within financial institutions [1]. This research delves into the perspectives of banks and supervisory authorities regarding Explainable AI within the financial sector, providing valuable insights from key stakeholders [2]. The study by De Lange et al. focuses on the use of Explainable AI for credit assessment in banks, highlighting its potential impact on risk management practices [3]. Carter and Hersh present evidence from a large bank demonstrating how Explainable AI can help bridge the skills gap related to artificial intelligence within banking institutions [4]. Hanif's work emphasizes the move towards achieving explainability in artificial intelligence systems within the banking and financial services industry [5]. This study examines how domain knowledge influences trust in Explainable AI systems and its impact on task performance using peer-to-peer lending as a case study [6]. The research by Fritz-Morgenthal et al. focuses on the role of Explainable AI in financial risk management to ensure trustworthiness and responsibility within AI applications [7]. This study outlines key requirements for achieving Explainable AI within statistical production systems at the European Central Bank [8]. Adams and Hagras propose a type-2 fuzzy logic approach to achieve explainability in AI systems for regulatory compliance and market stability within the global financial sector [9].

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Gramespacher and Posth explore how Explainable AI can be utilized to optimize return targets within a loan portfolio setting [10]. Based on previous research results, this study aims to analyze how explicable AI affects customer trust and satisfaction in the banking industry using data based on questionnaires.

2. Research Hypotheses

Explainable AI (XAI) has emerged as a critical component in the adoption of artificial intelligence systems, particularly in sensitive domains like banking and finance. The transparency and interpretability offered by XAI play a pivotal role in fostering Customer Trust (CT) within these industries. Trust is fundamental in customer relationships, especially when it comes to financial decision-making. When customers understand how AI algorithms arrive at recommendations or decisions, they are more likely to trust the system. This transparency reduces the perceived risk associated with automated processes and enhances accountability within institutions. Therefore, based on these premises, we hypothesize that there is a positive relationship between Explainable AI and Customer Trust (CT).

H1: *There is a positive relationship between Explainable AI and Customer Trust (CT).*

In the competitive landscape of banking and financial services, Customer Satisfaction (CS) stands out as a key metric for success. The implementation of Explainable AI has the potential to significantly impact customer experiences and satisfaction levels. Transparent explanations provided by XAI empower customers to make informed decisions, receive personalized recommendations, and navigate financial services with reduced friction. By enhancing user understanding and trust in AI systems, Explainable AI can lead to improved customer satisfaction levels. Therefore, we propose that there exists a positive relationship between Explainable AI and Customer Satisfaction (CS).

H2: *There is a positive relationship between Explainable AI and Customer Satisfaction (CS).*

3. Methodology

3.1. Data Collection

A structured questionnaire was employed to gather data from customers of various banks. The questionnaire was designed to assess customer perceptions regarding Explainable AI, Customer Trust (CT), and Customer Satisfaction (CS) within the banking sector. A total of 180 questionnaires were distributed among bank customers. Out of these, 169 responses were deemed valid for analysis.

3.2. Indicator Selection

In this section, we will discuss each indicator selected for the study and its significance in evaluating the impact of Explainable AI on customer trust and satisfaction within the banking sector.

Independent Variables:

Customer Age (CA): Customer age is a fundamental demographic variable that can influence attitudes and behaviors towards technology adoption and banking services.

Customer Education Level (CEL): Education level can indicate the customer's familiarity with technology and their ability to understand complex AI systems, potentially affecting their trust and satisfaction levels.

Customer Risk Appetite (CR): Customer risk appetite reflects the willingness to take risks in financial decisions, which can impact perceptions of AI-driven services and their reliability.

Customer's Previous Internet Experience (CPI): Past internet experience may shape customer expectations regarding online services, including AI applications in banking, influencing trust and satisfaction levels.

Customer's Previous AI Experience (CPA): Previous AI experience can affect how customers perceive and interact with Explainable AI systems, potentially impacting their trust in such technologies.

Customer Engagement (CE): Customer engagement measures the level of interaction customers have with banking services, which can affect their overall satisfaction with the service provided by AI systems.

Post-Use Feedback (PF): Post-use feedback from customers provides valuable insights into their experiences with AI-driven services, helping to assess satisfaction levels and areas for improvement.

Personalized Service (PS):Personalized service indicates the degree to which banking services are tailored to individual customer needs, potentially influencing trust and satisfaction levels.

Prediction Accuracy (PA): Prediction accuracy measures how effectively AI systems anticipate customer needs or behaviors, which can impact trust in the system's capabilities.

Data Privacy (DP):Data privacy concerns are crucial in building trust with customers using AI technologies, as ensuring data security can influence overall satisfaction levels.

System Reliability (SR):System reliability assesses the consistency and dependability of AI-driven services in meeting customer expectations, which is vital for building trust.

Service Efficiency (SE):Service efficiency evaluates how quickly and effectively banking services powered by Explainable AI address customer needs, impacting overall satisfaction levels.

Information Push (IP): Information push measures the proactive delivery of relevant information to customers by AI systems, potentially enhancing trust through transparency and communication.

Dependent Variables:

Customer Satisfaction (CS): Customer satisfaction is a key dependent variable that reflects the overall contentment and fulfillment customers experience with banking services enhanced by Explainable AI. It is crucial for assessing the effectiveness of AI applications in meeting customer expectations and needs.

Customer Trust (CT): Customer trust represents the confidence and belief customers have in the reliability, integrity, and competence of AI-driven banking services. Trust is essential for building long-term relationships with customers and fostering loyalty towards the bank.

These two dependent variables, customer satisfaction (CS) and customer trust (CT), are central to understanding how customers perceive and interact with Explainable AI in the banking sector. Evaluating these variables provides insights into the effectiveness of AI systems in enhancing customer experiences, improving service quality, and building sustainable relationships with customers.

By analyzing the relationships between these dependent variables and the selected independent variables, researchers can gain a comprehensive understanding of the impact of Explainable AI on customer trust and satisfaction within the banking industry.

3.3. Reliability and Validity Analysis

The reliability and validity of the questionnaire were evaluated to ensure the robustness of the data collected. The reliability coefficient, measured by Cronbach's alpha, was found to be 0.8202, indicating a high level of internal consistency among the survey items. This suggests that the questionnaire items reliably measure the intended constructs.

Similarly, the validity coefficient, which assesses the extent to which the questionnaire accurately measures what it intends to measure, was calculated to be 0.8176. This value indicates a strong level of validity in capturing customer perceptions related to Explainable AI, Customer Trust (CT), and Customer Satisfaction (CS).

By ensuring both reliability and validity in the data collection process, we can have confidence in the accuracy and consistency of the responses provided by bank customers in relation to their views on Explainable AI and its impact on Customer Trust and Satisfaction within the banking industry.

4. Results Analysis

4.1. Descriptive Statistics

The results of the analysis（Table 1）will provide insights into how each independent variable impacts customer trust and satisfaction in the context of Explainable AI in banking.

The variable CA (Customer Age) has a mean of approximately 3.98 with a standard deviation of around 1.61. The minimum age is 1, the maximum age is 7, and the median age is 4. The variable CEL (Customer Education Level) has a mean of about 3.83 with a standard deviation of roughly 1.67. The education level ranges from 1 to 7, with a median value of 4. Similar statistics are provided for the other variables CR, CPI, CPA, CE, PF, PS, PA, DP, SR, SE, IP, CS, and CT in terms of their means, standard deviations, minimum and maximum values.

These descriptive statistics offer insights into the central tendency (mean), data dispersion (standard deviation), data range (minimum and maximum values), and central position (median) of the sample data for each variable. This information provides an initial understanding of the characteristics of the sample data. By combining these descriptive statistics with regression analysis results, we can gain a more comprehensive understanding of the relationships and features among the variables studied.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max	Med
CA	3.982249	1.612722	1	7	4
CEL	3.83432	1.671471	1	7	4
CR	3.863905	1.721485	1	7	4
CPI	3.568047	1.538141	1	7	4
CPA	4.011834	1.669004	1	7	4
CE	3.692308	1.435104	1	7	4
PF	3.47929	1.539514	1	7	4
PS	3.727811	1.498966	1	7	4
PA	3.621302	1.603128	1	7	4
DP	3.928994	1.616779	1	7	4
SR	3.455621	1.475831	1	7	4
SE	3.627219	1.438242	1	7	4
IP	3.698225	1.446691	1	7	4
CS	3.60355	1.480906	1	7	4
CT	3.52071	1.418789	1	7	4

4.2. Ordered Probit Analysis

The ordered probit analysis results (Table 2) shed light on how each independent variable influences customer trust (CT) and customer satisfaction (CS) within the context of Explainable AI in banking. The coefficients provide insights into the strength and direction of these relationships.

Customer Trust (CT):

Customer Age (CA): Age does not significantly impact customer trust. Customer Education Level (CEL): Education level does not significantly influence customer trust. Customer Risk Preference (CR): A strong positive impact on customer trust, with a significant coefficient of 0.557***. Customer Perceived Innovation (CPI): Significantly and positively influences customer trust with a coefficient of 0.342***. Customer Perceived Accuracy (CPA): Strongly positively impacts customer trust, with a significant coefficient of 0.530***.

Factors like Customer Risk Preference (CR), Customer Perceived Innovation (CPI), and Customer Perceived Accuracy (CPA) show positive and significant effects on customer satisfaction. Variables such as Personal Finance Management (PF), Personal Security Concerns (PS), and Personal Assistance Needs (PA) do not have statistically significant impacts on customer satisfaction.

In summary, risk preference, perceived innovation, and perceived accuracy are crucial factors influencing both customer trust and satisfaction in the realm of Explainable AI in banking. These findings can guide banks in enhancing their AI services to better align with customers' expectations and needs.

Table 2. Ordered probit analysis.

	(1)	(2)
Variables	**CS**	**CT**
CA	0.060	−0.139
	(0.43)	(−1.01)
CEL	−0.044	−0.018
	(−0.32)	(−0.13)
CR	0.399 ***	0.557 ***
	(3.52)	(4.45)
CPI	0.442 ***	0.342 ***
	(3.39)	(2.70)
CPA	0.432 ***	0.530 ***
	(3.44)	(3.95)
CE	0.040	0.097
	(0.31)	(0.74)
PF	−0.168	0.054
	(−1.54)	(0.48)
PS	0.119	−0.174
	(0.95)	(−1.37)
PA	0.054	−0.294 **
	(0.45)	(−2.33)
DP	−0.025	0.075
	(−0.19)	(0.55)
SR	0.010	0.361 ***
	(0.08)	(2.73)
SE	0.141	0.069
	(0.97)	(0.47)
IP	−0.038	0.194
	(−0.27)	(1.38)
Observations	169	169

z-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Conclusions

The findings underscore the importance of factors such as risk preference, perceived innovation, and perceived accuracy in shaping customer trust and satisfaction within the realm of Explainable AI in banking. While variables like Personal Finance Management and Personal Security Concerns did not significantly impact customer satisfaction in this context, understanding these relationships can guide banks in optimizing their AI services to meet customer expectations effectively. By combining descriptive statistics with regression analysis results, this study provides valuable insights for enhancing customer experiences and building sustainable relationships through Explainable AI applications in the banking industry.

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Conflicts of Interest

The author declares no conflict of interest.

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