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Providing a Model of Customer Experience Management Based on Knowledge Management Models in the Field of Fintech Using Machine Learning

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ABSTRACT

This study explores the role of machine learning in managing knowledge of customer experience. Given the importance of high-quality knowledge for organizational innovation, this research aim is to address existing research gaps and propose a novel model for leveraging customer experiences in the fintech sector using machine learning. The main research question is to identify the key components and effective elements in developing a knowledge management of customer experience model using machine learning. Two secondary questions focus on identifying the most relevant knowledge management model for developing the knowledge management of customer experience model and assessing the suitability of machine learning capabilities for interpreting customer perceptions.
The research methodology is design science. Conceptual and structural equation models were developed, and hypotheses were tested and validated through model fitting. The findings led to the creation of a framework for future research and the development of the APO model into a seven-layer APO-CEM model, which includes preprocessing, coding, thematic categorization, and improved decision tree accuracy. The model was positioned and validated within the fintech ecosystem. Results confirm the model's effectiveness in enhancing growth, productivity, and customer satisfaction and demonstrate that machine learning can effectively measure and improve the quality of knowledge of customer experience through the cultivation of customer insights.

Keywords

Fintech, Knowledge management, Design science, Machine learning, Customer experience.

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1. Introduction

In today's rapidly evolving business environment, knowledge has become crucial for organizations seeking a competitive advantage. Specifically, customer-related knowledge has evolved into a key concept, encompassing knowledge about the customer, knowledge for the customer, and knowledge from the customer (Alryalat et al., 2008). Since a significant portion of knowledge is inherently stored in the human brain, the performance and perceptions of individuals fundamentally drive organizational outcomes (Zhou et al., 2020). Effective knowledge management (KM) focuses not on managing all knowledge but on leveraging collective knowledge from employees, customers, and stakeholders to enhance performance through differentiated products and services, ultimately meeting customer expectations (Alryalat et al., 2008). Transforming efficient experiences and data into actionable knowledge positively impacts decision-making speed, strategy implementation, and innovation (Teran et al., 2021).Despite the importance of customer experience as a multidimensional concept analyzed from various perspectives and industries (Barbu et al., 2021), the ability to effectively disseminate acquired experiences is critical (Schneider, 2009). Previous research shows tacit knowledge is obtained from experience (Jaziri, 2019) .Tacit knowledge gained from experience forms the foundation for interpreting and applying knowledge at its highest level : wisdom (Sanzogni et al., 2017). Knowledge management of customer experience involves systematically using customer knowledge to enhance organizational performance (Teran et al., 2021). This concept can be framed as an extension of KM if it is consistently applied (Schneider, 2009). Customer knowledge is categorized into "knowledge for," "knowledge about," and "knowledge from" (Desouza et al., 2005). So, customer experience can be identified as an indicator for discovering, extracting, and exploiting knowledge in a new knowledge management model (Jaziri, 2019).

Digital transformation has catalyzed the rise of Fintech, revolutionizing financial services and banking (Suryono et al., 2020). Innovations in financial technologies have significantly advanced the fintech ecosystem, receiving substantial attention from industry and academia (Anshari et al., 2018). Fintech represents the future of banking and finance, leveraging technology to provide more efficient financial services (Jagtiani et al., 2018). Integrating artificial intelligence with Fintech has enabled more intelligent financial processing (Wen et al., 2012), while a positive relationship between KM processes and AI algorithms has been established (Alghanem et al., 2020). Machine learning, a subset of AI, facilitates the development of accurate predictive models from data (Teran et al., 2021). However, machine learning algorithms find predicting customer experience outcomes challenging (Wen et al., 2012). Research highlights the significance of KM and decision tree algorithms for classifying knowledge quality and the advantages of applying machine learning in KM from theoretical and practical perspectives (Kaun et al., 2021).

1.1. Problem statement and innovation

Despite the advancements in Fintech and the potential of AI and machine learning, there needs to be a greater gap in the effective application of KM models specifically tailored for customer experience in the fintech domain. Current models often fail to integrate customer knowledge comprehensively and leverage it for enhanced organizational performance. This study aims to address this gap by developing the APO-CEM model, which integrates machine learning techniques to optimize customer experience management. This research's primary innovation lies in applying the APO-CEM model to systematically cultivate customer knowledge and assess its impact on growth, productivity, and satisfaction within the fintech ecosystem.

1.2. Research questions and hypotheses

The study investigates the following main questions and sub-questions:

Main Question:

- RQ1: What are the primary and effective components in developing a knowledge management model for customer experience through machine learning?

Sub-Questions:

- RQ2: Which KM models are most suitable for developing a knowledge management model for customer experience?
- RQ3: Is the decision tree algorithm effective for interpreting customer experience perceptions based on KM models?

The research hypotheses include:

(1) Applying AI technology (machine learning) significantly positively affects customer knowledge cultivation.
(2) Implementing KM components significantly positively affects customer knowledge cultivation.
(3) Customer knowledge cultivation significantly enhances developing a knowledge management model for customer experience.
(4) Customer experience management significantly contributes to the development of a knowledge management model for customer experience.
(5) Developing a knowledge management model for customer experience significantly impacts growth, productivity, and customer satisfaction.

2. literature review

Nowadays, marketing focus has shifted from products to providing services based on customer experience, challenging researchers to enable organizations to play a strategic role in interacting with customers (Maklan and Klaus, 2011). The consumer experience is a lived, subjective which can be transformed knowledge resulting from physical, praxiological, and rhetoric dimensions; all are integrated under a dynamic interaction between the consumer, the object, and the situation" (Jaziri, 2019). As cited in Jaziri (2019), customers are heterogeneous in terms of identity and want to be different from others through their shopping experiences (Cinotti, 2007).

Providing and managing customer experience across various digital channels and networks, including the fintech area, is critical for achieving business success, leading to investments in customer experience tied to effective business outcomes (Izogo et al., 2018). Customer experience management requires reliable measurement of customer perceptions. It is challenging because most customers cannot accurately assess why an experience could be good or bad. More importantly, the volume of data involved exceeds human capacity for analysis (Tsai et al., 2018).

Customer experience management is a global approach that stresses the brand experience design (Jaziri, 2019). Market researchers have identified suitable criteria for customer experience based on cognitive and emotional evaluation and the value of the purchase process from the customer's point of view rather than merely customer expectations (Maklan and Klaus, 2011). The customer experiential knowledge management approach is the fundamental theoretical framework that advanced the conversion of customer experience data into customer experiential knowledge (CEK) (Jaziri, 2019).

Measuring and evaluating customer experience is complex, and the researcher must determine which features impact customer experience and which are most important (Maklan and Klaus, 2011). Customer experience (CX) and customer experience management (CXM) are key principles of the management strategy paradigm (Wetzels et al., 2023). Effective customer experience management emphasizes converting customer experience data into actionable knowledge for the company (Jaziri, 2019). It requires extracting and applying knowledge as a conceptual model using knowledge management techniques and artificial intelligence (Izogo et al., 2018).

Studies in the customer experience area show that the feelings and emotions resulting from customer experiences meet their needs and enhance the experience by identifying the consumer's identity (Jaziri, 2019). Tacit knowledge, derived from individual experience, is not easily transferable to others (Weller et al., 2016). Competitive advantages of knowledge management can be assured only if intellectual capital is understood as knowledge that can be extracted and creates value (Teran et al., 2021).

The knowledge management framework includes five main processes: creating knowledge, discovering knowledge, storing knowledge, applying knowledge, and sharing knowledge (Alghanem et al., 2020). However, a process for recognizing and interpreting human emotions has not yet been adequately developed, as it cannot be easily explained or modeled (Sanzogni et al., 2017). Despite this, artificial intelligence has made significant strides in evolving knowledge management (Pinker, 2005).

Knowledge management requires tools to assist in creating, documenting, and sharing knowledge. KM tools are used to facilitate knowledge management through IT-based solutions to improve organizational performance (Alghanem et al., 2020). However, discovering and sharing tacit and practical knowledge in a structured format remains challenging, as knowledge in people's minds is not easily formalized (Weller et al., 2016).

In this regard, Jaziri (2019) conceptualized the customer experiential knowledge management approach (CEKM) as the association of the knowledge management process with the customer service experience in order to enhance the future customer service experience or/and to create an experience offer. CEKM is based on the tacit knowledge related to customer experiential knowledge (Jaziri, 2019). Knowledge creation is an applicant learning process in which people use their existing knowledge or experiences to understand new issues (Shi, 2019).

Fintech represents a new financial industry that applies technology to improve financial activities (Suryono et al., 2020). Digitization has led to the emergence of fintech companies, which provide services such as money transfer, exchange services, payment, internet banking, mobile banking, and IVR services (Ulusoya et al., 2019). Since fintech primarily involves technology-based aspects like big data, artificial intelligence, distributed databases, cloud computing, and cybersecurity solutions, it is assumed that fintech companies possess advanced IT expertise and engage in IT development and financial software production (Dranev et al., 2019).

Fintech is a paradigm where information technology drives innovation in the financial industry, evolving continuously and potentially overshadowing traditional financial markets (Lee et al., 2017). Fintech is an ecosystem that supports entrepreneurs, and governments should focus on the quantity and quality of innovative companies in the financial sector (Wonglimpiyarat, 2018).

Fintech aims to transform financial interactions by reducing costs, improving service quality, and creating a diverse and sustainable financial vision (Lee et al., 2017). Financial policies play a crucial role in guiding the development of innovative financial technology systems (Wonglimpiyarat, 2018). Studies show that 83% of financial institutions believe various aspects of their business are at risk of losing new ideas. Thus, investing in fintech creates a competitive advantage (Lee et al., 2017).

The classification of innovation dimensions in fintech includes company type, innovation type, maturity level, value chain situation, and business ecosystem nature (Drasch et al., 2018). The fintech ecosystem comprises five elements: 1) Fintech startups (payment, wealth management, loans, financial collective participation, capital market, and fintech insurance); 2) Technology developers (big data analytics, cloud computing, cryptography, and social media developers); 3) The government (as a regulator and legislator); 4) Traditional financial institutions (banks, insurance companies, stock brokerage firms, and investors) (Lee et al., 2017).

By focusing on technological advancements, fintech improves financial operations and is often delivered through mobile applications (Gai et al., 2018). Challenges in fintech include investment management, customer management, regulatory compliance, IT integration, privacy and security, and risk management (Lee et al., 2017). Fintech companies create opportunities for new financial products and solutions using innovative technologies (Gomber et al., 2017). Various knowledge management models exist, and the APO framework ensures that no crucial element is overlooked during implementation (Cahyaningsih et al., 2017). The APO framework defines knowledge management as a five-step process: 1) knowledge identification: 2) knowledge creation: 3) knowledge storage: 4) knowledge sharing: 5) knowledge application (Young, 2020). Additionally, the APO framework evaluates knowledge management and identifies areas for organizational focus (Khajouei et al., 2017).

Table 1. Summary of literature review on customer experience management and fintech innovations

Topic	Summary	References
Focus on Customer Experience	Shift from products to services based on customer experience, emphasizing its importance in strategic customer interactions.	Maklan and Klaus (2011)
Customer Experience Management	There is aneed to provide and manage customer experience across digital channels, including fintech, to achieve business success and effective outcomes.	Izogo et al. (2018)
Knowledge Management Models	Knowledge management includes five main processes: identification, creation, storage, sharing, and application of knowledge.	Alghanem et al. (2020)
APO Model	The APO model includes five stages: knowledge identification, creation, storage, sharing, and application	Young (2020)
Fintech Innovations	With advancements in AI and big data, fintech applies technology to improve financial activities. Fintech introduces new paradigms and challenges in the financial industry.	Suryono et al., (2020); Dranev et al., (2019)
Coordination and Engagement	More coordination with customers and customer engagement positively influence business customer experience.	Ruiz-Alba et al., (2023)
AI and Customer Experience	The connection between AI and customer experience is under-researched. Conversational AI models can impact customer experience, but further research is needed.	Abdelkader, (2023)

Figure 1. The APO knowledge management framework (Cahyaningsih et al., 2017)

Interpreting customer experience perception is crucial (Virginia et al., 2014). However, many companies have neglected this important issue, believing implementing customer experience perception correctly conflicts with purely human analysis and individual interpretation (Teran et al., 2019). A significant issue leading to the development of ineffective knowledge-based systems is the inadequate understanding of knowledge quality characteristics (Abdelrahman, 2019). Machine learning, a subset of AI, is a technique that can enhance knowledge quality and manage it more effectively (Malik et al., 2019). Human experiences, emotions, and perceptions are rooted in tacit knowledge that can inspire the development of new ideas (Busch, 2008).

Previous studies on the relationship between knowledge management processes and artificial intelligence systems indicate that the role of knowledge management processes and their impact on AI systems has been underexplored (Alghanem et al., 2020). Machine learning algorithms can potentially reduce costs associated with credit and operational decisions in fintech (Jagtiani et al., 2018). AI addresses customer expectations by extracting optimal results from fintech ecosystem databases (Hoeschel et al., 2006). Machine learning is valuable for knowledge management, and the decision tree algorithm shows strong potential in classifying knowledge quality (Kaun et al., 2021). Knowledge analysis is closely tied to various learning processes (Teran et al., 2021), and AI and KM are intricately related to the nature of knowledge (Sanzogni et al., 2017).

One of the most common and straightforward machine learning algorithms is the decision tree, known for its interpretability, efficiency, and flexibility in handling customer perceptions (Lamrini, 2020). Implementing the decision tree algorithm for classifying knowledge quality and machine learning's effect on knowledge-based systems proves effective in knowledge management (Kaun et al., 2021). The decision tree is a supervised learning algorithm valued for its interpretability, which aids users in making decisions based on interpreted perceptions (Lamrini, 2020). Among programming languages, Python is highly compatible with machine learning algorithms and offers visualization tools for this purpose (Raschka et al., 2020). The necessity of developing models and theorizing in fintech research subjects, machine learning, and customer experience management has been consolidated in previous studies (Rahmani et al., 2022). Enhanced coordination with customers and customer engagement positively influence business customer experience (Ruiz-Alba et al., 2023). Additionally, while the connection between AI and customer experience is infrequently studied, conversational AI models have the potential to positively impact these aspects. Further research is needed to understand the specific factors influencing the impact of conversational AI models on customer experience (Abdelkader, 2023).

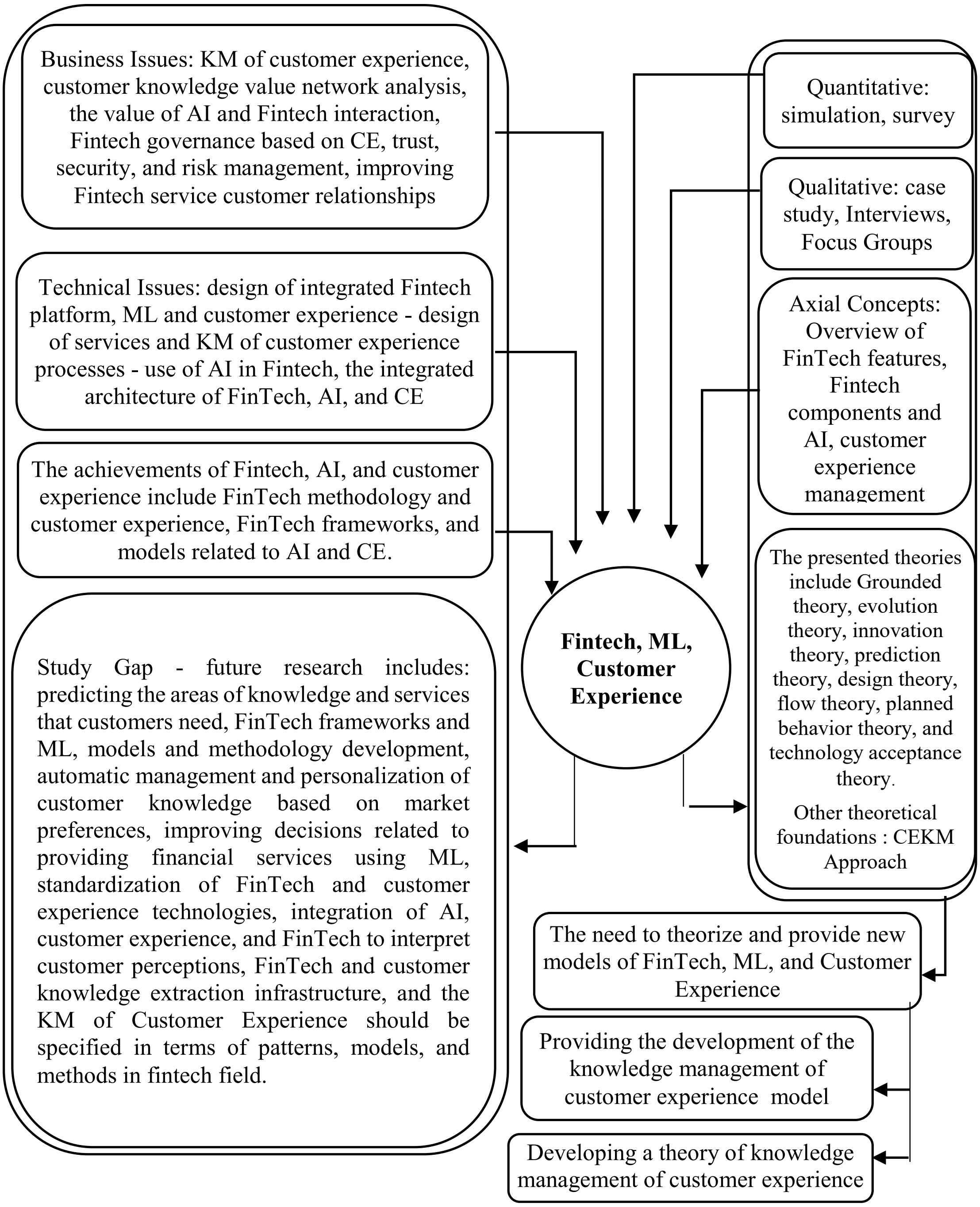

Figure 2. The proposed framework for the research in fintech, machine learning, and customer experience area (Rahmani et al., 2022).

3. Methodology

The research seeks to provide a customer experience management model based on a knowledge management model through machine learning in the fintech ecosystem. The research method is design science. The type of research in terms of purpose is applied. The customer experience data analysis segment is viewed as a quantitative undertaking based on artificial intelligence (machine learning). The interpretation section is based on interviews and will follow the design science method in a structured way. The research includes twelve main stages.First, to review the literature, selecting and processing articles was designed and used. Second, by identifying quality knowledge in the data obtained from the customers' experiences in the fintech area, the relationship between knowledge management and customer experience management and the relationship between knowledge management and machine learning were studied, and the research questions were determined. Third, the conceptual model was designed, the relationship between the model's components was determined, and the hypotheses were identified. In the fourth stage, the design of structural equation modeling, the questionnaire, validity and reliability, and the test and fitting of the model were carried out, and the significance level of the hypotheses was measured.

Fifth, the APO model was selected as the most appropriate model for classifying knowledge quality. Sixth, the data sets required for training and testing the decision tree algorithm were identified and coded, and the decision tree was drawn, modeled, and tested using the Python language and the VS-Code platform. Seventh, the research proposed model, APO-CEM, was designed as a new development of the APO model. The APO-CEM model was embedded in the fintech conceptual ecosystem in the eighth step. Ninth, the research questions were answered by analyzing the data .Tenth, the results from the perspective of theoretical and practical concepts were discussed. In the eleventh stage, the research concluded by pointing out the research limitations and suggestions for future research.

Drawing the processing processes is essential for studying and reviewing papers (Petersen et al., 2015). So, first, the process map of selection and review of sources for the research was designed—figure 3.

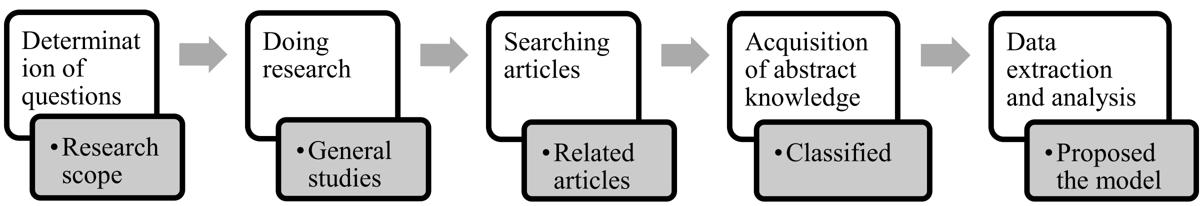

Figure 3. Process map of selection and review of articles.

After reviewing 75 credible articles, 45 articles were selected as main and most related references. Next, the research conceptual model was designed, and a questionnaire consisting of seven constructs and thirty questions was designed. The construct titles include 1) Productivity and customer satisfaction, 2) Perception analysis, 3) Application of KM components, 4) Usage of AI technology, 5) Development of knowledge management of customer experience model, 6) Customer experience management, and 7) Cultivating customer knowledge. In the end, five hypotheses were predicted.

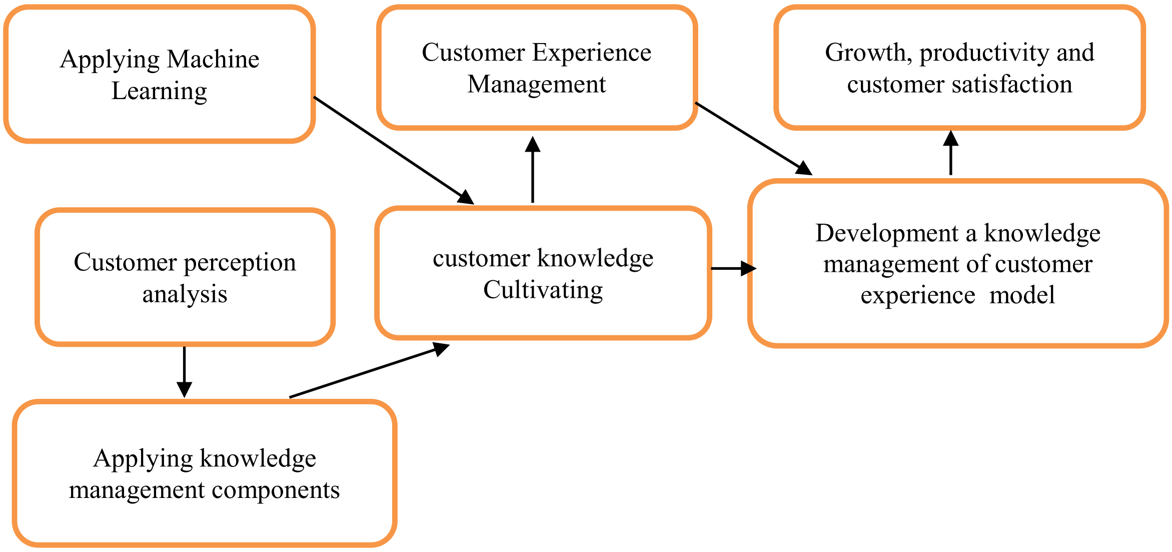

Figure 4. The research conceptual model

In the following, the data were processed and coded. The structural equation model was designed by SmartPLS, tested, and validated to validate the obtained results. Then, the reliability and model fit were examined and accepted. The target society in the research is the opinions of fintech users, which were prepared through the Dataheart website. The dataset contains 831 comments related to the 2021-to-2022 years, which users shared.

Data preprocessing (customers' opinions and experiences) was done through review preprocessing and using the "nltk" library. It includes: a) All text was converted to lowercase. b) The words with no emotional load were removed. Next, the feature vectors based on the clean data set were created for each clean text to classify and use in machine learning.

The steps of sentiment analysis using machine learning are presented in Table 2. This process typically involves several key stages: data collection, preprocessing (such as tokenization and removing stop words), feature extraction, model training using labeled data, and testing the model's accuracy. The final output is a sentiment classification (positive, negative, or neutral) based on the learned patterns in the data.

Table 2. Pseudo code of sentiment analysis using machine learning

Phase 1:Preprocessing
Input: Dataset
Outputs:Optimize comments
Opinion tokenization
Stop word removal
Symbols removal
Spell correction
Stemming (Lemmatization)
Phase 2: Classification
Input:Optimize comments
Outputs: Computing comments
Classification opinion with vectorize method
Phase 3: Sentiments analyzing
Inputs: Labeled comments matrix
Outputs: Sentiment's analysis comments
Sentiments Analysis by decision three algorithm
Phase 4:Accuracy optomization
Tuning hyperparameters

In the preprocessing stage, as shown in Table 3, customer feedback in the FinTech domain was collected, analyzed, and coded. This feedback was processed and visualized using Python programming and Visual Studio Code, leveraging natural language processing (NLP) methods and a decision tree model to analyze customer perceptions.In the quantitative research section, sentiment analysis techniques were employed. First, a customer feedback table was prepared, and numerical values were assigned to each feedback item, as illustrated in Table 4. Subsequently, customer perceptions were categorized based on these values, and relevant insights were extracted, as shown in Table 5. After preparing the dataset, the decision tree model was constructed for data analysis and prediction, as depicted in Table 6. Finally, by adjusting the hyperparameters of the model, the accuracy of the decision tree algorithm increased from 86% to 89%. This improvement demonstrates the enhanced efficiency of the algorithm in analyzing customer data.

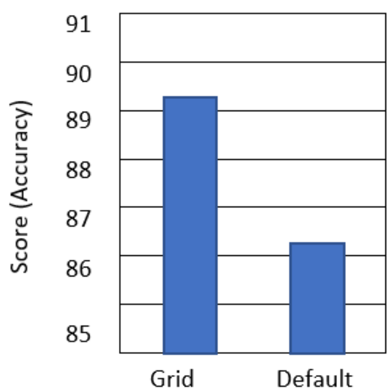

Figure 5. Comparison of the accuracy value in the optimal and default state for the decision tree

Table 3. Example of coding table and comments tag of fintech users, entrance for decision tree

Variable	**Tag (Dependent variable)**			
	0	1	2	3
Service speed	Excellent	Very Good	Average	Bad
Service quality	Very satisfied	Satisfied	Good	Poor
Performance quality	High quality	Acceptable	low quality	Awful
Brand trust	Authentic	Well-Known	Fake	Unknown
Innovation	High Tech	Very latest	New	Old

Table 4. Example of the dataset

Service speed	Excellent	It's great in every way	0
	Very Good	Thanks to (Fintech name)	1
	Average	Received late	2
	Bad	Finished	3
Service quality	Very satisfied	Really satisfied - full satisfaction - excellent in every way	0
	Satisfied	Not bad - I am satisfied - acceptable	1
	Good	Well - very well - worth it	2
	Poor	It is not recommended at all	3
Performance quality	High quality	Excellent - Excellent in every way	0
	Acceptable	Not Bad- So So	1
	low quality	Useless- Out of service	2
	Awful	Don't buy - Wrong purchase	3
Brand trust	Authentic	Prestigious - Valuable and authentic	0
	Well-Known	Well-known brand	1
	Fake	Fake–copy brand	2
	Unknown	Anonymous -nameless - unknown brand	3
Innovation	High Tech	Very advanced	0
	Very latest	Excellent - high technology - latest version	1
	New	Good appearance - High copy	2
	Old	It's no different - like the previous ones –old version	3

Table 5. Definition of variables and nodes

Row	**Variable name**	**Variable concept**	**Thematic category**	**Abundance**
1	Service speed	The need for the creation of customer satisfaction	360 customer experiences, Customization	%12
2	Service quality	The need for optimization	Personalization, 360 customer experiences	%27
3	Performance quality	The need for optimization	Customization	%17
4	Brand trust	The necessity of brand development	360 customer experiences	%18
5	Innovation	The need for innovation	Customization, personalization	%26
Customization = 31%		Customer experience 360 = 22%		Personalization = 35%

Table 6. Sample of the final coded dataset

Services Speed	Service quality	Performance quality	Brand trust	Innovation
0	1	0	1	2
0	0	0	1	0
1	0	0	0	0
1	3	3	3	2
1	1	1	3	2
3	3	3	3	3
0	1	1	2	3
2	3	3	1	0
3	3	3	2	1
1	2	1	3	3

By drawing a decision tree, customer needs were determined, and customer experience knowledge was modeled. Among the machine learning algorithms, the decision tree is one of the most common and simplest ones, with three notable features—interpretability, efficiency, and flexibility of customer perceptions (Lamrini, 2020). Finally, the acceptance status of the hypotheses was determined, and the questions were answered.

4. Results

The data collection was carried out using a questionnaire prepared by the researchers. The questionnaire was designed to evaluate the conceptual model of knowledge management of customer experience, focusing on using knowledge management and machine learning components to enhance customer knowledge and assess the model's effectiveness in growth, productivity, and customer satisfaction. The questionnaire consists of two main parts. The first part includes demographic information of the statistical population, including gender, age, years of work, and level of education. The second part consists of 30 questions related to 7 main constructs: 1) Customer perceptions, 2) Customer experience management, 3) Knowledge management components, 4) Customer knowledge cultivation, 5) Applying AI technology, 6) Growth, productivity, and customer satisfaction, and 7) Development of a model for knowledge management of customer experience.

The validity of the questionnaire was assessed using divergent and convergent methods, and construct validity was evaluated through Confirmatory Factor Analysis (CFA). For all dimensions, Cronbach's Alpha was calculated to be above 0.7; for the entire questionnaire, it was 0.80, which is considered acceptable. The combined reliability coefficient (CR), calculated using SEM and PLS software, was also examined. The values of Cronbach's Alpha and CR for each dimension are shown in Table 7, confirming the reliability of the questionnaire.

Table 7. The composition of questionnaire questions, cronbach's alpha, and CR values

	Construct	Questions NO	Cronbach's alpha	CR	Total
Knowledge management of customer experience	Growth, productivity, and customer satisfaction	1 to 5	0.753	0.864	**80%**
	Customer perceptions Analysis	6 to 9	0.902	0.921	
	Applying knowledge management components	10 to 12	0.822	0.896	
	Using AI technology-ML	13 to 17	0.793	0.801	
	Development of knowledge management of customer experience model	18 to 22	0.750	0.816	
	Customer Experience Management	23 to 26	0.711	0.814	
	Cultivating knowledge of customer experience	27 to 30	0.828	0.887	

The measurement scale of the questions was based on a 5-point Likert scale, with scores ranging from 1 (very little) to 5 (very much). The impact of each of the 30 indicators on the knowledge management of customer experience was assessed. Factors were identified based on theoretical foundations and interviews with experts in the field. For convergent validity, the Average Variance Extracted (AVE) was used. As shown in Table 8, all AVE values for the constructs exceed 0.5, confirming the convergent validity of the questionnaire to an acceptable level. A matrix was created to calculate divergent validity by comparing the squared AVE of each construct with the correlation coefficients between constructs. This matrix, shown in Table 9, demonstrates that the squared AVE of each construct is greater than the correlation coefficients with other constructs, indicating the acceptability of the constructs' divergent validity.

Table 8. Convergent validity values

Construct	AVE
Growth, productivity, and customer satisfaction	0.693
Customer perceptions Analysis	0.751
Applying knowledge management components	0.743
Using AI technology-Machine Learning	0.518
Development of knowledge management of customer experience model	0.530
Customer Experience Management	0.524
Cultivating knowledge of customer experience	0.667

Table 9. Divergent validity values

Factors Influencing on knowledge Management of Customer Experience / Factors influencing on knowledge management of customer experience	Using AI technology-Machine Learning	Appling KM components	Customer perceptions Analysis	Development of knowledge management of customer experience model	Growth, productivity, and customer satisfaction	Customer Experience Management	Cultivating knowledge of customer experience
Using AI technology-Machine Learning	0.719						
Appling KM components	0.122	0.862					
Customer perceptions Analysis	0.126	0.330	0.866				
Development of knowledge management of customer experience model	0.715	-0.231	-0.103	0.728			
Growth, productivity, and customer satisfaction	0.414	0.137	0.176	0.585	0.832		
Customer Experience Management	0.348	-0.334	-0,031	0.672	0.395	0.724	
Cultivating knowledge of customer experience	0.367	0.442	0.177	0.177	0.208	-0.203	0.816

Confirmatory factor analysis was used for model fitting. The result of running the model by Smart PLS software is shown in Figure 6 in a meaningful state. As Table 10 shows all t-test values are higher than 1.96, and the confidence level above 95% is confirmed.

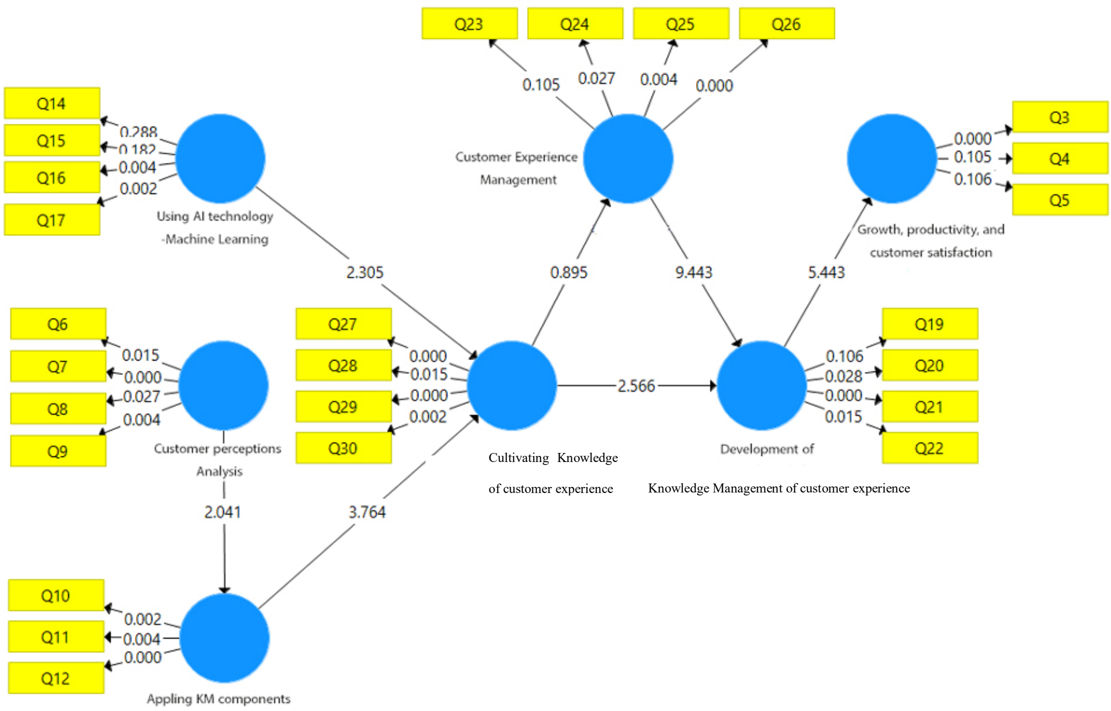

Figure 6. The research model in a meaningful state

For the research model, the standard estimation state was alsorun by Smart PLS. All factor loadings related to the questions were determined to be more than 0.4 and showed the strong influence of the effective indicators on customer knowledge management. The result is shown in Figure 7. Out of 30 questions, 26 indicators have a factor loading greater than 0.4, confirming the significance of their influence and showingthat the model has sufficient fit.

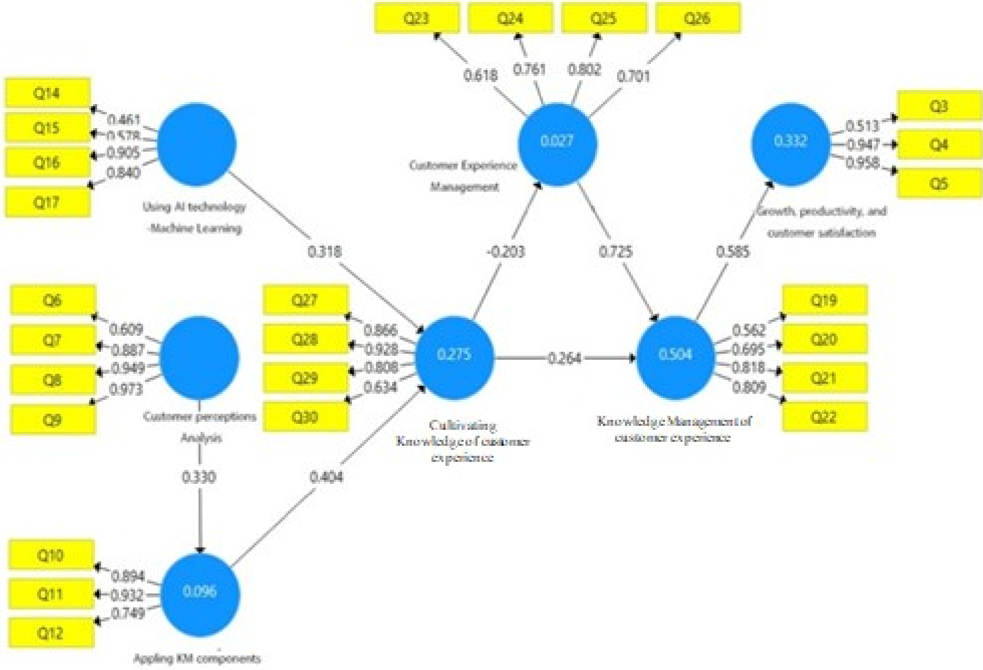

Figure 7. Research model in standard estimation state

The independent variables include the variable of applying AI-ML and the variable of customer perceptions analysis. The rest of the variables are dependent variables. The regression coefficients show that the hidden variable of customer experience management has the greatest impact on the hidden variable of development of the customer experience management model with a coefficient of 0.725. Also, developing the customer experience management model has a good effect on growth, productivity, and customer satisfaction, with a coefficient of 0.585. Only cultivating knowledge of customer experience has a negative and opposite effect on customer experience management. The model shows that the knowledge of the customer experience cultivation variable and the customer experience management variable explain and cover 50% of the variable of development of the customer experience management model. Also, the development variable of the customer experience management model explains 32% of the growth, productivity, and customer satisfaction variables.

4.1. Path analysis

The regression coefficients in the model for the determined hypotheses are all above 0.3, and the coefficients are in the significant range (Table 10). Also, the fitting indices in Table 11 show that the model fits well**.**

Table 10. The meaningful index values

Meaningful index	t-test statistic t >1.96	Regression coefficient >0.3
Applying AI-ML -> Customer knowledge cultivation	2.305	0.318
Applying KM components ->Customer knowledge cultivation	3.764	0.404
Development of knowledge management of customer experience model -> growth, productivity, and customer satisfaction	5.443	0.585
Customer Experience Management -> Development of knowledge management of customer experience model	6.443	0.725
Customer Knowledge Cultivation -> Development of Knowledge management of customer experience Model	2.566	0.264

4.2. Significance of hypotheses

In a significant state with a confidence level of 95%, all the obtained t-values were more than 1.96, so all the research hypotheses were evaluated as significant. The regression coefficients in this model for the determined hypotheses are above 3%, and the coefficients are in the significant range.

1. Applying AI-ML has a significant positive impact on customer knowledge cultivation .
2. Applying knowledge management components significantly positively impacts customer knowledge cultivation.
3. Customer knowledge Cultivation significantly impacts the knowledge management of customer experience model development.
4. Customer experience management has a significant positive impact on developing the knowledge management of the customer experience model .
5. The development of the knowledge management of the customer experience model significantly impacts growth, productivity, and customer satisfaction.

4.3. Model fitting

In order to model fitting, the Partial Least Squares method was used.

R-squared correlation: In the research, the model predictive power for variables of the development of knowledge management of customer experience model is evaluated, 518% value, and for the variable of growth, productivity, and customer satisfaction, the value is 342%, which was considered medium to high.

F Square: In the research model, the predictive power of the development of the knowledge management of customer experience model is evaluated with a strong value of 519%, and the variable of applying KM components with a value of 228% is evaluated as moderate.

Predictive correlation index Q2: In the research model, the predictive power of the model in internal constructs all have positive values, and model fitting was evaluated as good.

Model Fit:

Table 11. Model fitting results

SRMR	d_ULS	d_G	Chi-Square	NFI
0.010	0.465	0.263	138.95	0.757

Goodness of fit (GOF) Index: GOF = √average (AVE) × average (R2))

The calculated value for GOF is equal to 37.7%, which is higher than the value of 36%, so the model overall fit was evaluated as strong.

Normalized chi-square fit index x2/d.f (Acceptance limit > 1) : the value for the research model is equal to 1.33, which is more than the value of 1 and was approved.

4.4. *Decision tree*

The decision tree, with a depth of 5 and 81% accuracy, was drawn to clarify how to predict the target class (knowledge innovation) as a root node through Python in machine learning.

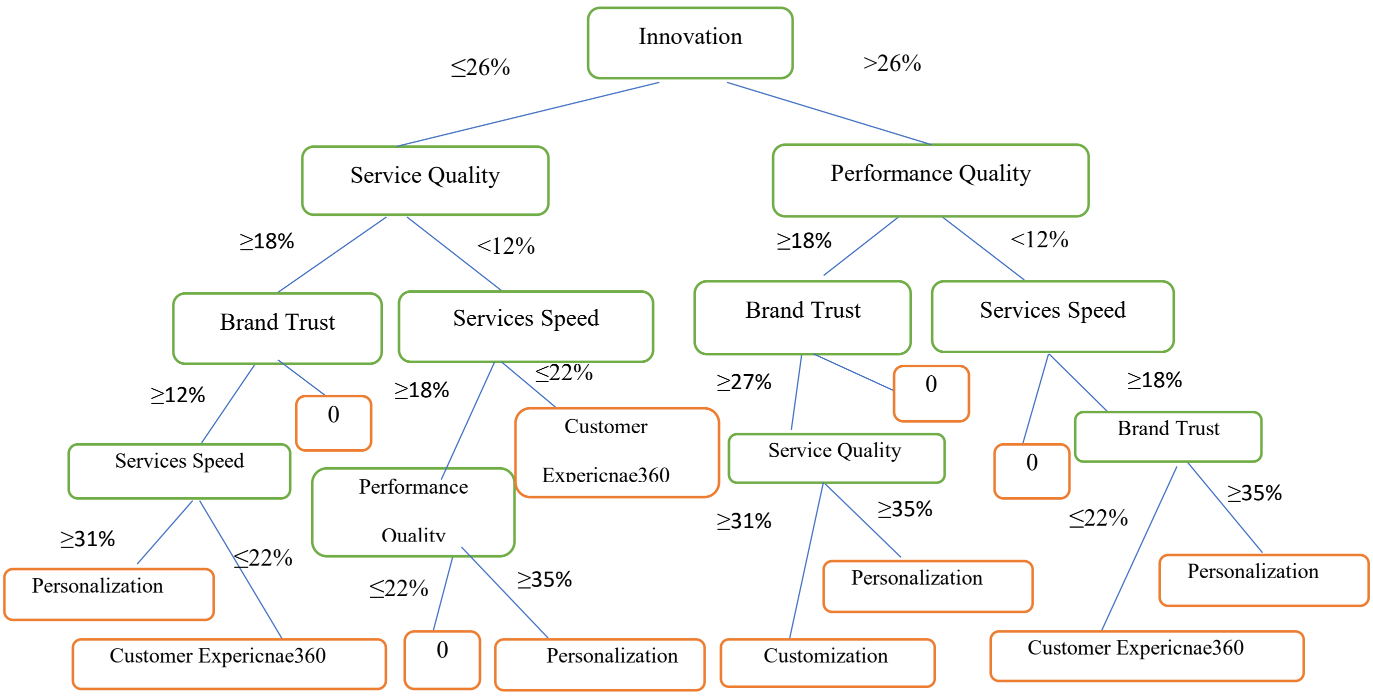

Figure 8. The drawn decision tree based on knowledge management of customer experience components

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4.4.1. Rule of decision tree

1- If the value of innovation is smaller than 26%, the value of performance quality is smaller than 12%, the value of service speed is greater than or equal to 18%, and the value of brand trust is greater than or equal to 35%, then the innovation goes towards Personalization.
2- If the value of innovation is smaller than 26%, the value of performance quality is smaller than 12%, the value of service speed is greater than or equal to 18%, and brand trust is smaller than or equal to 22%. The innovation goes towards Customer Experience 360.
3- If the value of innovation is smaller than 26%, the value of performance quality is greater than 18%, the value of brand trust is greater than 27%, and the value of service quality is greater than 35%, then the innovation goes towards Personalization.
4- If the value of innovation is smaller than 26%, the value of performance quality is greater than 18%, the value of brand trust is greater than or equal to 27%, and the value of service quality is smaller than 31%, then the innovation goes towards Customization.
5- If the value of innovation is greater than 26%, the value of service quality is smaller than 12%,. The value of service speed is smaller than 22%, then the innovation goes towards Customer Experience 360.
6- If the value of innovation is greater than 26%, the value of service quality is smaller than 12%, the value of service speed is greater than 18%, and the value of performance quality is greater than 35%, then the innovation goes towards Personalization.
7- If the value of innovation is greater than or equal to 26%, the value of service quality is greater than or equal to 18%, the value of the brand trust is greater than or equal to 12%, the value of service speed is smaller than or equal to 22%. The innovation goes towards Customer Experience 360.
8- If the value of innovation is greater than or equal to 26%, the service quality is greater than or equal to 18%, the brand trust is greater than or equal to 12%, and the service speed is greater than or equal to 31%, then innovation goes towards customization.

 DOI: 10.22067/JSTINP.2024.87413.1097

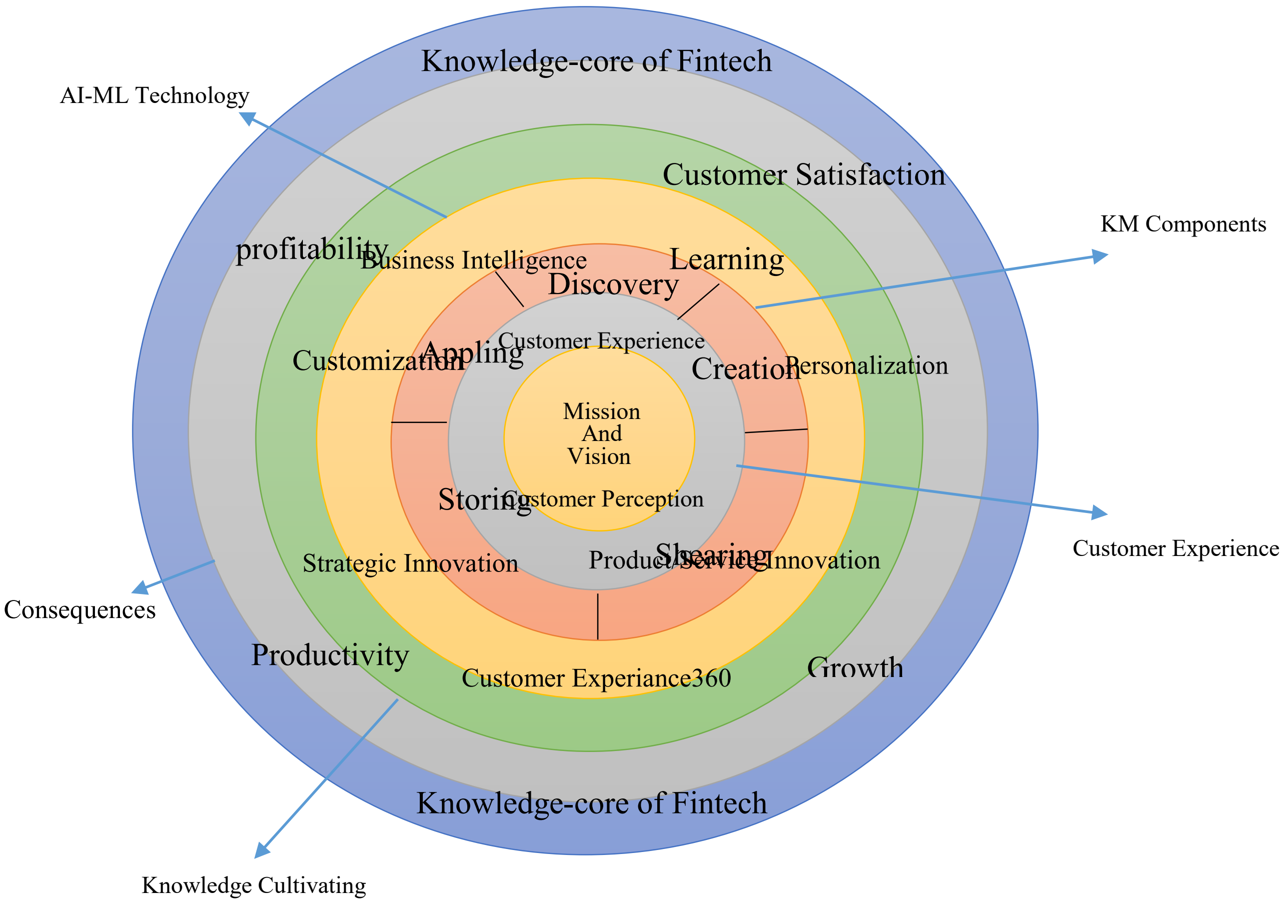

Figure 9. The research proposed model - Knowledge management of customer experience model APO-CEM

Here, the reasoning behind the algorithm used to reach the presented results is demonstrated. The rules have a logical structure. At the optimal level of data management of customer experiences, Personalization, Customization, and Customer Experience 360 are predicted with a probability of 97%. Consequently, through the proposed APO-CEM model, it is possible to acquire and store practical or tacit knowledge from customer experiences and cultivate it through AI to enhance the capabilities of Customization, Personalization, and Customer Experience 360. Indeed, Fintech service providers could utilize the cultivated knowledge to meet customers' needs, which can be shared with other customers.

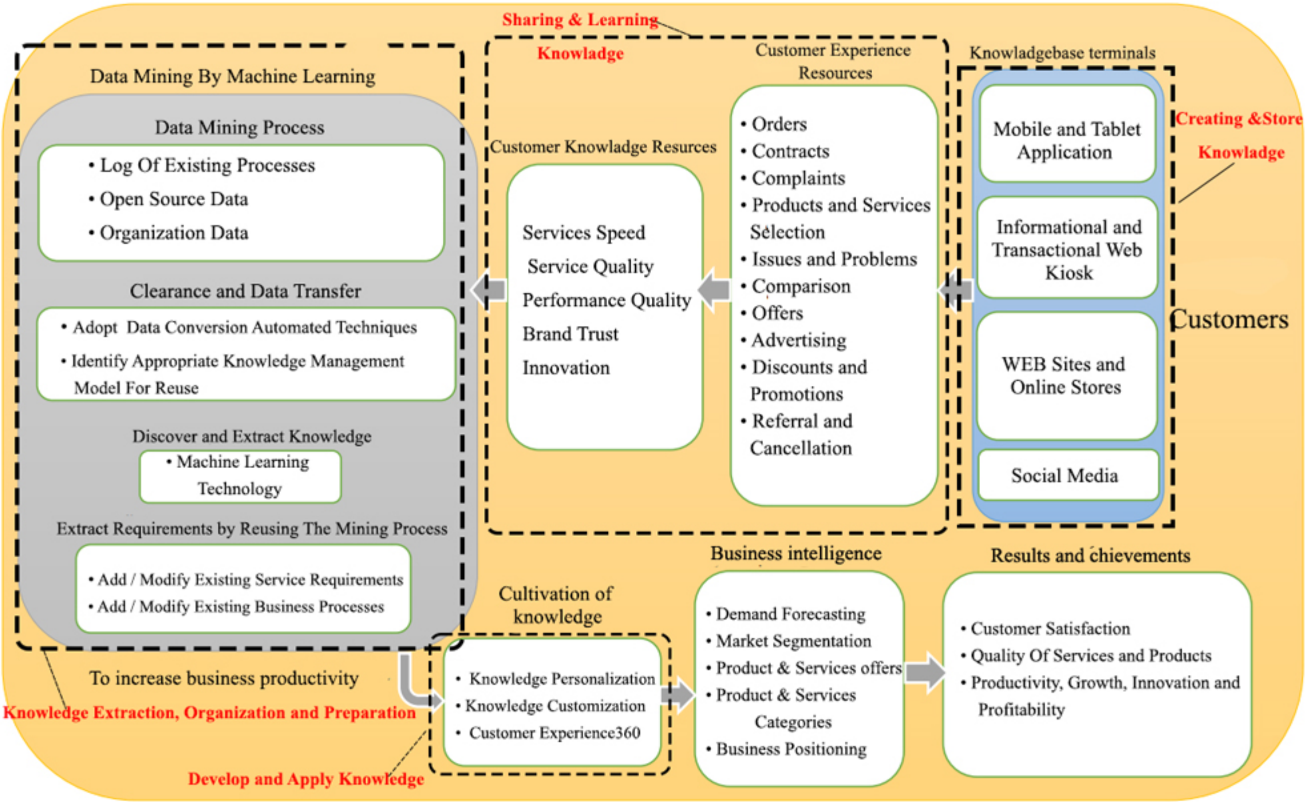

Figure 10. The APO-CEM model layout in the fintech ecosystem

The layout of the APO-CEM model in the fintech ecosystem, as shown in Figure 10, illustrates how different types of customers in fintech interact with services through knowledge terminals such as mobile applications, informational and transactional kiosks, fintech websites, and social networks. This interaction is where fintech customer experiences are created and stored. The customer experience resources include customer actions and perceptions related to ordering methods, contract types, service or product choices, product and service comparisons, complaints, comments, and personal experiences. These are evaluated through components such as performance quality, service quality, service speed, brand trust, and innovation, which collectively form the resources of customer knowledge.

In the next step, data mining and machine learning technologies are used to discover and extract customer experience knowledge. This knowledge cultivation involves personalization, customization, and a comprehensive customer experience (Customer Experience 360), which supports informed decision-making in demand forecasting, market segmentation, product offering, product categorization, and business positioning. Ultimately, the optimized fintech ecosystem enhances customer satisfaction, growth, and productivity by improving the quality of services and products.

4.4.2. Answer to the questions

RQ1: What are the main and effective components in providing the knowledge management of the customer experience model through machine learning?

Based on the tested conceptual model, SEM, and the APO-CEM model, the main and effective components in providing the customer experience management model include:

(1) Vision and Mission: The foundational goals and direction of the organization.
(2) Customer Perceptions: This includes service speed, service quality, performance speed, brand trust, and innovation.
(3) Applying KM Management Components: This involves identifying, creating, sharing, storing, and applying knowledge.
(4) Applying AI/ML Technology: This encompasses learning, business intelligence, service innovation, and product innovation.
(5) Customer Knowledge Cultivation: This involves Knowledge Personalization, Knowledge Customization, and Customer Experience 360.
(6) Consequences: The outcomes include profitability, customer satisfaction, and customer loyalty.
(7) Fintech Knowledge Core: The central knowledge base specific to the fintech industry.

RQ2: Which knowledge management model is the closest to developing the knowledge management of customer experience model?

Previous studies have demonstrated that the knowledge management model based on the APO framework is particularly effective, ensuring that no critical element is overlooked during implementation (Cahyaningsih et al., 2017). Additionally, the APO framework serves as a tool for evaluating knowledge management, offering insights into areas where the organization should focus its knowledge management initiatives and innovations (Khajouei et al., 2017).

RQ3: Is machine learning a suitable tool for interpreting customer experience perceptions based on knowledge management models?

By utilizing sentiment analysis techniques and a combined method of machine learning with a word-based approach, customer perceptions expressed in comment texts were categorized and coded using sentiment analysis algorithms. Subsequently, a decision tree was constructed through machine learning. Additionally, previous studies confirm that knowledge management and the decision tree algorithm effectively classify knowledge quality. They also highlight the advantages of using machine learning for the development of knowledge management from both theoretical and practical perspectives (Kaun et al., 2021).

5. Discussion and conclusion

This research aimed to present a knowledge management of customer experience model through machine learning. The paper's main contribution is the development of the APO-CEM model in the fintech domain. The study provides a comprehensive framework for integrating customer experience and knowledge management through artificial intelligence. The research confirms a substantial need to develop a knowledge management of customer experience model in fintech. This finding underscores the necessity for a robust theoretical framework in knowledge management of customer experience. The study highlights that existing models are insufficient in addressing the dynamic needs of fintech customers. The proposed customer experience management model based on the knowledge management framework introduces a significant innovation in fintech. This model incorporates customer perceptions such as innovation, performance quality, service quality, service speed, and brand trust, applying knowledge management components through artificial intelligence. The model's application of knowledge personalization, customization, and a 360-degree view of customer experience has been rigorously tested and validated. This comprehensive approach provides a more nuanced understanding of customer interactions and their impact on overall customer experience. The study demonstrates that artificial intelligence can enhance conceptual knowledge management tools by incorporating social perceptions into the knowledge process. The research examines AI's potential to support learning and knowledge development in three key areas: the necessity for learning, the learning system for interpreting customer perceptions, and the evolution of learning towards human-level intelligence. Integrating AI into knowledge management processes shows promise in advancing customer experience management. The research reveals that machine learning has significant potential when implemented as a coherent knowledge-based system. Specifically, machine learning improves comprehensive knowledge management models like APO and enhances new areas, such as text coding of customer opinions and experiences for decision tree applications. Enhancing decision tree accuracy through hyperparameter tuning is a key innovation, contributing to more precise and actionable insights.

Future research could explore using Bayesian networks and mixed-methods approaches, incorporating variables such as communication capital, intellectual values, and technology utilization. Further research could focus on developing a cultivation theory for customer experience knowledge using grounded theory methods and assessing its effectiveness in the fintech ecosystem. It is recommended that the APO-CEM model be specifically used to handle problems like assessing customer experience data in fintech firms and optimizing customer interactions to strengthen the suggestions. For example, organizations could use this model to personalize services and predict customer behavior. In conclusion, the APO-CEM model offers the potential for fintech organizations to enhance customer experiences and improve strategic decision-making. Integrating machine learning into knowledge management frameworks represents a critical advancement in understanding and optimizing customer interactions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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