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Explainable Ai In Customer Experience Management: Personalization Algorithms in Crm Systems

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Abstract: The article examines the features of integrating artificial intelligence algorithms (Explainable AI, XAI) into CRM systems aimed at enhancing customer experience (Customer Experience, CX). Based on an analysis of recent publications, the study explores the principles of personalization as well as approaches to the explainability of machine learning algorithms, including chatbots and recommendation systems. It demonstrates that transparency and interpretability of model outputs positively influence customer trust and loyalty while simultaneously improving the efficiency of internal business processes. The article analyzes the implementation experience of XAI in the banking sector, insurance call centers, and online retail, which has led to improvements in retention, conversion, and satisfaction metrics. The information presented in the article is intended for researchers and professionals in the field of artificial intelligence focused on developing interpretable machine learning algorithms, as well as for analysts seeking to optimize CRM systems to enhance customer experience management. In addition, the material is useful for professionals in corporate governance and marketing who aim to integrate advanced Explainable AI methods into personalization strategies and decision-making processes, ensuring the transparency and adaptability of services under dynamic market conditions.

Keywords: artificial intelligence, Explainable AI (XAI), Customer Experience (CX), personalization, CRM systems, machine learning, chatbots, recommendation systems

Introduction: Modern companies increasingly rely on artificial intelligence (AI) tools to manage customer relationships, including the personalization of services and products [4]. It is important not only to enhance the effectiveness of interactions but also to ensure the transparency of the algorithmic decisions made, since explainability (Explainable AI) becomes a decisive factor in users' trust [3]. In the context of ensuring a positive customer experience (Customer Experience, CX), such algorithmic "transparency" is gaining importance, as a lack of understanding of the mechanics behind recommendations or data analysis results can negatively affect consumer satisfaction and loyalty [5].

The literature review demonstrates a variety of approaches, ranging from conceptual models and theoretical reviews to empirical studies focused on the practical application of AI technologies across various industries. In the theoretical realm, Peruchini M., da Silva G. M., and Teixeira J. M. [1] review the interrelation between AI and customer experience, emphasizing the interdisciplinary nature of the issue, which is confirmed by the findings of Ameen N. et al. [3] and Dwivedi Y. K. et al. [4], who examine both the challenges and opportunities that arise when integrating AI into organizational processes. An additional contribution to the theoretical foundation is provided by the work of Robinson S. et al. [10], which proposes an evolved model of service interaction, as well as by the study of Phillips-Wren G., Daly M., and Burstein F. [17], which aims to integrate analytics, business intelligence, and decision support systems, collectively creating a solid basis for further empirical research in this area.

Empirical literature actively employs explainable AI approaches to assess service quality and analyze customers' emotional responses. In particular, Guo Y. et al. [2] propose a method for measuring service quality based on the analysis of customer emotions using explainable algorithms, allowing not only the prediction but also the interpretation of user reactions. A similar approach is confirmed in the work of Ceccacci S. et al. [12], where the use of facial expression analysis within the framework of auditing impressions from cultural events demonstrates the potential for objectively assessing the emotional component of customer experience.

Separate attention in the literature is devoted to the application of interactive systems, such as chatbots and voice assistants, which have a significant impact on the personalization of service. Abdelkader O. A. [5] examines the influence of ChatGPT on digital marketing, revealing moderating effects on the perception of customer experience, while the studies by Abdo A. and Yusof S. M. [8] demonstrate how voice chatbots contribute to improving the quality of customer interactions. The research of McLean G. and Osei-Frimpong K. [9] and Nguyen D. M., Chiu Y. T. H., and Le H. D. [13] focuses on the determinants of adopting such technologies in the banking sector, emphasizing the importance of adaptive algorithms in establishing sustainable customer relationships.

The banking and financial services sectors represent another area of AI application, where personalization and risk assessment play a key role. In the study by Ho S. P. S. and Chow M. Y. C. [11], the influence of AI on shaping customer preferences in retail banking is examined, while Bhattacharya C. and Sinha M. [14] underscore the strategic significance of AI for enhancing competitiveness through improved customer experience. In addition, Zhou J. et al. [16] demonstrate the application of integrated methods that combine increased data volume and model refinement for multistage credit risk assessment, an important aspect of personalization in financial services.

Equally interesting are studies dedicated to the specifics of AI application in the entertainment and events industries. Neuhofer B., Magnus B., and Celuch K. [7], using a scenario-based approach, analyze the influence of AI on event perception, while Puntoni S. et al. [6] offer an experiential perspective that reveals new facets of consumer interaction with artificial intelligence in the marketing environment. In turn, Wulff K. and Finnestrand H. [15] address the issue of AI explainability in the context of creating meaningful work, highlighting the importance of algorithm interpretability not only for customers but also for internal organizational stakeholders.

Thus, the analysis of the presented studies reveals contradictions between theoretical models proposing universal approaches to integrating AI into customer experience management and empirical works focused on narrow industries and specific aspects, such as emotion assessment or factors influencing the adoption of interactive systems. At the same time, the problem of comprehensive integration of explainable personalization algorithms into CRM systems remains underexplored, indicating the need for further research aimed at developing scalable and interpretable models capable of providing a unified solution for a wide range of customer scenarios.

The purpose of the research is to identify and analyze the mechanisms by which explainable artificial intelligence (Explainable AI) enhances customer trust and satisfaction when using personalization tools in CRM systems.

The scientific novelty lies in the proposal of a method that bridges the gap between understandable AI and personalized CRM strategies. This is achieved through a systematic review of current literature, a thorough empirical analysis across various industries, and expert evaluations that demonstrate how transparent algorithmic decision-making fundamentally enhances customer trust, engagement, and operational efficiency.

The hypothesis is based on the assumption that integrating Explainable AI into personalized CRM algorithms contributes to increased customer trust, which in turn positively affects Customer Experience metrics.

The methodological basis for the study is the analysis of existing research.

1. Theoretical foundations

Customer Experience (CX) is shaped at the intersection of consumer perception of the brand, interaction technology, and emotional customer engagement. In contrast to User Experience (UX), where the primary focus is on interface usability and functionality, CX encompasses the complete cycle of contacts and impressions formed during interactions with a company. Research indicates that a high level of CX leads to increased goodwill and positive recommendations, as well as serving as a competitive advantage [6,13].

At the same time, technological innovation alone does not guarantee a positive outcome; without sufficient transparency in artificial intelligence, both customers and managers may question the accuracy of the recommendations provided [5,17]. The concept of Explainable AI (XAI) emerges as a key element, emphasizing the importance of model interpretability to enhance trust and understanding of the underlying logic of algorithms [4]. Within the context of CX, this implies that transparency in the results of personalized recommendations and chatbot decisions can influence user satisfaction and subsequent behavior [1].

In recent years, chatbots and virtual assistants have been actively explored in academic circles as tools for improving service quality [8,14]. One advantage of these technologies is their ability to collect large volumes of textual or voice data, which facilitates a deeper understanding of customer interests and emotional responses [9]. However, the use of deep learning algorithms or recommendation systems often leads to a "black-box" effect, whereby neither users nor developers can clearly interpret the rationale behind a recommended action [10].

Table 1, presented below, illustrates the main approaches to applying artificial intelligence in CX identified in the literature, correlating them with specific challenges (such as the "black-box" effect) and potential benefits for both customers and companies.

Table 1. The main approaches in CX in terms of benefits and challenges [1, 4, 9, 11, 14]

Approach / Technology	Key Features and Benefits	Main Challenges
Machine Learning (recommendation systems, ML)	• Personalization of offers • Analysis of large datasets • Increased accuracy of predictive models	• Lack of interpretability (black-box) • Potential algorithm errors with incomplete data
Chatbots and Virtual Assistants	• 24/7 support • Reduced contact center costs • Convenience and speed of service	• Difficulties in humanizing responses • Risk of negative reactions due to incorrect answers
Emotion Processing (Emotion AI, sentiment analysis)	• Deeper understanding of customer intentions • Automatic identification of dissatisfied customers	• Need to maintain privacy • Technical challenges in capturing precise emotional data

Approach / Technology	Key Features and Benefits	Main Challenges
Explainable AI (XAI modules)	• Increased trust • Facilitation of AI integration in corporate environments • Opportunities for staff training	• Additional implementation costs • Potential trade-offs between accuracy and interpretability

Thus, the application of AI in CRM systems enables the analysis of increasingly complex aspects of customer behavior. However, a lack of transparency and clear explanations for users can adversely affect customer perception and trust in a company. For this reason, the study of Explainable AI is of great importance, as it allows for balancing high recommendation accuracy with interpretability.

2. Personalization algorithms and approaches to XAI in CRM

In modern CRM systems, personalization is considered one of the mechanisms for increasing conversion, retention, and customer satisfaction [3,15]. Such a system includes the selection of relevant recommendations, content, and individual interaction scenarios based on the analysis of customer data. The most common technological approaches are:

1. Collaborative filtering (collaborative filtering). Uses information about the preferences of similar customers; the algorithm "recommends" products or services that have appealed to other users with similar characteristics [13,16].

2. Content-based filtering (content-based filtering). Focuses on the inherent attributes of products or services; the system analyzes features characteristic of the objects preferred by customers and searches for similar elements [6,11].

3. Hybrid models. A combination of collaborative and content-based filtering to overcome typical shortcomings (for example, the "cold start" problem, when a new user has insufficient data on preferences) [14].

4. Deep learning models (deep learning). Employed for more complex personalization scenarios such as dynamic real-time recommendations and multimodal analytics (text, voice, images) [1].

Recommendation systems that are trained on large volumes of customer data (Big Data)—including demographics, purchase history, behavioral patterns, and even emotional reactions—are of particular interest [12]. However, the increasing complexity of models often gives rise to the "black-box" effect, where interpreting the output becomes challenging. As a result, the system may deliver highly accurate recommendations without any means of understanding the underlying decision-making logic.

Explainable AI (XAI) is designed to overcome the problem of algorithmic opacity. Specific XAI methods can be conditionally divided into three major groups:

1. Post-hoc explanation:

- LIME (Local Interpretable Model-Agnostic Explanations): builds local approximations of complex models, showing the contribution of individual features in a specific case [15].
- SHAP (SHapley Additive exPlanations): calculates the marginal contribution of each feature, combining them into a generalized interpretation akin to game theory [4].

2. Interpretable models:

- Decision trees and tree ensembles (Random Forest, XGBoost): although not always obvious when deep, they remain easier to understand than deep neural networks [11].
- Switch architectures (for example, transparent two-way networks), where each part is responsible for a specific set of features and follows an interpretable logic [2].

3. Integrated interpretation:

- Attention mechanisms in deep networks (Transformer-based models) allow visualization of which parts of the input data the model focuses on most [10].
- Explainable-by-design: the use of simplified architectures or specialized layers that automatically formulate the output logic in a more transparent format [5,8].

In practice, the choice of an XAI approach is determined by the balance between model accuracy and the required level of transparency. In CRM systems, where the cost of an error is low (for example, recommending a product of limited value), hybrid or "black-and-white" schemes may be applied, whereby part of the model remains deeply trained (and less transparent) while the "upper level" is responsible for generating explanations understandable to both managers and customers [14].

Below, Table 2 presents examples of practices for integrating XAI into personalized CRM algorithms and their expected effects on key metrics.

Table 2. Examples of XAI integration into personalized CRM projects [4, 5, 9, 11, 15]

Practice of XAI integration	Description of mechanism	Expected effect
1. Visualization of recommendation "reasons" (explanation panel)	• A supplementary window or panel that describes the factors influencing the recommendation, using simple language for both the customer and the manager	• Increased trust; reduced time required to explain the product
2. Feedback on feature weights	• Highlighting key parameters (click behavior, purchase history, demographics) with threshold visualization of the contribution of each feature	• Enhanced transparency; optimization of marketing campaigns
3. "Dual approach" (ENSEMBLE + XAI)	• The use of an ensemble combining a deep model with an interpretable model, comparing outputs and generating understandable explanations	• A compromise between accuracy and explainability; reduction of errors
4. Risk scoring	• Providing a "risk rating" for the decision to the customer or manager, indicating the probability of model error	• Increased system "honesty"; enabling rapid response

Thus, personalized algorithms (recommendation systems, chatbots, ML models) yield the greatest benefits when complemented by explainability mechanisms. This not only enhances customer satisfaction but also facilitates system scalability within a company by easing decision-making regarding model adjustments and settings under changing business conditions.

3. Implementation and evaluation of effectiveness

The successful implementation of Explainable AI in the context of CRM personalization largely depends on specific business scenarios and company capabilities. A number of studies indicate that voice assistants and chatbots supplemented with explainable modules are capable of reducing service costs while simultaneously increasing customer satisfaction [8,14]. Special attention in such projects is given to service support: the transparency of the chatbot algorithm helps managers better understand the logic behind responses, and customers receive explanations for recommendations in an understandable form.

In call centers focused on mass service, methods of voice analytics and automatic emotion recognition are actively researched to improve service quality [2]. In these cases, explainable models enable the identification of negative communication episodes and prompt responses to potentially dissatisfied customers. For example, a system may signal an increased "stress level" of the interlocutor and provide the contact center employee with clear recommendations on the necessary actions [4].

An interesting example is provided by Peruchini M., da

Silva G. M., and Teixeira J. M. [1], who analyzed the implementation of XAI in an online retail company. As a result of integrating explainable recommendation systems (combining deep learning with SHAP interpretations) into the e-commerce platform, both conversion rates and internal business processes related to algorithm quality control improved. Managers gained the ability to independently adjust product selection priorities for customers based on transparent metrics of feature contribution [1].

When implementing Explainable AI in CRM, architectural and organizational characteristics must be taken into account. According to Wulff K. and Finnestrand H. [15], successful projects often follow a phased approach, beginning with small-scale experiments (proof of concept) before scaling the solutions. Important factors include:

- The availability of high-quality data: proper model explainability requires a consistent set of customer data [9].
- Adaptive infrastructure: employing a modular approach that allows the flexible integration of post-hoc interpreters (LIME, SHAP) with existing ML modules [11].
- Staff training: the introduction of XAI modules is accompanied by programs aimed at enhancing the qualifications of managers and contact center operators so that they can competently work with the explanations [2].
- Compliance with confidentiality standards: explainable models, especially those handling emotional or behavioral data, must address issues of privacy and security [14].

An important stage in the integration of XAI is verifying the quality and relevance of the generated explanations for different user groups. The evaluation of systems employing Explainable AI should consider both technical and business metrics. Technical metrics typically include accuracy, recall, F1-score, and other classification metrics for algorithmic solutions. Business metrics often comprise conversion, customer retention, growth in average transaction value, and satisfaction (for example, Net Promoter Score, NPS) [3]. In CX studies, emotional indicators reflecting the level of stress or satisfaction during interactions with a chatbot or operator are also highlighted [12].

Below, Table 3 provides an example structure for evaluating the effectiveness of implementing Explainable AI in CRM, adapted from several projects described in the literature.

Table 3. Example of the structure for evaluating the effectiveness of implementing Explainable AI in CRM [2,8]

Evaluation level	Key metrics	Tools and methods of collection	Expected outcome
Technical accuracy of the algorithm	• Accuracy, Precision, Recall, F1-score • Latency	• CRM system logs • Reports on ML module performance	• Improved model stability • Reduction of technical errors
Explainability and transparency	• Assessment of explanation clarity (survey-based) • Number of requests for manual review	• Customer/manager surveys • LIME/SHAP monitoring panels	• Reduction in negative inquiries • Increased trust
Impact on CX	• Customer satisfaction (CSAT) • Net Promoter Score (NPS) • Repeat purchases (retention)	• Surveys • Transaction analytics • Customer segmentation analysis	• Growth in loyalty and recommendations • Improved brand perception

Evaluation level	Key metrics	Tools and methods of collection	Expected outcome
Financial and economic effects	• ROI, ROMI • Revenue from additional sales • Cost savings in contact centers	• Financial reports • BI system dashboards	• Demonstration of company benefits • Optimization of operational costs

Thus, experience shows that the implementation of XAI in CRM, particularly for personalization algorithms, makes a measurable contribution to key business metrics by increasing customer satisfaction, reducing operational costs, and fostering growth in trust. At the same time, a comprehensive evaluation approach is necessary to assess both technological and marketing aspects. The successful implementation of explainable approaches in CRM personalization requires clear planning at both the architectural and organizational levels, as well as consistent monitoring of outcomes based on diverse metrics. This approach not only minimizes risks associated with insufficient AI transparency but also enables the targeted development of competitive advantages by focusing on customer satisfaction, trust, and goodwill.

CONCLUSION

The conducted research confirmed the importance of explainable artificial intelligence (XAI) algorithms for creating and maintaining a high level of customer experience (CX) in CRM systems. Standard personalization technologies, whether chatbots, recommendation engines, or emotion analysis systems, demonstrate high efficiency; however, they suffer from the "black-box" effect, which diminishes user trust and complicates the interpretation of outputs. Therefore, integrating XAI approaches becomes a critical condition not only for increasing conversion and retention but also for enhancing customer satisfaction and trust.

The analysis of practical cases showed that transparent algorithms enable managers to respond more promptly to problematic situations, better understand the logic behind suggestions and recommendations, and allow end users to feel more secure when interacting with digital services. This directly impacts business performance indicators: CSAT and NPS increase, contact center costs decrease, and the ROI from implementing CRM solutions improves.

Thus, the comprehensive application of Explainable AI in CRM systems opens up new opportunities for developing competitive advantages. The methodological approaches developed, the metrics proposed during the study, and the practical recommendations can serve as a guide for companies seeking to implement or refine AI technologies in managing customer relationships. In the future, further research may focus on the development of generative XAI models as well as on the ethical and legal aspects of ensuring algorithmic transparency and accountability.

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