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Original Article

Customer Experience Optimization Using Machine Learning: A Systematic Review

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Abstract - *Customer experience (CX) is now a pivotal factor in the success of organizations in the digital and customer-focused markets and has necessitated the data-driven approaches to comprehend, forecast, and optimize customer engagement. The continuous growing volume of customer data that is generated by various digital touchpoints has provided possibilities to use machine learning (ML) and deep learning (DL) methods to maximize CX in different fields, such as e-commerce, banking, retail, and customer service. The systematic review is based on the research published in the period between 2013 and 2022 and it focuses on the general overview of ML and DL applications in CX optimization. On a predetermined PRISMA-based approach, 27 articles were picked by undertaking a thorough screening and quality checks of leading academic databases. The review investigates the tendencies of methodology strategies, application fields, data sources, and customer experience dimensions presenting the transformation of the traditional ML models of structured data to advanced DL models and mixed frameworks that are able to handle unstructured and multimodal data. The main methodological issues that were observed are the low use of real-time and streaming data, lack of explainability, no longitudinal or causal modelling, uneven evaluation measures, and little cross-domain validation. In summing up the available evidence, outlining key gaps, and emphasizing emerging trends, this review would serve as a fundamental source of information to scholars and practitioners who need to create strong, interpretable, and effective ML/DL-based methods to improve customer experience in various industry environments.*

Keywords *- Customer Experience, Machine Learning, Deep Learning, Customer Engagement, Artificial Intelligence, Customer Satisfaction, Hybrid Models.*

I. INTRODUCTION

The Customer Experience (CX) has emerged as a primary concern of companies aiming at gaining sustainable competitive advantage in the ever-digitized and customer-oriented markets. With the customer interaction growing on a variety of different online and offline touchpoints, the management and optimization of this interaction has become a de facto complex, data intensive challenge[1]. The customer experience optimization means ongoing measurement and enhancement of customer perception, customer emotion, and customer behaviour along the customer journey, and it directly relates to customer retention, customer loyalty, and customer satisfaction[2][3]. The conventional techniques of CX management that rely more on surveys and descriptive analytics are constrained by their inability to reflect dynamic and nonlinear customer behaviour. The increasing amount, speed, and types of customer data recorded on digital platforms require more sophisticated analytical tools that can derive useful patterns and facilitate informed decision-making, which predetermine the establishment of data-driven CX optimization.

To address these issues, machine learning has become an influential paradigm of converting raw data on customers into usable insights that could be used to optimize customer experience[4]. ML techniques can help companies to model complicated behaviour trends and predict future customer behaviour and scale personalize interaction using historical and real-time customer data[5]. Tasks that are solved with supervised learning models like predicting customer satisfaction and churn have become popular, whereas deep learning models were proven to be more successful in handling unstructured and sequential data, like customer reviews, social media content, and interaction logs[6]. The growing attention to the combination of natural language processing and representation learning has also contributed to the level of capturing customer sentiments, feelings, and the contextual information. Nevertheless, the fast uptake of various ML methods on various CX applications have caused a diverse literature, which has diverse goals, data, and measurement standards.

The versatility and disunity of the current research on machine learning-based customer experience optimization are what makes the necessity of a multi-dimensional and multi-methodological synthesis of the literature. Although many studies record encouraging results, the unavailability of standardized procedures and uniform assessment systems complicate the comparison of results and determining the overall efficiency of various methods of ML[7][8]. Current reviews tend to be rather limited in the scope of their topics and frequently focus on a particular component of CX or an individual machine learning application, thus the general picture of the CX optimization strategy is lacking. This means that a systematic review is necessary to systematize and critically evaluate the existing research through a step-by step methodology that is transparent and reproducible. In this way, it possible to identify the current trends and dominant machine learning methods, unresolved issues, as well as identify the way the research should be carried out in the future to further the idea of optimizing customer experience based on machine learning in both scholarly and industrial communities.

A. Main Contributions of the Study

This study provides a thorough analysis of deep learning (DL) and machine learning (ML) techniques for improving the customer experience, highlighting key developments, dimensions of customer experience, and methodological issues. It also offers practical information as well as research agendas to scholars and practitioners.

- **Comprehensive Systematic Review:** Provides a rigorous synthesis of 27 studies (2013–2022) on ML and DL approaches for customer experience (CX) optimization, highlighting trends, application domains, and modelling techniques.
- **Identification of Key CX Dimensions:** The classification of CX metrics, including satisfaction, engagement, loyalty, personalization, trust, and optimization of the holistic journey, demonstrates the changing focus areas in the research.
- **Analysis of ML vs. DL Approaches:** Provides comparative information about the strengths of approaches, weaknesses and applicability of these models to structured and unstructured data.
- **Mapping Methodological Challenges and Gaps:** Highlights gaps including limited real-time and multimodal data use, minimal explainable AI adoption, inconsistent evaluation metrics, and underexplored domains.

B. Paper Outline

The paper outline as follows: Section II provides the methodology of systematic review, including data sources, search strategy as well as the method of analysis. The results are given in the section III and include the characteristics of the study, the techniques of ML/DL, and the dimensions of CX. Section IV regards trends, ML vs. DL insights, CX focus, and methodological issues. Section V refers to the research gaps, and Section VI suggests research directions and study limitations in the future. Section VII gives a literature review background, and Section VIII ends with some important findings and contributions.

II. MATERIALS & METHODS – A SYSTEMATIC REVIEW PROTOCOL

In this section, the systematic approach that was taken towards conducting a complete review of the literature on customer experience optimization under Methods for DL and ML are explained. It outlines the research design, the sources of data, search, study selection, data extraction and the analysis procedures in the synthesis of the available literature to establish major trends, dilemmas and the future prospects in the field.

A. Research Design

The study does a meta-analysis of the literature on ML and DL methods to customer experience enhancement using the systematic literature review (SLR) technique. The systematic review was selected to provide transparency, reproducibility and to cover the relevant studies in a comprehensive manner. The PRISMA (Preferred Reporting Items of Systematic Reviews and Meta-Analyses) criteria (see Figure. 1) serve as the foundation for this review, which offers an orderly framework of identifying, screening, and qualitative assessment of the literature.

B. Data Sources and Search Strategy

To locate excellent publications on customer experience enhancement using machine learning (ML) and deep learning (DL) techniques, a thorough literature search was conducted. The extensive academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, were examined to get area coverage. The selection of these data bases was based on the fact that they index numerous journals and conference proceedings on the fields of business, marketing, service management and data analytics.

The search strategy was based on structured key word searches using both title and abstract, and author keywords with the help of Boolean operators. The main search query was:

- ("customer experience" OR "customer satisfaction" OR "customer engagement")
- AND
- ("machine learning" OR "deep learning" OR "artificial intelligence")
- NOT ("survey" OR "review")

This query was to get original empirical research but not surveys and review articles. It included only English-language publications published after 2013 and before 2022 because it is the time when the implementation of the ML/DL-based methods of customer experience research started to increase.

In the first search, 261 articles were found. The series of refinement steps were undertaken to make it relevant and of quality:

- **Filtering by document type:** Conference papers and peer-reviewed journal publications were excluded, but not pre-prints and technical reports, among other non-peer-reviewed documents, which left 58 articles.
- **Publisher quality screening:** Another quality screening was the restriction to quality publishers to narrow down the dataset to 27 articles.

These 27 studies were considered in a shallow review to determine the overall research trends, areas of focus of application, popular ML/DL methods, and the type of datasets that were used. A list of studies that met the methodological rigor, relevance, and contribution to optimization of customer experience criteria was subsequently narrowed down to a smaller set of studies to be included in the second phase (deep review), allowing an in-depth examination of model architectures, feature engineering methods, evaluation metrics, and reported results.

The multi-step and organized search strategy allowed having a strong, transparent, and reproducible process, which can offer a full-range of bases to synthesize the present developments, difficulties, and potential paths for applying ML and DL to enhance the consumer experience.

C. Inclusion and Exclusion Criteria

The following standards were applied to get a high degree of methodological rigor and relevance:

Inclusion Criteria

- Peer-reviewed conference or journal articles.
- Target customer experience, interaction or satisfaction.
- Employ ML or DL techniques
- Full-text available in English

Exclusion Criteria

- Non-academic literature (blogs, theses, reports).
- Evidence that researches only on customer churn and nothing to do with experience.
- Duplicate publications.
- Articles that have ambiguous techniques.
- Non-business, non-marketing, non-service studies.

D. Study Selection Process

The selection of the study was based on the PRISMA screening phases:

- Sorting and removing duplications of all records retrieved.
- Title and abstract screening to remove irrelevant studies.
- Full-text review to assess eligibility against predefined criteria.

The screening was done by two reviewers. Solutions to disagreements were arrived at by discussion and agreement. Qualitative synthesis was done on the last group of research. A PRISMA flow diagram (visualised in fig. 1) is used to visualise the selection process.

E. Data Extraction and Classification

In both studies, each of the chosen articles had the relevant information extracted in a systematic way to facilitate the comparison of the literature. The parameters that were extracted are:

- **Application domain** (e.g., e-commerce, retail, banking, telecom, hospitality)
- **Models and techniques of machine learning / artificial intelligence** that have been used (e.g., SVM, Random Forest, Artificial Neural Networks, ensemble and deep learning models).
- **Data sources utilized** (e.g., online customer reviews, survey data, transactional records, clickstream data, CRM logs)
- **Dimensions of customer experience (CX)** evaluated (e.g. personalization, satisfaction, engagement, loyalty, service quality, seamlessness).

Using these parameters, the chosen researches were categorized based on application settings, type of model and the CX focus and a consistent and significant comparison of the applications of various ML/AI techniques across different areas to promote customer experience could be made. It is also through this classification that one is able to identify the prevailing trends in research, the patterns of the methodology and the gaps in the research that exist within the literature.

F. Analysis Approach

Qualitative content analysis has been conducted to determine research trends, patterns and gaps. The methods of ML/DL were compared and evaluated, with the emphasis on:

- Predictive and model effectiveness
- Interpretability and practical applicability
- Recounted methodology issues (e.g. data imbalance, noisy feedback)

The synthesis also presents shortcomings and future research directions that were reported in the reviewed studies.

G. Two-Phase Review Strategy

In order to maintain breadth and depth, a two-stage review was used:

1. **Shallow overview:** General screening to detect broad trends, areas of large use and generally used techniques of ML/DL.
2. **In-depth analysis:** Critical examination of the most relevant studies that were chosen due to the rigor of the methodology, contribution to the optimization of the customer experience, and technical information about the model architectures, feature engineering, and assessment frameworks.

H. 2.8 Overview of Methodological Framework

The systematic review incorporates a clear search strategy, screening, and analytical system to present an overall evaluation of the ML/DL-based strategies of the customer experience optimization. Through synthesis, both broad and deep, the paper identifies the major trends, issues, and prospects of future research on this field. The systematic review included all the following inclusion criteria, which are summarized in Table I:

TABLE 1: SYSTEMATIC SEARCH STRATEGY AND CRITERIA

Section	Details
Databases	Scopus, Web of Science, IEEE Xplore, ScienceDirect, Google Scholar
Time Frame	2013 – 2022
Keywords	("customer experience" OR "customer satisfaction" OR "customer engagement") AND ("machine learning" OR "deep learning" OR "artificial intelligence") NOT ("survey" OR "review") — applied to title, abstract, keywords
Inclusion Criteria	Peer-reviewed papers; focus on customer experience/engagement/satisfaction; use ML/DL; full-text in English
Exclusion Criteria	Non-academic sources; studies only on churn; duplicates; unclear methodology; outside business/marketing/service domains
Study Selection	PRISMA-guided: deduplication → title/abstract screening → full-text review by two reviewers with consensus
Data Extraction	Year, domain (e-commerce, banking, telecom, hospitality), CX dimensions, ML/DL methods (SVM, RF, NN), data sources (reviews, surveys, logs, social media), evaluation metrics (accuracy, precision, recall, F1, ROC-AUC, RMSE)
Analysis	Qualitative content analysis to identify trends, patterns, gaps; compare ML/DL techniques on performance, interpretability, applicability, challenges
Review Strategy	Two phases: 1) Shallow review – broad trends; 2) Deep review – detailed analysis of high-relevance studies (methods, models, features, evaluation)

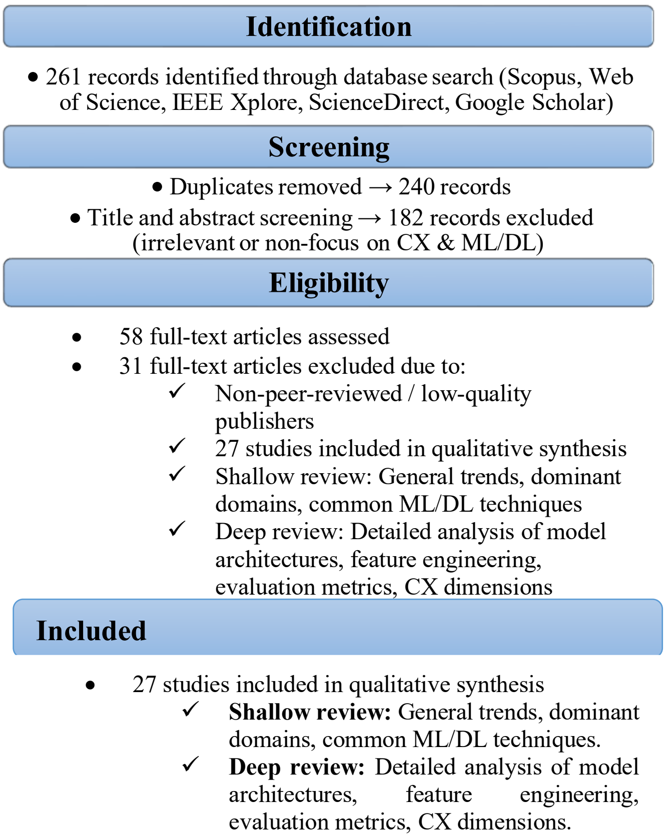

Figure 1. PRISMA Flow – ML/DL for Customer Experience Optimization

III. RESULTS OF THE SYSTEMATIC REVIEW

The primary studies selected were 27 papers published since 2013 and 2022 depending on the outlined inclusion and exclusion criteria. These works cover various aspects of applications and use diverse machine learning (ML) and deep learning (DL) methods to target different customer experience (CX) dimensions. The findings are structured to reflect the trends of publications, areas of application, adopted methods of ML/AI, data source and CX dimensions covered.

A. Descriptive Characteristics of Inclusion Studies

Table II shows the number of studies used in the selected studies over the years. As it can be seen in Table II, the output on research was low in the early years (2013-2016), and there was a single study annually. An evident positive trend can be observed since 2017, which explains the largest number of publications.

The most effective research studies were found in 2022 (n = 10) due to the rapid increase in the use of ML and DL methods and their maturity in terms of the study of customer experience. In general, a greater part of the chosen studies (more than two-thirds) was not older than 2017, which proves the rise in scholarly and practical attention to the optimization of CX with the help of ML/DL.

TABLE 2. YEAR-WISE DISTRIBUTION OF SELECTED STUDIES

Year	No. of Studies	Cumulative Total
2013	1	1
2014	1	2
2015	1	3
2016	1	4
2017	2	6
2018	3	9
2019	1	10
2020	3	13
2021	4	17
2022	10	27

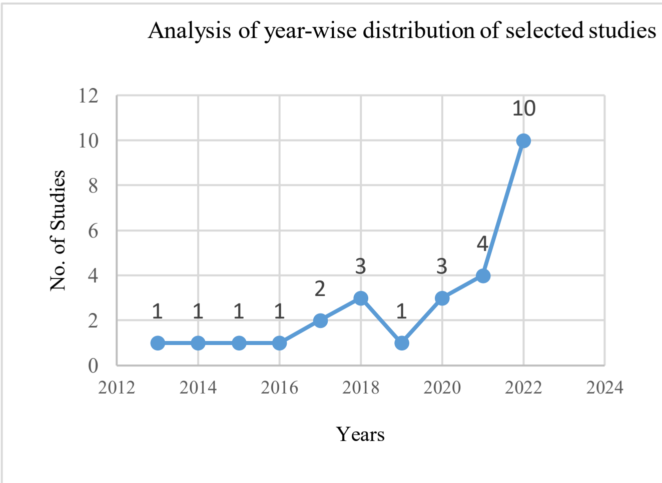

Figure 2. Analysis of Year-Wise Distribution Of Selected Studies (2013-2022)

The temporal distribution of publications depicted in Figure. 2 indicates that the initial period (2013-2016) has low and steady output, after which it gradually grows since 2017, showing a minor drop in 2019, and then returns to steady growth. This sharp increase in 2022 represents the intensive development of ML and DL usage in optimizing customer experience in recent years.

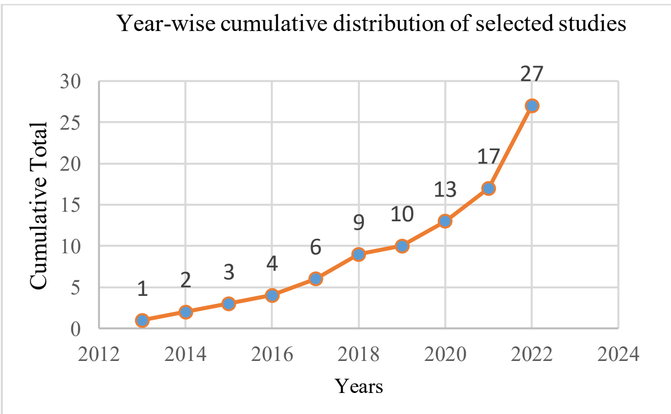

Figure 3. Cumulative Analysis of Year-Wise Distribution Of Selected Studies

Figure 3 shows the cumulative distribution of the number of studies that were selected to use in the review by years and shows the increment in the number of studies over time. The cumulative number reflects a slow growth between 2013 and 2016, which implies the lack of early adopters, after which it grows steadily between 2017 and 2019. Better growth is seen after 2020, and the number of studies increases significantly to reach a total of 27 by 2022. This tendency indicates the growing rate of current research and the proliferation of machine learning and artificial intelligence methods into areas related to customer experience over the past several years.

A. Application Domains, ML/AI Techniques, and CX Dimensions

An in-depth overview of the chosen studies is presented in Table III, where they were sorted as per their field of application, methods of ML/AI, data sources, and dimensions of customer experience.

E-commerce, online services, retail, banking, and customer service are the most commonly researched areas of application, as outlined in Table III. The traditional ML algorithms, including RF, SVM, NB, clustering and regression models, are the most common in older research, with the emergence of DL models, ensemble methods, and AI-powered systems gaining prominence in research published more recently.

In regard to data sources, customer surveys, behavioral data, transactional records, online reviews and secondary literature are habitually used. Regarding CX dimensions, the studies under analysis are largely dedicated to customer satisfaction, engagement, loyalty, personalization, trust, and journey optimization, which presupposes the progressive transition to holistic and experience-based evaluation models.

B. Summary of Key Observations

In general, the literature under consideration shows a definite shift of the exploratory and conceptual literature to the data-focused and AI-driven customer experience optimization frameworks. Newer research is primarily focusing on hybrid ML/DL systems, real-time analytics and end to end customer journey analysis. Nevertheless, differences in evaluation measures, insufficient cross-domain testing, and lack of concerned focus on model explicability can still be observed, which points to significant research directions in the future.

TABLE 3. ML/AI AND CUSTOMER EXPERIENCE BASED STUDIES BASED ON SYSTEMATIC LITERATURE REVIEW STUDIES

Study	Year	Application Domain	ML / AI Model / Technique	Data Source	CX Dimension
[9]	2013	Education / MOOCs	K-means clustering, Apriori association rules	Moodle LMS course data	Personalization, Course recommendation
[10]	2014	E-commerce	Neural Networks (BPN, HPNN), Regression	Online product reviews	Information usefulness, Decision support
[11]	2015	Web Services	Classification, Regression models	Real & simulated web service performance data	Service quality, Performance optimization
[12]	2016	Telecom / Banking	Review of ML algorithms	Prior churn prediction studies	Retention, Churn prevention
[13]	2017	E-commerce	Naïve Bayes, SVM, Decision Tree	Online product reviews	Sentiment, Satisfaction
[14]	2017	Product Design / E-commerce	Supervised ML classifiers	Online reviews & ratings	Perceived product quality
[15]	2017	Retail / Grocery	ANN, DT, Boosting, Bagging	Transactional & behavioral data	Retention, Loyalty
[16]	2018	Services / CX Strategy	Conceptual framework (Digital–Physical–Social)	Prior theoretical & empirical studies	Holistic customer experience
[17]	2018	Insurance	Tree-boosted ML models	Policyholder & pricing data	Pricing fairness, Customer behavior
[18]	2019	Telecom	Naïve Bayes, SVM, Decision Trees	IBM Watson & Cell2Cell datasets	Retention, Churn reduction
[19]	2020	CX Management	TCQ nomenclature framework	143 CX research papers	Touchpoints, Context, Experience quality
[20]	2020	Retail / Services	AI-enabled technology framework	Literature-based	Journey-wide experience
[21]	2020	Economics / Marketing	DL, Hybrid ML, Ensemble models	Prior economic & business studies	Decision quality
[22]	2020	E-commerce	Logistic Regression, XGBoost, Model Fusion	Online shopping behavior data	Prediction accuracy, Experience efficiency
[23]	2021	Marketing / CRM	K-means clustering	Customer behavioural data	Segmentation, Targeting
[24]	2021	Fashion Retail	PLS-SEM	Omnichannel customer survey	Seamlessness, Integration
[25]	2021	Financial Services	CRM analytics, BI dashboards	Omnichannel CRM interaction data	Personalization, Engagement

[26]	2021	Financial Services	AI-powered cloud CRM, NLP, ML	Cloud CRM & financial interaction data	Omnichannel CX, Trust
[27]	2022	Hospitality	AI quality models, SEM	Hotel guest surveys	Flow, Brand identification, Advocacy
[28]	2022	Customer Service	Chatbot functional taxonomy	Chatbot literature	Service quality, Responsiveness
[29]	2022	Marketing	ML use-case taxonomy	Academic & business literature	Value creation
[30]	2022	Retail / Customer Journey	AI tools (Chatbots, IVR, Recommenders)	Literature-based framework	Engagement, Relationship building
[31]	2022	Retail	AI-driven automation, Predictive analytics	Case studies & literature	Personalization, Satisfaction
[32]	2022	UX Design	ML-based SLR (PRISMA)	IEEE, Scopus, WoS, ACM	Usability, UX enhancement
[33]	2022	Customer Service	Chatbot-related ML factors	40 empirical studies	Satisfaction, Trust
[34]	2022	Healthcare	DL (EfficientNet-B4), Optimization	Chest X-ray images	Diagnostic experience (Indirect CX)
[35]	2022	Retail Analytics	ML + Advanced Computing pipelines	Transactional & clickstream data	Omnichannel CX, Fulfillment

IV. DISCUSSION

This section provides an interpretation of the results of the systematic review based on the review of the trends that emerge, the main areas of application, the similarities and differences of ML and DL methodologies and the aspects of customer experience that are covered in the studies that were reviewed, as well as the main methodological challenges that were identified in the reviewed articles.

A. Trends in ML and DL Adoption for Customer Experience

The literature reviewed demonstrates a distinct temporal shift in the usage of the techniques of both ML and DL to optimize customer experiences. Preliminary investigations in the literature in 2013-2016 were mainly based on conventional machine learning, including classification, regression, and clustering, usually of structured survey or transactional data. Since 2017, the trend is towards more advanced ML and deep learning methods, which is associated with a greater availability of large-scale customer data and computing resources. Figure 4 indicates that the studies reviewed show a profound change in the traditional ML methods to the modern DL methods and hybrid AI-based methods as time progressed.

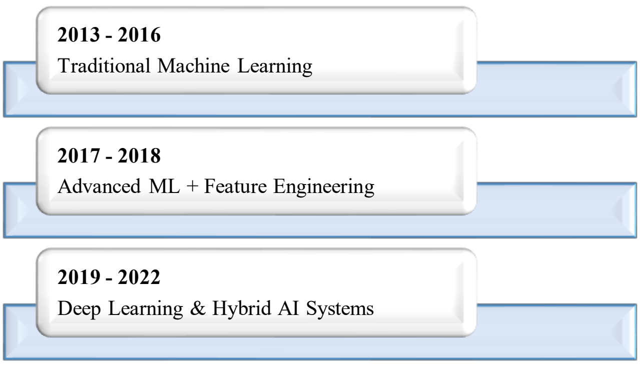

Figure 4. Layered evolution of ML and DL approaches for customer experience optimization (2013–2022)

This stratified development brings out the extent to which methodological finesse in CX studies has grown concurrently with data accessibility as well as the capacity to compute. Namely, more recent research published since 2018 utilizes deep learning architectures, hybrid ML/DL models, and AI-enabled systems in solving difficult customer experience issues. This shift is part of a bigger trend of replacement of exploratory and descriptive analytics with predictive and prescriptive customer experience management, which can allow progressively more personalized, real-time, and data-driven decisions.

B. Dominant Application Domains

The review has shown that the research is highly clustered around e-commerce, online retail, and customer service settings, where digital touchpoints can produce a large amount of customer interaction data. Such areas offer appropriate settings to apply ML and DL methods to scale satisfaction, engagement, and personalization. The banking, insurance, and telecommunications are minor application sectors, which are mostly about customer engagement, retention, and modeling loyalty.

On the other hand, the other fields like health, education, and government services are comparatively under-represented in the literature under review. Although these areas have been focused on user experience service delivery, they pose special data, ethical, and regulatory issues that have potentially restricted the use of high-end AI-based customer experience analytics. This discrepancy indicates the presence of major opportunities to expand the research in the field of ML/DL-driven CX to less established yet socially relevant areas.

C. Machine Learning versus Deep Learning: Comparative Insights

A comparative study of ML and DL methods contains different advantages and disadvantages. Conventional ML such as RF, SVM, and LR models still perform very well when the data is structured, and they have the benefit of being more interpretable, more stable and less mathematically complex. These features predispose ML techniques to the situation when it is necessary to have transparency and explainable decisions.

Deep learning models on the other hand have high performance on unstructured data, including text reviews, behavioral history, and multimodal customer data. Nevertheless, such improvements in predictive accuracy tend to be accompanied by interpretability decreasing and increased complexity of implementation. The recent trend of the increased use of hybrid and ensemble models can be viewed as a new attempt to strike a balance between predictive performance and robustness and realistic useability, integrating the advantages of both of the mentioned paradigms.

D. Customer Experience Dimensions Addressed

The studies examined are mostly concerned with the areas of customer satisfaction, engagement, loyalty, and personalization, as conventional metrics of customer experience studies. Newer literature starts to include new dimensions, including trust, flow experience, experiential value, and end-to-end customer, and is an initial indication of a slow transition towards more experience-focused and careful assessment models.

Although this has been the case, most studies have been able to discuss CX dimensions separately with little focus on multidimensional or holistic models. The absence of unified models that involve emotional, behavioral, and cognitive components of customer experience simultaneously is one of the significant gaps in the literature, especially in dynamic and omnichannel settings.

E. Methodological Challenges Identified

Various methodological issues also arise throughout the reviewed studies. The problems of data, such as imbalance of classes, noisy customer feedbacks, and lack of data on certain behavior and customers are major impediments to model reliability and generalizability. Furthermore, the increased use of deep learning models presents the problem of explainability and transparency of their models, which restricts their applicability to regulated or high-stakes decision-making environments.

Moreover, there are no standardized datasets and evaluation protocols that limit meaningful cross-study comparison and benchmarking. Differences in the data sources, feature engineering behaviors, and performance measurements impede the steady advancement of understanding in the area of customer experience research using ML/DL. Table IV summarizes a set of these recurrent methodological and conceptual issues and the related research opportunities. These challenges should be tackled to achieve the strength, equity, and effective implementation of AI-based CX optimization systems.

TABLE 4. SYNTHESIS OF KEY DISCUSSION THEMES IN ML/DL-BASED CUSTOMER EXPERIENCE RESEARCH

Discussion Theme	Key Findings	Observed Gaps / Opportunities
ML & DL Adoption Trends	Shift from traditional ML to DL and hybrid models after 2017	Limited longitudinal and real-time CX modeling
Application Domains	Dominance of e-commerce and online retail	Underrepresentation of healthcare, education, public services
ML vs DL Performance	ML offers interpretability; DL excels with unstructured data	Need for explainable and hybrid models
CX Dimensions	Focus on satisfaction, loyalty, personalization	Lack of holistic, multidimensional CX frameworks
Methodological Issues	Data imbalance, noise, lack of benchmarks	Absence of standardized datasets and evaluation protocols

V. RESEARCH GAPS IDENTIFIED

The systematic review reveals that there are a number of key gaps that restrict the progression and use of deep learning and ML techniques for improving the customer experience. These gaps can be summarized as in Table V.

TABLE 5. RESEARCH GAPS IN ML AND DL APPROACHES FOR CUSTOMER EXPERIENCE OPTIMIZATION

Gap Category	Identified Gaps	Impact / Limitation

Data-Related Gaps	- Limited use of real-time and streaming customer experience (CX) data - Reliance on static or historical datasets - Underexplored multimodal data integration (text, image, voice)	- Models cannot capture evolving or moment-to-moment CX dynamics - Restricts richer, holistic CX representation, especially in omnichannel environments
Model-Related Gaps	- Minimal adoption of explainable AI (XAI) techniques - Lack of longitudinal or causal modeling approaches - Focus on short-term prediction rather than causal relationships	- Limits managerial trust and regulatory compliance - Constrains proactive intervention design in customer journeys
Evaluation-Related Gaps	- Inconsistent performance metrics across studies - Rare use of standardized benchmarking datasets - Limited cross-domain validation	- Challenges in comparing ML/DL techniques across domains - Raises concerns about generalizability and robustness in real-world contexts

VI. FUTURE RESEARCH DIRECTIONS AND STUDY LIMITATIONS

Based on the research gaps detected, the following section provides major directions on how the future research should develop the ML/DL-led customer experience (CX) optimization, as well as future research opportunities are guided by the constraints of existing research.

A. Intelligent AI Models to optimize customer experience

Future studies need to consider transformer-based architectures and foundation models to describe complicated contextual and sequential trends in customer dealings. Moreover, reinforcement learning methods offer a substantial potential of dynamically optimizing CX because by letting the system to learn the best course of action in a multitask (interaction and feedback) communication with customers in various touchpoints.

B. Explainable and Ethical AI for CX Analytics

To improve the transparency, trust, and acceptance by managers, it is important to incorporate explainable AI (XAI) methods in the ML and DL models. In future research, interpreting CX models that can be used to make informed decisions should be developed that can address ethical considerations like reduction of bias, fairness, and accountability especially in sensitive areas of application such as finance, healthcare, and personalized services.

C. Customer Real-Time/Proactive Customer Experience Management

There is a growing demand of real time and streaming analytics structures that can handle the contagious stream of customer data. The research in the future should focus on predictive and prescriptive CX systems that are not only capable of predicting customer needs and dissatisfaction, but also prescribing timely and contextual interventions and allowing customers to manage the experience proactively.

D. Industry-Oriented and Cross-Domain Validation

In order to address the gap between practice and theory, deployment-oriented research designs, such as field experiments and practical applications, need to be used in future studies. Moreover, it is crucial that the cross-industry and cross-domain validation of ML/DL models would be conducted to determine the scalability, transferability, and practical relevance of the models to the context of different service ecosystems.

E. Study Limitations and Future Research Opportunities

This review has a number of limitations in spite of its contributions. It is confined to English-language peer-reviewed journal and conference articles included in selected academic databases, which may not cover any relevant gray literature and practitioner-focused research. Recent progress in generative AI and foundation models of CX analytics might be incompletely reflected in the review period (2013-2022). Besides, the synthesis is qualitative and does not involve a meta-analysis of effect sizes or model performance. These limitations can be overcome in future studies by summarizing more extensive data, over longer periods, and using quantitative methods of synthesis.

VII. LITERATURE REVIEW

The section includes a short description of machine learning-based methods of customer experience and CRM optimization. The literature uses hybrid, sentiment analysis, and customer segmentation with traditional and deep learning models, enhancing customer satisfaction and pointing to the problem of data heterogeneity, interpretability, and evaluation as summarized in Table VI.

Alsayat (2022) In order to understand the selection of large social data by tourists at hotels in Mecca, Saudi Arabia, a hybrid strategy combining supervised learning, text mining, and segmentation machine learning algorithms is being developed. Specifically, use k-means, latent Dirichlet allocation (LDA), and support vector regression with sequential minimum optimization (SMO) to create the hybrid approach. TripAdvisor user reviews serve as the foundation for statistics on internet reviews of Mecca hotels. These data are divided and the satisfaction of travelers is disclosed depending on the segment according to their online hotel reviews. The results show that the strategy works well for segmenting visitors in Mecca hotels and handling massive volumes of social data. The results are discussed, and a few suggestions and fixes for hotel management to enhance their offerings and client pleasure are provided[36].

Ledro, Nosella and Vinelli (2022) Offers a systematic review of the customer experience optimization through machine learning to summarize the existing knowledge, define gaps in research, and provide a scope of the future research opportunities. After a systematic and repeatable review procedure, peer-reviewed articles published over a specified period of time were systematically located, sifted and evaluated with the help of clearly stipulated inclusion and exclusion criteria. The literature chosen was reviewed to categorize customer experience dimensions, ML methods, sources of data and assessment measures that were used in studies. The analysis of the results shows that Predicting consumer happiness using deep learning and ML models, customer churn, customer sentiment and customer personalization is on the rise, but the analysis also demonstrates that there exist issues pertaining to heterogeneity of data, interpretability of the models, privacy and real-time application [37].

De Mauro, Sestino and Bacconi (2022) provide a taxonomy of machine learning applications in marketing based on a thorough analysis of academic and commercial literature. It have identified 11 typical use scenarios that fall into four homogenous groups that represent the core areas of ML's power in marketing: financial effect, decision-making, consumer fundamentals, and consumption experience. They comment on the common themes discovered within the taxonomy and suggest a conceptual model of how to interpret it and further, with emphasis on useful consequences to the marketer and researcher [29].

Noori (2021) another system of classifying and forecasting customer moods was offered. The reviews of the customers were gathered in a global hotel. The customer reviews are then processed upon and finally fed into several machine learning algorithms in the next step. Support vector machines (SVM), artificial neural networks (ANN), naïve bayes (NB), decision trees (DT), C4.5, and k-nearest neighbour (K-NN) were the methods used in this article. Among these algorithms, the DT produced superior outcomes. Additionally, with the help of the DT, the most important elements of the excellent customer experience were condensed. Finally, it was discovered that the effects of feature count on machine learning algorithms were also quite intriguing[38].

Markoulidakis et al. (2020) The task of businesses is to maximize NPS by enhancing the most significant CX features. But the statistical analysis indicates that the clear and accurate association between NPS and the scores of CX attributes is not obvious. They discuss the said deficiency in this paper through a new classification method, which was constructed by utilizing logistic regression and evaluated by several state-of-the-art machine learning (ML) models. The given approach was implemented on a large-scale data set related to the telecommunication industry and the outcomes were rather encouraging with a considerable enhancement in the majority of statistical indicators [39].

TABLE 6. COMPARATIVE SUMMARY OF MACHINE LEARNING–BASED CUSTOMER EXPERIENCE STUDIES

Study	Objective		Domain	ML Techniques Used	CX Focus	Key Findings	Limitations
Alsayat (2022)	Develop a hybrid ML framework for analysing traveller decision-making		Hospitality; TripAdvisor hotel reviews (Mecca)	SVR with SMO, LDA, K-means	Customer satisfaction, segmentation	Hybrid model effectively analyses big social data and identifies traveller segments	Domain-specific; limited generalizability
Ledro et al. (2022)	Systematically review ML-driven CX optimization		Multi-domain; peer-reviewed studies	ML, DL, NLP (review-based)	Satisfaction, churn, sentiment, personalization	Identifies dominant ML trends, challenges, and research gaps	No experimental validation
De Mauro et al. (2022)	Provide a taxonomy of ML applications in marketing		Marketing; academic & business literature	ML-based taxonomy	Consumption experience, decision-making	Identifies 11 ML use cases grouped into 4 strategic families	Conceptual focus; lacks empirical testing
Noori (2021)	Predict and categorize customer sentiments		Hospitality; international hotel reviews	SVM, ANN, NB, DT, C4.5, KNN	Sentiment, experience factors	Decision Tree outperformed other models; key CX factors identified	Dataset size and domain limited
Markoulidakis et al. (2020)	Improve NPS prediction using ML		Telecommunications; customer survey data	Logistic Regression, ML classifiers	CX attributes, NPS	Proposed model improves prediction accuracy over statistical methods	Focused on NPS metric only

VIII. CONCLUSION

Optimization of customer experience (CX) is a strategic focus in the current and digitalized settings with extensive data. The volume and complexity of customer interaction information are growing, and this needs sophisticated methods of analysis to gain insight into dynamic behaviors. Machine learning (ML) and deep learning (DL) have become useful in converting raw data into actionable insights to personalized and predictive CX management. This literature review of 27 articles published between 2013 and 2022 demonstrates a transition to new DL, hybrid, and AI-driven systems in unstructured and multimodal data versus traditional ML models of structured data. The main areas of application are e-commerce, retail, banking, and customer service, whereas more unexplored areas are such as healthcare, education, and government. There are still issues of data quality, interpretability of the model, inconsistent evaluation procedures and ability to do longitudinal or real time analysis. This review outlines an organized base of the study in the future because it is categorized in terms of domains, techniques, data types, and dimensions of CX. The results highlight the need to have explainable, ethical, and real-time AI designs to create robust, scalable, and implementable (for use in practice) CX optimization solutions.

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