



Exploring User Experience by User Review Using LDA-Topic Modeling and HEART Framework: A Systematic Literature Review

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Abstract

This study aims to evaluate the integration of the HEART framework (Happiness, Engagement, Adoption, Retention, and Task Success) with computational modeling techniques such as Latent Dirichlet Allocation (LDA) for measuring User Experience (UX). A Systematic Literature Review (SLR) was conducted on articles published between 2015 and 2025, selected from reputable databases including Scopus. The selected studies emphasize the use of HEART metrics in conjunction with machine learning approaches, particularly LDA, and were assessed based on the Scimago journal quartile ranking system. The findings categorize the studies into five main research objectives: predicting user satisfaction and emotional response, optimizing usability, analyzing user-generated content, evaluating learning performance through gamified systems, and assessing system requirements in relation to UX. This classification reveals growing trends in applying hybrid methods that combine qualitative metrics with automated modeling techniques. The results underline the importance of developing more adaptive and scalable UX evaluation frameworks that align human-centered insights with machine learning-driven analysis. This study offers a foundational reference for future research in building integrative models that advance the depth and scale of UX assessments in complex digital environments.

Keyword: HEART, LDA, Machine Learning, Systematic Literature Review, User Experience, UX Evaluation

1. INTRODUCTION

Evaluating User Experience (UX) effectively is critical in designing successful digital products and services. One prominent UX evaluation framework is the HEART framework, introduced by Google researchers in 2010. The HEART framework consists of five dimensions including Happiness, Engagement, Adoption, Retention, and Task Success, which allow designers and developers to quantify UX through clear, measurable signals tied directly to business and product objectives [1]. Over the years, HEART metrics have been extensively implemented across various domains, such as e-commerce, education, government websites, and mobile applications, due to their straightforward yet robust capacity to capture user perceptions and behaviors systematically [2], [3].

Numerous empirical studies demonstrate the successful application of HEART metrics in evaluating UX across diverse digital platforms. For example, Santosa employed HEART metrics to evaluate user satisfaction in e-commerce platforms, revealing that the dimensions of Happiness and Task Success significantly influenced positive UX [4]. Similarly, Mutawa and Sruthi highlighted the use of HEART metrics to measure student interactions and satisfaction in online learning environments, showcasing how HEART provides detailed insights into user behaviors and preferences in educational contexts [5].

Meanwhile, topic modeling techniques, especially Latent Dirichlet Allocation (LDA), have become increasingly prominent in analyzing large-scale textual user data, particularly user-generated content such as application reviews, uncovering latent themes and patterns within unstructured user-generated feedback. Initially proposed by Blei et al., LDA enables researchers to detect hidden thematic structures in documents by modeling words probabilistically, facilitating the identification of meaningful insights from qualitative data [6]. Compared to other natural language processing techniques, LDA is relatively easy to implement, computationally efficient, and capable of uncovering latent patterns without the need for predefined categories, making it highly suitable for exploratory analysis in UX research. Several studies have validated the utility of LDA in UX contexts, such as analyzing user reviews in mobile applications, healthcare platforms, and customer service systems [7], [8]. These applications underscore the effectiveness of LDA in

extracting user sentiments, concerns, and attitudes, providing designers with qualitative depth that quantitative measures alone often cannot capture. Moreover, the selection of 1-star and 2-star reviews in such studies is based on the assumption that these ratings are strong indicators of negative user sentiment. By focusing on low-rated reviews, researchers can bypass the need for explicit sentiment analysis while still gaining insights into user dissatisfaction, product weaknesses, and potential areas of improvement. Figure 1 represents the star categories and their characteristics.



Figure 1. Star Categories and Their Characteristics [9]

Furthermore, the selection of 1-star and 2-star reviews as the object of analysis is grounded in established literature. Prior studies consistently categorize these low-star ratings as strong indicators of negative sentiment, often marked by explicit dissatisfaction, criticism of system failures, or unmet expectations [9], [10], [11]. By focusing on extreme negative reviews, researchers can bypass the semantic ambiguity commonly found in mid-range ratings (3–4 stars) and improve the granularity of extracted topics [12], [13]. This approach streamlines topic modeling while ensuring that the analysis captures the most critical signals of user discontent.

Despite the widespread adoption of both HEART metrics and topic modeling techniques individually, most studies still treat them as separate approaches. UX research utilizing HEART metrics largely emphasizes quantitative assessments derived from predefined signals and survey instruments, often overlooking the rich qualitative insights embedded in user-generated textual feedback. Conversely, studies applying topic modeling frequently analyze user feedback in isolation, detached from the structured strategic framework that HEART provides. This separation creates a critical gap both academically and practically. From an academic standpoint, it leaves a methodological weakness where computationally extracted themes are not grounded in established UX theory. From a practical standpoint, it limits the actionability of insights, as organizations may capture numerical signals without fully understanding the underlying reasons reflected in user narratives.

Integrating HEART with topic modeling, therefore, becomes both necessary and urgent. In the context of digital products that continuously generate massive volumes of reviews, comments, and surveys, failing to connect qualitative insights with structured UX dimensions risks overlooking signals of dissatisfaction or opportunities for improvement. An integrated approach would allow quantitative indicators (e.g., retention rates) to be enriched by nuanced themes (e.g., reasons for discontinuation), enabling more comprehensive UX evaluation. Such integration advances both theory and practice by deepening behavioral interpretation, producing actionable design recommendations, and aligning UX evaluation more closely with user needs and business goals.

The novelty of this study lies in positioning such integration not merely as a descriptive mapping, but as a critical contribution compared to earlier SLRs in UX. While prior reviews have typically focused either on standardized frameworks such as HEART or on computational techniques such as topic modeling, this review is among the first to systematically examine their intersection. By highlighting methodological gaps (e.g., lack of validation between metrics and topics) and practical implications (e.g., scalability in handling large-scale feedback), the study contributes both academically by strengthening theoretical foundations and practically by informing design and product strategies.

Given this urgency, the present Systematic Literature Review (SLR) aims to explore and synthesize existing work that integrates computational modeling methods, particularly LDA, with the HEART framework. Accordingly, three research questions are posed: How does existing literature up to 2020 describe and implement the integration of computational modeling methods, particularly LDA, with HEART metrics in UX evaluation?, What methodological approaches, challenges, and best practices are reported in studies attempting to combine HEART metrics with topic modeling techniques?, What theoretical and practical implications can be derived from such integration for advancing UX research, informing product design strategies, and improving organizational decision-making?.

2. RELATED WORKS

The increasing adoption of digital technologies and interactive platforms has significantly heightened the need for structured approaches in evaluating UX. One of the most widely referenced frameworks in UX evaluation is the HEART framework, originally introduced by Rodden, Hutchinson, and Fu [1]. Although

proposed earlier, the HEART framework continues to be highly relevant from 2019 to 2025 due to its comprehensive nature and adaptability to various platforms. It includes five dimensions: Happiness, Engagement, Adoption, Retention, and Task Success. These dimensions are designed to help practitioners measure UX in a goal-oriented and scalable manner across digital products and services [14].

Between 2019 and 2025, several empirical studies have implemented the HEART framework in diverse domains such as e-learning platforms, mobile applications, and government digital services. Garcia-Lopez et al. examined user interactions in educational platforms and demonstrated how HEART metrics effectively revealed insights related to student satisfaction, engagement, and continued usage [15]. Similarly, Hussain et al. used the HEART framework to evaluate mobile health applications and found strong correlations between application design factors and user happiness [16]. These studies collectively highlight how the HEART framework has been utilized to address both functional and emotional aspects of UX.

In addition to structured UX metrics, computational modeling techniques have gained prominence, especially for analyzing qualitative data such as user reviews, feedback, and comments. LDA is one of the most widely used topic modeling methods and has been employed to extract themes and patterns from large volumes of textual data. Cheng and Jin used LDA to analyze Airbnb user reviews, identifying key factors that influence user satisfaction such as cleanliness, communication, and location [8]. These studies illustrate how topic modeling techniques provide depth to UX analysis by uncovering implicit user needs and concerns.

Despite the growing use of both HEART metrics and topic modeling methods, few studies explicitly integrate the two approaches into a unified UX evaluation framework. Most research treats them as separate methods, either focusing on quantitative measurements through HEART metrics or exploring textual data through modeling techniques. For example, while Cheng and Jin revealed important user insights through LDA, they did not connect these insights to structured UX metrics such as engagement or retention [8]. Furthermore, Liu et al. applied topic modeling in analyzing brand-related user-generated content on social media platforms like Twitter [17]. This gap presents an opportunity for future studies to integrate metric-based frameworks with data-driven modeling approaches in order to achieve a more comprehensive understanding of UX.

The novelty of this literature review lies in its focus on synthesizing studies from 2015 to 2025 that combine the HEART framework with computational modeling methods. The review categorizes studies based on the objective of the research, the type of data utilized, and the analytical methods applied. By examining how these methods are used together, this study aims to identify methodological patterns, highlight existing research gaps, and provide guidance for future UX research that integrates structured measurement with data-driven analysis.

3. METHOD

This research employs a quantitative approach to systematically review existing literature concerning the application and integration of UX evaluation using HEART metrics and computational modeling techniques. Specifically, this study utilizes the SLR methodology, a structured approach designed to systematically identify, analyze, synthesize, and interpret research findings from prior academic studies. Literature selected for review exclusively comprises peer-reviewed research articles published between 2015 and 2025, ensuring the analysis includes current and relevant developments in UX research and computational modeling. Subsequently, the selected studies are organized according to the purpose of the research, the types of data utilized, and the computational techniques applied. An overview of the research methodology steps is illustrated in Figure 2.

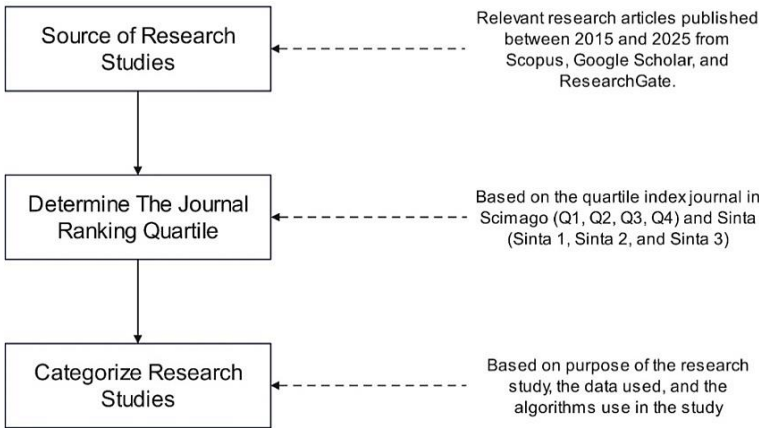


Figure 2. Research Methodology

The comprehensive methodology used in this SLR is visually summarized in the research flow diagram depicted in Figure 2. The diagram details each step of the systematic review process clearly, starting from initial literature identification, followed by rigorous screening and selection based on inclusion criteria, quartile ranking validation using the Scimago database, and finally, the systematic categorization and detailed analysis of the selected studies according to research purposes, data characteristics, and computational algorithms applied.

Several instruments were employed to ensure rigor and transparency. Literature was retrieved from academic databases including Scopus, IEEE, ScienceDirect, Emerald, and Taylor & Francis. A search string combining keywords such as “HEART framework,” “user experience metrics,” “topic modeling,” “Latent Dirichlet Allocation (LDA),” and “UX evaluation” was used to identify relevant studies. The inclusion criteria required articles to be (1) published between 2015 and 2025, (2) peer-reviewed journal or conference papers, (3) explicitly addressing UX evaluation using HEART, LDA, or their integration, and (4) available in full text. Exclusion criteria involved non-academic literature, duplicated records, and studies unrelated to UX evaluation.

To assess study quality, the Scimago Journal Ranking (SJR) was adopted to categorize journals into quartiles (Q1–Q4). In addition, a structured data extraction matrix was employed to record essential details from each study, including research objectives, type of data, computational techniques, and key findings. These instruments collectively ensured a systematic and replicable review process.

4. RESULTS AND DISCUSSION

At this stage, the selected 20 research studies fall within the broader field of UX evaluation and computational modeling, particularly those that combine structured metrics like the HEART framework with techniques such as LDA and other machine learning methods. These studies were collected from databases such as Scopus (Elsevier, Emerald, Science Direct, Taylor Francis, IEEE, etc) publication years between 2015 and 2025. The aim of this literature review is to map the landscape of recent developments by classifying the studies based on journal ranking, research objectives, data sources, and analytical methods used.

Journal ranking was determined using the Scimago Journal & Country Rank (SJR) index. This classification helps assess the quality of journals and the academic contribution level of each study. The quartile categories used in Scimago (Q1–Q4) allow the literature to be grouped accordingly. Table 1 presents the results of the journal ranking classification.

Table 1. Results from Journal Ranking

Title	Journal Ranking	Citation
The Personal Health Applications of Machine Learning Techniques in the Internet of Behaviors	Q1	[2]
Usability and Optimization of Online Apps in User’s Context	Q1	[3]
Enhancing Human–Computer Interaction in Online Education: A Machine Learning Approach to Predicting Student Emotion and Satisfaction	Q1	[5]
Consumer-Generated Visual Advertisements in Social Media Brand Communities	Q1	[7]
What do Airbnb Users Care about? An Analysis of Online Review Comments	Q1	[8]
Are customer star ratings and sentiments aligned? A deep learning study of the customer service experience in tourism destinations	Q2	[10]
Creating Domain-Specific Sentiment Lexicons via Text Mining	Q2	[11]
Measuring the Effects on Learning Performance and Engagement with a Gamified Social Platform in an MSc Program	Q2	[15]
Examining the Impact of Luxury Brand’s Social Media Marketing on Customer Engagement: Using Big Data Analytics and Natural Language Processing	Q1	[17]
Employing Structural Topic Modelling to Explore Perceived Service Quality Attributes in Airbnb Accommodation	Q1	[18]
Sentiment Analysis from Customer-Generated Online Videos on Product Review Using Topic Modeling and Multi-Attention BLSTM	Q1	[19]
Different Voices Between Airbnb and Hotel Customers: An Integrated Analysis of Online Reviews Using Structural Topic Model	Q1	[20]
A New Topic Modeling Based Approach for Aspect Extraction in Aspect Based Sentiment Analysis: SS-LDA	Q1	[21]
User Reviews: Sentiment Analysis using Lexicon Integrated Two-Channel CNN–LSTM Family Models	Q1	[22]
User Experience Quantification Model from Online User Reviews	Q2	[23]
Development of Methodology for Classification of User Experience (UX) in Online Customer Review	Q1	[24]
User Experience Design Using Machine Learning: A Systematic Review	Q1	[25]
Machine Learning Algorithms for Improved Product Design User Experience	Q1	[26]
Deep Learning-Based User Experience Evaluation in Distance Learning	Q2	[27]

Title	Journal Ranking	Citation
Towards Machine Learning Based Analysis of Quality of User Experience (QoUE)	Q2	[28]
LDA Ensembles for Interactive Exploration and Categorization of Behaviors	Q1	[29]
Analyzing Tourism Reviews using an LDA Topic-Based Sentiment Analysis Approach	Q1	[30]
Cross-Domain Aspect Detection and Categorization using Machine Learning for Aspect-based Opinion Mining	Q1	[31]
Uncovering Concerns of Citizens Through Machine Learning and Social Network Sentiment Analysis	Q2	[32]
Exploring E-Commerce Product Experience Based on Fusion Sentiment Analysis Method	Q1	[33]
Medical Service Quality Evaluation Based on LDA and Sentiment Analysis: Examples of Seven Chronic Diseases	Q1	[34]
The Impact of User Perception on Continued Knowledge Purchase Intention: A Study Utilizing the LDA Topic Analysis Method	Q1	[35]
Emergency Care and the Patient Experience: Using Sentiment Analysis and Topic Modeling to Understand the Impact of the COVID-19 Pandemic	Q1	[36]
Exploring Sources of Patient Dissatisfaction in Mobile Health Communication: A Text Analysis Based on Structural Topic Model	Q2	[37]
Exploring the Evolution of Educational Serious Games Research: A Topic Modeling Perspective	Q2	[38]

Based on Table 1, the selection of journals and articles was carried out through a rigorous screening process to ensure both academic quality and thematic relevance. Only peer-reviewed studies indexed in reputable databases such as Scopus, IEEE, Elsevier, ScienceDirect, Taylor & Francis, and Emerald were included. The Scimago Journal & Country Rank (SJR) was adopted as the primary instrument to classify journals into quartiles (Q1–Q4), thereby providing an objective measure of scholarly quality and impact. The majority of selected articles fall within Q1 and Q2 journals, demonstrating that the integration of HEART metrics with computational modeling methods has gained recognition in high-impact venues. This distribution not only reflects the strong methodological rigor of the studies but also highlights the growing scholarly interest across diverse domains such as health applications, e-commerce, education, tourism, and mobile platforms. After establishing journal quality, the next step is to categorize the research according to its objectives within the field of UX and computational modeling, as presented in Table 2.

Table 2. The Purpose of UX Metrics and Computational Modeling

Aim/ Purpose	Citation
Predict user emotion, satisfaction, or behavioral responses using machine learning or big data	[2], [5], [10], [17], [19], [21], [22], [23], [31], [32], [38]
Evaluate and optimize app usability and UX metrics in digital platforms	[3], [24], [25], [26], [27], [28], [29]
Analyze user-generated content to extract insights on preferences, satisfaction, and engagement	[7], [8], [18], [30], [33], [34], [35], [36], [37]
Measure learning outcomes and engagement in gamified or educational systems	[11], [15]
Assess the role of system or design requirements in determining UX success	[20]

Based on Table 2, it is evident that recent research on UX and computational modeling has focused on five main objectives. First, several studies have applied machine learning to predict user satisfaction, emotional response, or behavioral intention in the context of health applications, online education, and social engagement platforms. Second, UX optimization through usability evaluation and structured frameworks like HEART is emphasized in studies aiming to enhance user interactions in apps and digital systems. Third, studies such as explore the analysis of user-generated content, particularly from social media and review platforms, to uncover latent user preferences. Fourth, engagement and learning performance are investigated through the lens of UX in gamified learning platforms. Lastly, study focuses on how software or system requirements influence the overall UX, showing a process-oriented perspective in UX evaluation. This classification helps to identify patterns and priorities in the field and serves as a foundation for further synthesis in data classification in Table 3.

Based on Table 3, the most frequently used data category is transaction data. This includes app usage logs, user behavior data, online interaction patterns, and engagement metrics gathered from digital platforms. Studies rely on this type of data to train machine learning models or evaluate system usability. The second most used category is user-generated content (UGC), which consists of user reviews, social media posts, and feedback that are analyzed for sentiment or topic extraction. Device data, which includes data collected from user devices or sensors (e.g., emotion detection, motion tracking). Lastly, descriptive data, such as documentation, system specifications, or project requirements. This classification of data types provides

insight into the dominant forms of information used in UX and computational modeling research, and forms the basis for the next stage of analysis, which focuses on the models or algorithms applied Table 4.

Table 3. Data Categories

Data Category	Citation
Transaction Data	[2], [3], [5], [10], [17], [24], [28], [30], [32], [37]
UGC Data (data generated by the user)	[7], [8], [21], [26], [31], [33], [35], [36]
Device Data	[2], [5], [15], [29]
Descriptive Data	[18], [19], [20], [22], [25], [27], [34], [38]

Table 4. Algorithm / Model / Technique Used

Algorithm / Model / Technique	Citation
Machine Learning Classification Models	[2], [5], [11], [15], [23], [26], [28], [31], [32]
Usability Testing / UX Metrics Framework	[3], [15], [21]
Sentiment Analysis / Natural Language Processing (NLP)	[7], [10], [17], [19], [22], [24], [27], [33], [34], [36], [37]
Topic Modeling (Latent Dirichlet Allocation - LDA)	[8], [18], [20], [29], [30], [34], [35], [36], [38]
Descriptive / Document Analysis	[25]

Based on Table 4, the most frequently used approaches in UX and computational modeling studies include machine learning classification models, usability frameworks, and text-based analysis techniques. Machine learning methods are commonly used to predict user satisfaction, emotional states, or interaction outcomes. Usability testing and structured frameworks like HEART are used to evaluate and quantify UX in various digital environments. Sentiment analysis and natural language processing are applied to extract emotional and attitudinal patterns from user-generated content. Topic modeling using LDA helps to uncover latent themes in review texts. Lastly, descriptive or document-based approaches are employed to examine system requirements and their impact on UX. These techniques reflect a strong trend toward data-driven and hybrid UX evaluation, combining structured measurement tools with advanced modeling of unstructured feedback.

However, the analysis of the reviewed studies also reveals several important limitations. Most studies still apply HEART metrics and topic modeling as separate tools rather than as an integrated framework. For instance, research employing LDA typically limits its analysis to identifying thematic clusters or latent topics, but rarely connects these outputs to structured UX dimensions such as Engagement, Retention, or Task Success. This creates a methodological gap where qualitative insights are not systematically aligned with quantitative indicators, reducing the explanatory power of the findings. In addition, several studies rely on relatively narrow or domain-specific datasets such as single-platform reviews or context-limited user groups making it difficult to generalize the insights to broader UX contexts.

Another limitation lies in methodological transparency and validation. While advanced algorithms such as topic modeling, sentiment analysis, and machine learning classifiers are widely used, many studies do not provide a clear rationale for how these computational results are interpreted in relation to UX constructs. The absence of cross-validation between computational outputs and UX frameworks like HEART raises concerns about replicability and consistency. Furthermore, although technical sophistication is evident, practical implications for design and organizational strategy are often underdeveloped. This leaves a gap between academic contributions and the actionable insights needed by practitioners.

These limitations suggest the necessity for future research to move beyond descriptive mappings and towards more integrative and critical approaches. Specifically, studies should aim to design frameworks that explicitly link computationally extracted themes to established UX dimensions, ensuring both theoretical robustness and practical usability. There is also a need to test such integrative models across multiple domains and at scale for example, applying HEART-LDA integration in mobile health applications, e-learning platforms, or government digital services to validate their generalizability. By addressing these limitations, future work can contribute to the development of UX evaluation methods that are not only rigorous and replicable but also directly relevant to product design and user-centered decision-making.

5. CONCLUSION

This study conducted an SLR on the integration of the HEART framework with computational modeling techniques, particularly LDA, in evaluating UX across digital platforms. From a pool of studies published between 2015 and 2025, twenty key papers were analyzed, covering domains such as health applications, e-commerce, education, tourism, and mobile platforms.

The review identifies five dominant research objectives: (1) predicting user behavior and satisfaction, (2) optimizing usability through HEART-based metrics, (3) analyzing user-generated content for behavioral insights, (4) evaluating UX in gamified learning environments, and (5) examining the role of system requirements in UX performance. Across these objectives, two major trends emerge: first, the growing

application of hybrid methods that combine structured metrics with computational analysis; and second, the increasing importance of user-generated content as a complementary data source to traditional survey- and log-based metrics.

The contribution of this SLR lies in explicitly connecting HEART and topic modeling approaches, which have largely been treated in isolation in prior reviews. By systematically mapping how these methods intersect, this study provides a clearer methodological pathway and highlights practical benefits, such as enhancing the actionability of UX insights and supporting scalability in handling large-scale user feedback. Compared to earlier reviews that focused solely on either HEART metrics or computational modeling, this study demonstrates how their integration strengthens both theoretical grounding and practical relevance in UX evaluation.

For future research, more applied studies are needed to test HEART-LDA integration in specific domains. For instance, in mobile health apps, LDA could extract themes from patient feedback that map onto Happiness and Retention metrics; in e-learning platforms, topic modeling could uncover patterns of student engagement that align with HEART's Engagement and Task Success dimensions. Such applications would not only validate the integrative framework but also provide concrete guidelines for designers and organizations.

REFERENCES

- [1] K. Rodden, H. Hutchinson, and X. Fu, "Measuring the User Experience on a Large Scale: User-Centered Metrics for Web Applications," in *SIGCHI Conference on Human Factors in Computing Systems*, 2010, pp. 2395–2398.
- [2] Z. Amiri *et al.*, "The Personal Health Applications of Machine Learning Techniques in the Internet of Behaviors," *Sustainability*, vol. 15, no. 16, pp. 1–41, Aug. 2023, doi: 10.3390/su151612406.
- [3] M. W. Iqbal, K. Shinan, S. R. Shahid Rafique, A. Alourani, M. U. Ashraf, and N. Z. A. Rahim, "Usability and Optimization of Online Apps in User's Context," *PeerJ Comput. Sci.*, vol. 10, pp. 1–27, Dec. 2024, doi: 10.7717/peerj-cs.2561.
- [4] P. I. Santosa, "Measuring User Experience in an Online Store Pusing Pulse and Heart Metrics," *J. Ilm. Kursor*, vol. 7, no. 3, pp. 145–154, 2014.
- [5] A. M. Mutawa and S. Sruthi, "Enhancing Human-Computer Interaction in Online Education: A Machine Learning Approach to Predicting Student Emotion and Satisfaction," *Int. J. Human-Computer Interact.*, vol. 40, no. 24, pp. 8827–8843, Dec. 2024, doi: 10.1080/10447318.2023.2291611.
- [6] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet Allocation," *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, 2003.
- [7] H.-F. Lin, P.-C. Lin, and Be. Yeo, "Consumer-Generated Visual Advertisements in Social Media Brand Communities," *Int. J. Commun.*, vol. 18, pp. 982–1005, 2024.
- [8] M. Cheng and X. Jin, "What do Airbnb Users Care about? An Analysis of Online Review Comments," *Int. J. Hosp. Manag.*, vol. 76, pp. 58–70, Jan. 2019, doi: 10.1016/j.ijhm.2018.04.004.
- [9] M. Arief and N. A. Samsudin, "Neutral Class Handling for Customer Sentiment Analysis In Binary Classification: A Comparative Study of Supervised Machine Learning Classification Algorithm," *2023 8th Int. Conf. Informatics Comput. ICIC 2023*, vol. 1, pp. 1–8, 2023, doi: 10.1109/ICIC60109.2023.10381911.
- [10] E. Bigne, C. Ruiz, C. Perez-Cabañero, and A. Cuenca, *Are customer star ratings and sentiments aligned? A deep learning study of the customer service experience in tourism destinations*, vol. 17, no. 1. Springer Berlin Heidelberg, 2023. doi: 10.1007/s11628-023-00524-0.
- [11] K. Labille, S. Gauch, and S. Alfarhood, "Creating Domain-Specific Sentiment Lexicons via Text Mining," *IEEE Int. Conf. Progr. Compr.*, vol. 2022-March, pp. 36–47, 2022.
- [12] D. Monett and H. Stolte, "Predicting star ratings based on annotated reviews of mobile apps," *Proc. 2016 Fed. Conf. Comput. Sci. Inf. Syst. FedCSIS 2016*, vol. 8, no. June 2015, pp. 421–428, 2016, doi: 10.15439/2016F141.
- [13] P. Rodrigues, I. S. Silva, G. A. R. Barbosa, F. R. dos S. Coutinho, and F. Mourão, "Beyond the Stars: Towards a Novel Sentiment Rating to Evaluate Applications in Web Stores of Mobile Apps," in *Proceedings of the 26th International Conference on World Wide Web Companion*, in WWW '17 Companion. Republic and Canton of Geneva, CHE: International World Wide Web Conferences Steering Committee, 2017, pp. 109–117. doi: 10.1145/3041021.3054139.
- [14] J. Sauro and J. R. Lewis, *Quantifying the User Experience Practical Statistics for User Research*. London: Morgan Kaufmann, 2016.
- [15] A. Garcia-Cabot, E. Garcia-Lopez, S. Caro-Alvaro, J. Gutierrez-Martinez, and L. De-Marcos, "Measuring the Effects on Learning Performance and Engagement with a Gamified Social Platform in an MSc Program," *Comput. Appl. Eng. Educ.*, vol. 28, no. 1, pp. 207–223, Jan. 2020, doi: 10.1002/cae.22186.

- [16] A. Hussain, E. O. C. Mkpojiogu, and F. M. Kamal, "The Role of Requirements in the Success or Failure of Software Projects," *Int. Rev. Manag. Mark.*, vol. 6, no. 7, pp. 306–311, 2016.
- [17] X. Liu, H. Shin, and A. C. Burns, "Examining the Impact of Luxury Brand's Social Media Marketing on Customer Engagement: Using Big Data Analytics and Natural Language Processing," *J. Bus. Res.*, vol. 125, pp. 815–826, Mar. 2021, doi: 10.1016/j.jbusres.2019.04.042.
- [18] K. Ding, W. C. Choo, K. Y. Ng, and S. I. Ng, "Employing Structural Topic Modelling to Explore Perceived Service Quality Attributes in Airbnb Accommodation," *Int. J. Hosp. Manag.*, vol. 91, pp. 1–10, Oct. 2020, doi: 10.1016/j.ijhm.2020.102676.
- [19] Z. Wang, P. Gao, and X. Chu, "Sentiment Analysis from Customer-Generated Online Videos on Product Review Using Topic Modeling and Multi-Attention BLSTM," *Adv. Eng. Informatics*, vol. 52, pp. 1–11, Apr. 2022, doi: 10.1016/j.aei.2022.101588.
- [20] B. Gao, M. Zhu, S. Liu, and M. Jiang, "Different Voices Between Airbnb and Hotel Customers: An Integrated Analysis of Online Reviews Using Structural Topic Model," *J. Hosp. Tour. Manag.*, vol. 51, pp. 119–131, Jun. 2022, doi: 10.1016/j.jhtm.2022.03.004.
- [21] B. Ozyurt and M. A. Akcayol, "A New Topic Modeling Based Approach for Aspect Extraction in Aspect Based Sentiment Analysis: SS-LDA," *Expert Syst. Appl.*, vol. 168, pp. 1–14, Apr. 2021, doi: 10.1016/j.eswa.2020.114231.
- [22] W. Li, L. Zhu, Y. Shi, K. Guo, and E. Cambria, "User Reviews: Sentiment Analysis using Lexicon Integrated Two-Channel CNN–LSTM Family Models," *Appl. Soft Comput.*, vol. 94, pp. 1–11, Sep. 2020, doi: 10.1016/j.asoc.2020.106435.
- [23] J. Hussain, Z. Azhar, H. F. Ahmad, M. Afzal, M. Raza, and S. Lee, "User Experience Quantification Model from Online User Reviews," *Appl. Sci.*, vol. 12, no. 13, pp. 1–24, Jul. 2022, doi: 10.3390/app12136700.
- [24] Y. Son and W. Kim, "Development of Methodology for Classification of User Eexperience (UX) in Online Customer Review," *J. Retail. Consum. Serv.*, vol. 71, pp. 1–13, Mar. 2023, doi: 10.1016/j.jretconser.2022.103210.
- [25] A. M. H. Abbas, K. I. Ghauth, and C.-Y. Ting, "User Experience Design Using Machine Learning: A Systematic Review," *IEEE Access*, vol. 10, pp. 51501–51514, 2022, doi: 10.1109/ACCESS.2022.3173289.
- [26] X. Wang and B. Hu, "Machine Learning Algorithms for Improved Product Design User Experience," *IEEE Access*, vol. 12, pp. 112810–112821, 2024, doi: 10.1109/ACCESS.2024.3442085.
- [27] R. Sadigov, E. Yildirim, B. Kocaçınar, F. Patlar Akbulut, and C. Catal, "Deep Learning-Based User Experience Evaluation in Distance Learning," *Cluster Comput.*, vol. 27, no. 1, pp. 443–455, Feb. 2024, doi: 10.1007/s10586-022-03918-3.
- [28] C. I. Nwakanma, M. S. Hossain, J.-M. Lee, and D.-S. Kim, "Towards Machine Learning Based Analysis of Quality of User Experience (QoUE)," *Int. J. Mach. Learn. Comput.*, vol. 10, no. 6, pp. 752–758, Dec. 2020, doi: 10.18178/ijmlc.2020.10.6.1001.
- [29] S. Chen *et al.*, "LDA Ensembles for Interactive Exploration and Categorization of Behaviors," *IEEE Trans. Vis. Comput. Graph.*, vol. 26, no. 9, pp. 2775–2792, Sep. 2020, doi: 10.1109/TVCG.2019.2904069.
- [30] T. Ali, B. Omar, and K. Soulaïmane, "Analyzing Tourism Reviews using an LDA Topic-Based Sentiment Analysis Approach," *MethodsX*, vol. 9, pp. 1–10, 2022, doi: 10.1016/j.mex.2022.101894.
- [31] A. F. Pathan and C. Prakash, "Cross-Domain Aspect Detection and Categorization using Machine Learning for Aspect-based Opinion Mining," *Int. J. Inf. Manag. Data Insights*, vol. 2, no. 2, pp. 1–18, Nov. 2022, doi: 10.1016/j.jjime.2022.100099.
- [32] S. Kumi, C. Snow, R. K. Lomotey, and R. Deters, "Uncovering Concerns of Citizens Through Machine Learning and Social Network Sentiment Analysis," *IEEE Access*, vol. 12, pp. 94885–94913, 2024, doi: 10.1109/ACCESS.2024.3426329.
- [33] H. He, G. Zhou, and S. Zhao, "Exploring E-Commerce Product Experience Based on Fusion Sentiment Analysis Method," *IEEE Access*, vol. 10, pp. 110248–110260, 2022, doi: 10.1109/ACCESS.2022.3214752.
- [34] J. Dai, F. Lyu, L. Yu, Z. Zhou, and Y. He, "Medical Service Quality Evaluation Based on LDA and Sentiment Analysis: Examples of Seven Chronic Diseases," *Digit. Heal.*, vol. 10, pp. 1–20, Jan. 2024, doi: 10.1177/20552076241233864.
- [35] Y. Liu, F. Du, and H. Li, "The Impact of User Perception on Continued Knowledge Purchase Intention: A Study Utilizing the LDA Topic Analysis Method," *SAGE Open*, vol. 15, no. 2, pp. 1–22, Apr. 2025, doi: 10.1177/21582440251339667.
- [36] S. Chekijian, H. Li, and S. Fodeh, "Emergency Care and the Patient Experience: Using Sentiment Analysis and Topic Modeling to Understand the Impact of the COVID-19 Pandemic," *Health Technol. (Berl.)*, vol. 11, no. 5, pp. 1073–1082, Sep. 2021, doi: 10.1007/s12553-021-00585-z.
- [37] J. Liu, P. Ding, and H. Jiang, "Exploring Sources of Patient Dissatisfaction in Mobile Health

- Communication: A Text Analysis Based on Structural Topic Model,” *Digit. Heal.*, vol. 10, pp. 1–12, Jan. 2024, doi: 10.1177/20552076241287890.
- [38] H. Ozyurt, O. Ozyurt, and D. Mishra, “Exploring the Evolution of Educational Serious Games Research: A Topic Modeling Perspective,” *IEEE Access*, vol. 12, pp. 81827–81841, 2024, doi: 10.1109/ACCESS.2024.3411094.