Kenan Mahmutović
University of Bihać
Faculty of Economics in Bihać
77000 Bihać, Bosnia
and Herzegovina
kenan.mahmutovic@unbi.ba

JEL: M31, C55, D12, G21
Original scientific article
https://doi.org/10.51680/ev.38.2.6

Received: June 24, 2025
Revision received: August 26, 2025
Accepted for publishing: August 26, 2025

ANALYZING USER-GENERATED REVIEWS TO IDENTIFY EXPERIENCE DIMENSIONS AND THEIR IMPACT ON SATISFACTION WITH MOBILE BANKING APPLICATIONS

Abstract

Purpose: This study aims to identify key experience dimensions derived from user-generated reviews and examine their influence on satisfaction with mobile banking applications. By analyzing unsolicited user feedback, the study aims to provide a data-driven understanding of what drives satisfaction and dissatisfaction in m-banking services across Southeast Europe.

Methodology: A total of 56,074 reviews of mobile banking apps from Bosnia and Herzegovina, Croatia, and Serbia were analyzed. The study employed BERT-based sentiment analysis and BERTopic modeling to extract thematic experience dimensions from reviews categorized by sentiment polarity. Multiple linear regression was used to assess the predictive power of these dimensions and sentiment polarity on user-assigned satisfaction ratings.

Results: Eleven distinct experience dimensions were identified and confirmed as significant predictors of satisfaction. These dimensions, derived through topic modeling and sentiment analysis, were quantitatively modeled and qualitatively interpreted based on review content, offering rich contextual insights into user perceptions. The regression model explained 58% of the variance in rating behavior. Additionally, sentiment polarity emerged as a strong predictor, further enhancing the model's explanatory power and underscoring the emotional weight embedded in user reviews.

Conclusion: This study shows that user satisfaction in mobile banking is shaped by a combination of functional and emotional factors, which can be effectively identified through text mining. Including sentiment polarity alongside experience dimensions offers a more robust framework for evaluating digital service quality. These insights can support academic model development and practical efforts to optimize m-banking app design and communication.

Keywords: Customer satisfaction, mobile banking, user-generated reviews, sentiment analysis, topic modeling, user experience

1. Introduction

The widespread adoption of smartphones and the growing demand for digital financial services have positioned mobile banking (m-banking) as an important channel for customer interaction in the banking sector (Shaikh & Karjaluoto, 2015). This shift has transformed how banks deliver services and redefined user expectations and experiences (Iswani, 2023). In increasingly competitive digital markets, user experience (UX) has emerged as a key determinant of mobile app success, influencing customer satisfaction, trust, and long-term loyalty (Hassenzahl & Tractinsky, 2006). Despite the critical importance of UX in mobile banking, prior research has primarily relied on structured instruments, surveys, interviews, and expert-driven models to assess satisfaction and perceived quality (Sharma & Malviya, 2011; Orehovački et al., 2023). However, such approaches often fail to capture spontaneous and user-driven expressions of satisfaction and dissatisfaction, particularly as reflected in user-generated content such as app store reviews (Amirkhalili & Wong, 2025). These textual reviews offer rich insight into how users interpret, evaluate, and emotionally respond to their banking app experiences, an insight that often eludes traditional models.

The research problem in this study addresses the limited understanding of which experiential dimensions users emphasize in unsolicited mobile banking app reviews and how these dimensions relate to their satisfaction levels, as measured by app ratings. While previous models have proposed theoretical constructs of mobile service quality, they often lack empirical grounding in authentic, user-expressed feedback. Analyzing app reviews offers academic and practical value: for researchers, it reveals emergent and experience-based dimensions of app quality that legacy frameworks may not capture, while for practitioners, it informs UX and product design by pinpointing what truly matters to users. Moreover, identifying the latent structure of user experience as expressed in natural language helps bridge the gap between quantitative app ratings and the qualitative drivers behind them. Beyond its descriptive value, identifying these UX dimensions contributes to developing more precise and context-specific measurement tools, including validated scales for assessing satisfaction with mobile banking applications. By empirically grounding such instruments in real-world user narratives, this research supports the construction of psychometrically robust tools for academic inquiry and industry benchmarking.

The objectives of this paper are twofold:

RO1: To identify the thematic dimensions that users spontaneously express in mobile banking app reviews.

RO2: To examine how these identified dimensions relate to users' satisfaction, as proxied by their app rating scores.

These objectives are addressed through a mixed-methods approach combining transformer-based sentiment analysis with BERTopic modeling to analyze over 50,000 user reviews of mobile banking applications in Bosnia and Herzegovina, Croatia, and Serbia.

The remainder of the paper is structured as follows. Section 2 reviews the literature on mobile banking, application quality, user experience, and the use of sentiment and topic modeling in UX research. Section 3 details the research methodology, including sampling, data collection, and analysis procedures. Section 4 presents the empirical findings, focusing on the most prominent experiential dimensions and their influence on app ratings. Section 5 discusses theoretical and practical implications. Finally, Section 6 offers a comprehensive conclusion by synthesizing the main findings, highlighting the study's academic and practical contributions, and discussing its limitations and directions for future research.

2. Theoretical background

This section synthesizes links between mobile-banking app quality, UX, and customer satisfaction, justifies using reviews, and outlines modeling to derive dimensions and hypothesized effects.

2.1 The role and evolution of mobile banking in the digital era

Mobile banking (m-banking), a rapidly evolving segment of electronic banking (e-banking), refers to the use of mobile devices such as smartphones and tablets to access a range of financial and non-financial services anytime and anywhere. These include functionalities such as checking account balances, transferring funds, paying bills, reviewing transaction history, and managing payment cards, typically via proprietary applications developed by financial institutions (Ayala Gavilanes et al., 2023; Iswani, 2023). As a component of e-banking, mobile banking coexists with other digital channels, such as internet banking portals and automated teller machines (ATMs), jointly reshaping how customers interact with financial services (Adhikari & Gyawali, 2023; Mwakisoba & Meela, 2024). The growing demand for mobile banking is primarily driven by customers' rising expectations for immediacy, convenience, and constant accessibility, coupled with banks' objectives to reduce operational costs and enhance service efficiency (Shaikh & Karjaluoto, 2015). Mobile banking has become the dominant digital touchpoint in many markets due to the widespread adoption of smartphones, improved mobile internet infrastructure, and the increasing availability of intuitive and feature-rich mobile apps (Ayala Gavilanes et al., 2023). Notably, mobile banking is no longer limited to transactional services but has expanded to include real-time alerts, savings tools, investment tracking, and financial planning features, transforming it into a comprehensive digital experience. From a strategic perspective, mobile banking represents more than a technological advancement. It signifies a paradigm shift in the way financial institutions engage with customers. User experience (UX) has become a pivotal criterion for app success in this new context.

2.2 Linking application quality, user experience, and satisfaction in mobile banking

In mobile banking, application quality, user experience (UX), and satisfaction are interrelated but distinct constructs. Application quality refers to an app's technical and experiential attributes, including usability, reliability, security, and performance (Grady, 1992; ISO/IEC, 2011). Early models such as SERVQUAL (Parasuraman et al., 1988) and E-S-QUAL (Parasuraman et al., 2005) conceptualized quality as the discrepancy between expectations and perceived performance, later extended to digital interfaces. Hoehle and Venkatesh (2015) and Garcia and Casas (2020) emphasized usability and visual design as core to mobile app quality, aligning with the notion of Quality of Experience (QoE).

UX, defined by ISO 9241-210 (2010), includes perceptions and emotional responses before, during, and after interaction with an app. While quality contributes to UX, the experience integrates affective and contextual dimensions (Hassenzahl & Tractinsky, 2006). For instance, efficient functionality may yield poor UX if emotional engagement is lacking (Iswani, 2023). Studies show that UX in mobile banking is shaped by digital touchpoints, e.g., responsiveness, personalization, and perceived security, which influence satisfaction (Oh & Kim, 2022; Adhikari & Gyawali, 2023; Sugiono et al., 2025). UX also varies by user characteristics, i.e., younger users value speed and design, while older users emphasize trust and security (Iswani, 2023; Sharma et al., 2024).

Satisfaction is the evaluative judgment after usage (Oliver, 1997), shaped by quality and UX. Definitions stress affective, functional, and contextual factors (Hammouri et al., 2020; Alkhafaji, 2016; Ranjitha & Agarwal, 2024; Finley et al., 2018). In mobile banking, many users lack prior expectations shaped by experience. Instead, expectations are formed via brand messaging (Jiang et al., 2017), peer influence (Oyekunle et al., 2023; Sällberg et al., 2022), analogical reasoning (Al-Shamaileh & Sutcliffe, 2023), and dominant digital norms (Alam et al., 2024; Zimmermann et al., 2022; Squillaro, 2021). Self-efficacy further informs expectations and adoption intentions, especially among inexperienced users (Compeau & Higgins, 1995). Empirical studies confirm its role in app usage and satisfaction (Liu et al., 2022; Keith et al., 2011).

Sentiment analysis of 90,000 reviews (Oh & Kim, 2022) identified ease of use, convenience, security, and support as key drivers of satisfaction, reflecting both functional and emotional elements. These findings align with the technology acceptance model (Davis, 1989) and the role of trust as a key emotional mediator (Gentile et al., 2007; Sugiono et al., 2025).

In summary, application quality is a key antecedent of UX, which serves as a mediator toward satisfaction. The three constructs are conceptually distinct but form a causal chain shaping user perceptions, emotions, and engagement with mobile banking apps.

2.3 Online reviews as a source of customer insight

Online customer reviews have become a powerful lens on user satisfaction, expectations, and service experiences in the digital economy. Unlike surveys or interviews constrained by researcher-defined questions, reviews capture spontaneous, user-driven narratives in the consumer's language (Oh & Kim, 2022; Garcia & Casas, 2020). Traditional surveys, grounded in predetermined quality dimensions (Zeithaml et al., 1993; Parasuraman et al., 1988; 2005), secure statistical comparability but can overlook emergent issues. For instance, a mobile banking user who assigns a 4/5 rating provides no clue whether the missing point reflects login delays, confusing navigation, or absent real-time alerts. These nuances surface only in free-form reviews. These narratives, therefore, complement numeric scores by isolating the features that drive delight or frustration, especially in contexts where rapid transactions coexist with poor support. Empirical work across hospitality, e-commerce, and banking confirms this diagnostic value: ostensibly high-scoring services still attract complaints about cleanliness, responsiveness, trust, or disruptive updates (Kim & Kim, 2022; Kubrusly et al., 2022; Amirkhalili & Wong, 2025). Large-scale analyses of mobile banking apps further show that usability, security, and transaction reliability dominate review discourse, underscoring functional and affective dimensions of satisfaction (Khabour et al., 2023; Islam et al., 2023). Text-mining of reviews can therefore serve as a scalable, near-real-time diagnostic for identifying critical experience dimensions (Vargas-Calderón et al., 2021), so long as researchers mitigate selection bias, compensate for sparse demographic data, and detect or filter potential review manipulation through rigorous validation and triangulation procedures (Askalidis & Malthouse, 2016; Zhu et al., 2022; Fatima & Khan, 2024; Gandhi et al., 2025; Zhang et al., 2023).

2.4 *Sentiment analysis and topic modeling in UX research*

Digital feedback requires tools that reveal what users talk about and how they feel. Sentiment analysis classifies emotion and polarity, evolving from the lexicon and classic ML (e.g., SentiWordNet; Naïve Bayes, SVM) to deep-learning and transformer models such as BERT and its multilingual version, which excel across languages (Liu, 2012; Devlin et al., 2019; Wu & Dredze, 2019).

Topic modeling uncovers latent themes. LDA laid the groundwork (Blei et al., 2003) but falters on short, noisy texts. BERTopic overcomes this by pairing BERT embeddings with class-based TF-IDF, yielding clearer, interactive topics (Grootendorst, 2022).

Together, BERT-based sentiment and BERTopic provide a scalable, context-sensitive lens on UX. Recent applications range from tracking mental-health discourse on Reddit (Cai et al., 2023) to monitoring post-COVID e-commerce moods (Öztürk Birim, 2024) and diagnosing fintech app issues (Sangaraju et al., 2022). This combined approach helps researchers surface emerging problems, gauge trust, and refine user-centered design.

2.5 *Models of mobile banking app evaluation and dimensions of quality and satisfaction*

Early studies assessed m-banking largely with SERVQUAL and E-S-QUAL, prioritizing reliability and responsiveness (Parasuraman et al., 1988; 2005). Although still relevant (Aghdaie & Faghani, 2012; Sharma & Malviya, 2011), these instruments overlooked mobile-specific needs such as usability and interface design. Subsequent work broadened the lens. Ahmed et al. (2020) added trust and perceived value to E-S-QUAL, showing technical features affect satisfaction indirectly, while Adhikari & Gyawali (2023) blended TAM with service-quality items to demonstrate that functional ease and emotional assurance jointly shape acceptance in emerging markets. Inductive, user-centered analyses deepened this shift. Jun and Palacios (2016) and Shankar et al. (2020) mined reviews to surface dimensions like mobile convenience, privacy, and interactivity, structural models later confirmed the salience of interface design and system reliability (Zhou et al., 2021; Nisha, 2016). Arcand et al. (2017) bridged utilitarian and hedonic views, finding that while functionality builds trust, enjoyment and sociality more strongly drive satisfaction. Hussain et al. (2014) refined usability into learnability, error prevention, and task efficiency, stressing cognitive simplicity. Recent sentiment-aware mining (Halvadia et al., 2022; Amirkhalili & Wong, 2025) corroborates these findings at scale, highlighting usability, security, and support, factors often absent from surveys. Collectively, the literature has moved from generic checklists to multidimensional, context-sensitive frameworks that integrate functional performance (reliability, efficiency, security) with experiential qualities such as trust, aesthetics, enjoyment, social interaction, and perceived control (Jun & Palacios, 2016; Arcand et al., 2017; Oh & Kim, 2022). The result is a more nuanced understanding of service quality as the interplay between technical adequacy and user-centric design.

3. Methodology

This section succinctly summarizes a mixed-methods design deriving dimensions from app-store reviews and estimating association with satisfaction via regression.

3.1 Research design

This study employs a mixed-method approach combining natural language processing techniques and quantitative modeling to explore how user experience dimensions extracted from online reviews relate to satisfaction with mobile banking applications. The goal was to move beyond predefined survey instruments by leveraging unsolicited user feedback on app stores, providing spontaneous and context-rich insights.

3.2 Sample definition and app identification

All banks operating in Bosnia and Herzegovina, Croatia, and Serbia that offer mobile banking services were identified based on official national banking registries. The corresponding mobile banking application on the Google Play platform was located and verified for each bank. The inclusion criterion required that the app be actively maintained and have received user reviews on the Google Play store as of April 2025.

3.3 Data collection

The data were collected in the Python programming environment during April 2025 using the `google_play_scraper` package. The scraper was customized to extract all available user reviews for the identified mobile banking applications, applying language and country filters to ensure contextual relevance. A total of 56,074 reviews were collected across all three countries.

3.4 Data preprocessing

All collected reviews were processed to standardize language and encoding. Reviews written in Cyrillic script were converted to Latin script to ensure consistency during text analysis. Basic cleaning procedures included lowercasing, removing punctuation, and eliminating duplicate or empty entries. No reviews were excluded based on sentiment or rating content.

3.5 Sentiment analysis and topic modeling

Each review was subjected to sentiment analysis using the transformer-based model `nlptown/bert-base-multilingual-uncased-sentiment` via the Hugging Face `pipeline` function. The model classified each review as expressing either "positive," "neutral," or "negative" sentiment. Topic modeling was then conducted using "BERTopic" and applied separately to each sentiment group. This allowed the extraction of distinct semantic themes relevant to different emotional tones. Topics were interpreted through a two-step process: (1) analysis of keywords, and (2) qualitative coding of 50 randomly sampled reviews per topic. Semantically similar topics were grouped into higher-order "user experience dimensions" through this process.

3.6 Dimensional assignment procedure

The BERTopic model generated a probability distribution across identified topics for each review. The topics with the highest, second-highest, and third-highest probabilities were retained and designated as the *primary*, *secondary*, and *tertiary* topics, respectively, for subsequent analysis. Each dimension was operationalized as a separate column in the dataset, with the relevant topic probability recorded as the degree of association. This probabilistic assignment enabled each review to contribute proportionally to the dimensional structure of the dataset.

3.7 Statistical analysis

Descriptive analysis was first conducted on the total dataset to summarize the sample's structure and examine the sentiment distribution across reviews. This step allowed for identifying dimensions that most frequently appeared in positively and negatively classified reviews, providing insights into the key experiential drivers of satisfaction and dissatisfaction.

A linear regression model was then estimated in R to assess the impact of individual user experience dimensions on perceived satisfaction. The app rating score (on a 1–5 scale) served as the dependent variable. In contrast, the independent variables included both the identified experience dimensions, operationalized through topic probabilities, and the sentiment classification of each review (positive, neutral, or negative).

4. Results

This section reports the corpus profile, eleven dimensions, and regressions linking dimensions/sentiment to ratings, highlighting key predictors and sentiment's added explanatory power.

4.1 Sample profile

The analytical process in this study relied on user-generated content collected from the Google Play platform. The dataset consisted of 56,074 reviews submitted by users of 49 mobile banking applications offered by banks in Bosnia and Herzegovina, Croatia, and Serbia. These reviews were used for topic modeling and the inductive identification of user experience dimensions. The most significant portion of reviews originates from Croatia (53.4%), followed by Serbia (38.2%) and Bosnia and Herzegovina (8.4%). In terms of sentiment distribution, the reviews are almost evenly split between positive (43.6%) and negative (46.6%) sentiment, with neutral reviews representing a smaller share (9.8%). Serbia recorded the highest proportion of negative sentiment (53.8%), while Bosnia and Herzegovina had the highest share of neutral reviews (12.5%). Croatia showed the most balanced sentiment distribution, with nearly equal proportions of positive (47.5%) and negative (42.6%) feedback. These figures highlight important regional differences in user experience perceptions and serve as a basis for further analysis of market satisfaction drivers.

Table 1 Distribution of reviews per country and per sentiment category – Initial dataset

Country	Banks	Reviews (% of total)	Positive sentiment num. (% of row)	Negative sentiment num. (% of row)	Neutral sentiment num. (% of row)
Bosnia and Herzegovina	19	4,716 (8.4%)	2,266 (48%)	1,862 (39.5%)	588 (12.5%)
Croatia	17	29,960 (53.4%)	14,225 (47.5%)	12,764 (42.6%)	2,971 (9.9%)
Serbia	13	21,398 (38.2%)	7,963 (37.2%)	11,514 (53.8%)	1,921 (9%)
Total	49	56,074	24,454 (43.6%)	26,140 (46.6%)	5,480 (9.8%)

Source: Author

Each review in the dataset is accompanied by an app rating ranging from 1 (lowest satisfaction) to 5 (highest satisfaction). A descriptive analysis of rating scores in the initial dataset revealed the following distribution, which is presented in Table 2.

Table 2 Distribution of rating scores by country

Country	Rating score						
	Mean	SD	5	4	3	2	1
Bosnia and Herzegovina	3.48	1.69	47.4%	11.3%	8.5%	7.6%	25.2%
Croatia	3.33	1.79	47.5%	8.4%	5.7%	6.5%	31.9%
Serbia	2.87	1.84	37.5%	6.6%	5.2%	6.5%	44.1%
Total*	3.17	1.82	43.7%	8.0%	5.7%	6.6%	36.0%

Note: * The sums of percentage ratings by country may deviate from 100% due to rounding to one decimal place.
Source: Author

The analysis of rating score distribution reveals notable differences across countries. On average, users in Bosnia and Herzegovina gave the highest ratings (M = 3.48, SD = 1.69), with nearly 47.4% of reviews awarding the maximum score of 5 and a relatively lower proportion of negative ratings (25.2%). In Croatia, the average score was slightly lower (M = 3.33, SD = 1.79), with a similar share of 5-star ratings (47.5%) but a higher proportion of 1-star ratings (31.9%), indicating a more polarized distribution. Serbia had the lowest average rating (M = 2.87, SD = 1.84), with less than 38% of reviews awarding five stars and a notably high share (44.1%) of 1-star ratings, suggesting greater user dissatisfaction. Overall, the total average rating across all reviews was 3.17, with the most frequent ratings being either five stars (43.7%) or 1 star (36.0%), indicating a bimodal pattern and emphasizing the presence of strong polar opinions in user feedback.

4.2 Identified user experience dimensions

Following sentiment analysis using a BERT-based model and subsequent topic modeling with BERTopic, 135 topics related to positive reviews, 39 topics related to neutral reviews, and 63 topics related to negative reviews were identified. For each topic, keyword analysis and content review of 50 randomly selected reviews were conducted to determine the thematic orientation. Based on this process, each topic was assigned to one of the relevant user experience dimensions. In total, 11 distinct dimensions were identified and are presented in Table 3.

Table 3 Dimensions of user experience with m-banking apps – Distribution per sentiment

Dimension	Description	Negative	Neutral	Positive
D1 - Ease of Use	This dimension includes the app's simplicity, clarity, and ease of interaction. It encompasses intuitive design, clear navigation, transparent layout, and straightforward task execution. It reflects a user-friendly interface that supports smooth and efficient application use.	2,865 (5.1%)	2,580 (4.6%)	24,454 (43.6%)
D2 - Performance Speed	This dimension includes the application's speed, responsiveness, and efficiency. It covers fast command execution, low latency, quick loading times, and immediate system feedback. It applies to navigation within the app and the timely processing of user requests.	23 (0.04%)	353 (0.63%)	24,454 (43.6%)
D3 - Operational Reliability and Stability	This dimension includes the consistency and stability of the application's functioning. It covers error-free operation, predictable performance, and system reliability. It encompasses app crashes, freezing, software bugs, installation errors, and failures that prevent access to the app. It also includes disruptions caused by unstable performance or malfunctioning features.	25,841 (46.1%)	578 (1%)	10,034 (17.9%)
D4 - Functional Utility	This dimension includes the availability and usefulness of features that support everyday banking needs, such as account management, payments, and self-service options. It reflects how functionally complete the app is and how much it replaces in-branch services while simplifying users' daily routines.	1,045 (1.9%)	0	2,451 (4.4%)
D5 - Payment Functionality	This dimension includes all aspects of initiating and processing payments through the app. It covers features such as QR code payments, photo bill scanning, NFC-based payments, and integration with third-party services like Google Pay. It reflects the availability, reliability, and practicality of in-app payment options.	1,521 (2.7%)	550 (1%)	185 (0.3%)
D6 - Security	This dimension includes data protection, secure authentication, and user privacy. It covers security mechanisms such as PINs, biometric login, token-based access, and the app's permission requirements. It reflects concerns about unauthorized access, protection of sensitive information, and the overall trust in the app's security protocols.	2,336 (4.2%)	127 (0.2%)	266 (0.5%)
D7 - Version Experience	This dimension includes user feedback related explicitly to experiences with different app versions. It encompasses reactions to updates, including improvements or problems introduced in newer versions. It covers functionality loss, interface changes, delayed notifications, and differences in performance after updates.	25,503 (45.5%)	286 (0.5%)	5,814 (10.4%)

Dimension	Description	Negative	Neutral	Positive
D8 - Service Access	This dimension includes accessing core services within the app. It covers issues such as unavailable features, geographic or language restrictions, lack of integration with tools like Google Pay, and the inability to open or process certain documents. It reflects how technical, regional, or functional restrictions impact the application's usability.	1,902 (3.4%)	326 (0.6%)	471 (0.8%)
D9 - Customer Support Experience	This dimension includes user feedback related to their interactions with customer support. It encompasses perceived professionalism, helpfulness, friendliness, and responsiveness of support staff. It reflects how effectively customer inquiries, issues, or requests are handled through the app or associated service channels.	0 (0%)	40 (0.07%)	532 (0.95%)
D10 - Emotional Expression	This dimension includes emotionally charged statements that reflect strong user sentiments such as frustration, delight, excitement, or disappointment. It covers expressions like "worst bank ever" or "finally!" that communicate emotion without specifying reasons or referencing specific app features. It reflects the affective tone rather than the functional content of the feedback.	11,501 (20.5)	5,163 (9.2%)	16,866 (30.1%)
D11 - General satisfaction	This dimension includes general expressions of satisfaction or dissatisfaction with the app. It reflects an overall impression without reference to specific features or issues. It encompasses statements that describe the app as "excellent," "very satisfied," "everything works fine," or "completely dissatisfied," focusing on the global user experience.	0 (0%)	21 (0.04%)	9,201 (16.4%)

Source: Author

4.3 *Impact of experience dimensions and sentiment on rating scores*

Multiple linear regression analysis was conducted using R to examine how user experience dimensions and sentiment polarity influence rating behavior. The dependent variable was the user-assigned rating score (ranging from 1 to 5), while the independent variables comprised probabilistic indicators of eleven predefined user experience dimensions derived from topic modeling. Each review was associated with up to three topics with the highest associated probabilities, as identified by the BERTopic model. A review was assigned to a particular user experience dimension if any associated topics (with sufficient probability) matched the set of topics defining that dimension for the corresponding sentiment category. Each dimension was represented as a separate variable in the dataset, and the topic probabilities were aggregated per dimension. This probabilistic aggregation allowed for a weighted contribution of each review to the multidimensional representation of user experience.

In the baseline specification (Model 1), only the eleven user experience dimensions were included as predictors. This model accounted for approximately 28.1% of the variance in user-assigned rating scores (*Adjusted* $R^2 = 0.281$), indicating a moderate explanatory capacity based solely on experiential content derived from topic modeling. All eleven dimensions exhibited statistically significant effects on rating behavior. Among the most potent positive predictors were Performance Speed ($\beta = 2.55$, $p < 0.001$), Functional Utility ($\beta = 2.49$, $p < 0.001$), Emotional Expression ($\beta = 2.22$, $p < 0.001$), General Satisfaction ($\beta = 3.35$, $p < 0.001$), and Customer Support Experience ($\beta = 2.03$, $p < 0.001$), suggesting that these dimensions are closely aligned with users' perceptions of high-quality service. Additionally, Ease of Use ($\beta = 1.12$), Security ($\beta = 0.64$), and Service Access ($\beta = 0.90$) were positively associated with higher ratings. Conversely, Operational Reliability and Stability ($\beta = -0.72$), Version Experience ($\beta = -0.73$), and Payment Functionality ($\beta = -0.42$) demonstrated significant negative associations with rating scores.

To further enhance explanatory power, sentiment polarity (positive, negative, neutral [reference]) was added in Model 2. This extension significantly improved the model, raising Adjusted R^2 to 0.581, thus accounting for more than half of the variance in rating behavior. Both sentiment predictors emerged as highly significant: reviews labeled as *negative* were associated with a 1.71 point reduction in rating scores ($\beta = -1.711$, $p < 0.001$), while *positive* sentiment led to a 0.94 point increase ($\beta = 0.941$, $p < 0.001$). These findings emphasize the critical role of emotional tone in shaping rating behavior, reinforcing the notion that sentiment not only complements but also amplifies the explanatory power of topic-based dimensions.

To assess multicollinearity among predictors in Model 2, Variance Inflation Factors (VIFs) were computed. The vast majority of variables demonstrated low VIF values (GVIF^(1/(2*Df)) < 1.2), indicating negligible multicollinearity. The highest observed VIFs were for *Ease of Use* (2.43) and *Performance Speed* (2.48), suggesting moderate collinearity, likely due to the conceptual overlap in how users perceive usability and responsiveness. Nonetheless, these values remain well below the standard thresholds of concern (VIF > 5), affirming the model's robustness (Hair et al., 2019). Overall, the results indicate that the content (i.e., what users discuss) and the affective tone (i.e., how users feel) are vital in predicting satisfaction outcomes. The joint modeling of topic-derived dimensions and sentiment polarity provides a comprehensive understanding of the drivers behind rating behavior.

Table 4 Regression estimates for Model 2

Term	Estimate	Std. Error	t-value	Sig.
(Intercept)	3.45	0.02	195.30	***
Ease of Use	0.13	0.06	2.33	*
Performance Speed	0.56	0.06	9.69	***
Functional Reliability & Stability	0.13	0.04	3.26	**
Functional Utility	0.88	0.06	13.72	***
Payment Functionality	0.18	0.08	2.24	*
Security	-0.20	0.10	-2.07	*
Version Experience	-0.43	0.05	-8.0	***
Service Access	0.29	0.08	3.52	***
Customer Support Experience	0.78	0.13	6.04	***
Emotional Expression	0.37	0.03	11.81	***
General Satisfaction	0.45	0.06	7.00	***
Sentiment - Negative	-1.71	0.02	-95.79	***
Sentiment - Positive	0.94	0.02	50.164	***

Note: Significance codes: p < 0.001 "***", p < 0.05 "*".
Residual standard error: 0.9506 on 8,791 degrees of freedom
Multiple R-squared: 0.5283, Adjusted R-squared: 0.5276
F-statistic: 757.5 on 13 and 8,791 DF, p-value: < 2.2e-16
Source: Author

5. *Discussion*

This study combines BERTopic-based topic modeling with sentiment-augmented regression to clarify how content cues and emotional tone shape satisfaction with mobile banking apps. Analysis of 56,074 unsolicited reviews from three Southeast European markets uncovered eleven experience dimensions that extend traditional service-quality constructs.

Regarding functional and affective drivers, dimensions tied to core system performance, Performance Speed ($\beta = 0.56$, p < .001) and Functional Utility (β

= 0.88, p < .001), proved the most potent positive predictors, confirming that fast, comprehensive functionality remains central to perceived value. Ease of Use (β = 0.13) and Operational Reliability (β = 0.13) acted more as hygiene factors: their absence provokes complaints, yet their presence yields only incremental gains. More minor but significant effects emerged for Payment Functionality (β = 0.19) and Service Access (β = 0.29). The former shows that smooth payment features incrementally boost satisfaction. The latter indicates that users reward apps that offer broad geographic or language coverage and all the services and functions they expect.

Sources of dissatisfaction cluster around Security (β = −0.20) and Version Experience (β = −0.43). Intrusive authentication or unstable updates erode trust and violate expectations set by earlier app versions, echoing expectancy-disconfirmation logic. Customer Support (β = 0.78) offsets these risks; although mentioned in only 1% of reviews, responsive assistance markedly lifts ratings, underscoring the enduring value of human help in digital finance.

Emotional resonance also matters. Affect-laden themes, Emotional Expression (β = 0.37) and General Satisfaction (β = 0.45), show that users often judge the app through their broader relationship with the bank. Adding sentiment polarity improved explanatory power substantially (Adj. R^2 = 0.58); strong positive (β = 0.96) and negative (β = −1.70) coefficients confirm that affective language is an efficient proxy for satisfaction.

These results refine classic frameworks. Reliability, responsiveness, and security remain pertinent, yet their influence is eclipsed by digital-specific factors such as speed and functional breadth, dimensions rarely addressed in earlier models. This supports earlier critiques by Jun and Palacios (2016) and Shankar et al. (2020), who emphasized the inadequacy of conventional models for capturing the dynamic and interactive nature of mobile banking. Compared to TAM-based models (Davis, 1989; Venkatesh & Davis, 2000), which highlight perceived ease of use and usefulness, our findings nuance these constructs. While ease of use is frequently mentioned, it exhibits only a modest effect on satisfaction, functioning as a hygiene factor rather than a satisfier, echoing the expectancy-disconfirmation theory (Oliver, 1980). *Ease of Use* behaves as a threshold attribute, while *Functional Utility* broadens "perceived usefulness" to encompass transactional completeness.

The strong influence of customer support experience validates claims by Amirkhalili and Wong (2025) and Arcand et al. (2017) that human interaction retains value in digital contexts. This dimension rarely features in classical models but proves crucial for digital adoption, especially among low-literacy users, a fact highlighted in developing market studies (Adhikari & Gyawali, 2023). The dimension version experience, emerging as a strong negative predictor, has been rarely treated in prior service quality models. Its significance underscores the unique challenges of platform volatility and update inconsistency in app-based services, a theme Hussain et al. (2014) raised in usability research but not fully integrated into most frameworks. The prominence of update stability and customer support lends weight to recent calls for context-sensitive, multidimensional models. Finally, quantifying sentiment's additive value demonstrates that affective cues enhance prediction beyond behavioral variables, offering a replicable template for future UX analytics. Overall, satisfaction with mobile banking arises from the interplay of speed, functional richness, version stability, supportive service, and emotional tone. Models that ignore these digitally specific and affective elements risk misdiagnosing what truly matters to users.

6. Conclusion

This study contributes to the digital service analytics literature by demonstrating how user-generated textual feedback can be transformed into actionable experience dimensions using sentiment-aware topic modeling. The empirical identification and validation of eleven experience dimensions, confirmed as significant predictors through regression analysis, provide a robust foundation for refining satisfaction measurement frameworks and developing more context-sensitive instruments. In addition to these content-derived insights, incorporating sentiment polarity into the regression model marks a notable methodological advancement. The significant coefficients for both positive and negative sentiment support the argument that affective language can be a surrogate measure of satisfaction, enhancing explanatory power beyond what traditional behavioral predictors offer. This is further validated by the model's improved performance (Adjusted $R^2 = 0.58$), confirming that sentiment polarity is not merely an auxiliary variable but a quantifiable and impactful predictor of user satisfaction.

From a practical standpoint, key drivers of satisfaction such as Performance Speed, Functional Utility, and Customer Support Experience offer clear priorities for mobile banking app developers. At the same time, negative feedback clustered around Version Experience and Security points to the need for rigorous testing, transparent update processes, and more reliable authentication mechanisms. The predictive power of sentiment polarity further highlights the need for institutions to monitor emotional cues in user feedback as early signals of satisfaction or discontent. Overall, the study bridges the gap between unstructured feedback and structured evaluation models, offering valuable insights for researchers and practitioners seeking to improve digital banking service quality.

Like all empirical studies, this research has limitations. First, while the dataset is large and diverse, it focuses exclusively on user reviews from three Southeast European countries, which may limit the generalizability of findings to other regions or cultural contexts. Second, the reliance on algorithmically derived dimensions, though grounded in real user language, may overlook subtleties that a mixed-methods approach could capture. Lastly, the sentiment model, while effective, interprets affective tone at the review level, not at the sentence or feature-specific level.

Future research should explore cross-country comparisons to validate the stability of identified dimensions across cultural and regulatory environments. Integrating qualitative interviews or survey-based validations with topic modeling would enhance construct validity. Additionally, fine-grained sentiment analysis and temporal tracking of user feedback could offer deeper insights into how satisfaction evolves over time and in response to feature updates or policy changes.

References

1. Adhikari, U. & Gyawali, S. (2023). Customer satisfaction of service quality: Assessing mobile banking practices. *Journal of Tilottama*, *1*(1), 125-139. https://doi.org/10.3126/jtilottama.v1i1.64561
2. Aghdaie, S. F. & Faghani, F. (2012). Mobile banking service quality and customer satisfaction: Application of SERVQUAL model. *Journal of Internet Banking and Commerce*, *17*(1), 1-19.
3. Ahmed, R. R., Romeika, G., Kauliene, R., Streimikis, J. & Dapkus, R. (2020). ES-QUAL model and customer satisfaction in online banking: Evidence from multivariate analysis techniques. *Oeconomia Copernicana*, *11*(1), 59-93. https://doi.org/10.24136/oc.2020.003
4. Al-Shamaileh, O. & Sutcliffe, A. (2023). Why people choose Apps: An evaluation of the ecology and user experience of mobile applications. *International Journal of Human-Computer Studies*, *170*, 102965. https://doi.org/10.1016/j.ijhcs.2022.102965
5. Alam, M. M., Islam, M. S. & Rahman, M. M. (2024). The Impact of Usability, Security, and Service Quality on User Satisfaction and Experience in Digital Platforms: A Correlation Study. *Journal of Marketing and Consumer Research, 93*, 56-66.
6. Alkhafaji, S. (2016). User Satisfaction on Mobile Apps: An Analytical Study on Omani Business Environment. *Archives of Business Research*, *4*(1), 62-71. https://doi.org/10.14738/abr.41.1798
7. Amirkhalili, Y. & Wong, H. Y. (2025). Banking on Feedback: Text Analysis of Mobile Banking iOS and Google App Reviews. *arXiv preprint arXiv:2503.11861*.
8. Arcand, M., PromTep, S., Brun, I. & Rajaobelina, L. (2017). Mobile banking service quality and customer relationships. *International Journal of Bank Marketing, 35*(7), 1068-1089. https://doi.org/10.1108/IJBM-10-2015-0150
9. Askalidis, G. & Malthouse, E. C. (2016). Understanding and overcoming biases in customer reviews. *arXiv preprint arXiv:1604.00417*. https://doi.org/10.1016/j.dss.2017.03.002

10. Ayala Gavilanes, M. G., Rojas Sánchez, H. A., Fierro Barragán, S. E. & Alban Yanez, E. H. (2023). Customer Satisfaction in Mobile Banking: A Literature Review of Key Factors. *Remittances Review*, 8(4), 1466-1478.

11. Blei, D. M., Ng, A. Y. & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*, 993-1022.

12. Cai, Y., Wang, F., Wang, H. & Qian, Q. (2023). Public sentiment analysis and topic modeling regarding ChatGPT in mental health on Reddit: Negative sentiments increase over time. *arXiv preprint arXiv:2311.15800*.

13. Compeau, D. R. & Higgins, C. A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS Quarterly, 19*(2), 189-211. https://doi.org/10.2307/249688

14. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

15. Devlin, J., Chang, M.-W., Lee, K. & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of NAACL-HLT 2019 Vol. 1* (pp. 4171-4186). Minneapolis, MN: The Association for Computational Linguistics. https://doi.org/10.48550/arXiv.1810.04805

16. Fatima, K. & Khan, R. H. (2024). Influence of demographic characteristics on consumers' online review-based purchase behavior. *Journal of Business Analytics*, *44*(2), 203-218.

17. Finley, B., Boz, E., Kilkki, K., Manner, J., Oulasvirta, A. & Hämmäinen, H. (2018). Does network quality matter? A field study of mobile user satisfaction. a*rXiv preprint* a*rXiv:1809.03918*. https://doi.org/10.48550/arXiv.1809.03918

18. Gandhi, A., Hollenbeck, B. & Li, Z. (2025). Misinformation and Mistrust: The Equilibrium Effects of Fake Reviews on Amazon.com (NBER Working Paper No. 31836). Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w34161

19. Garcia, A. C. & Casas, S. (2020). Quality of experience in mobile applications: A systematic mapping of metrics and tools. *International Journal of Interactive Mobile Technologies*, *14*(8), 4-23. https://doi.org/10.3991/ijim.v14i08.12819

20. Gentile, C., Spiller, N. & Noci, G. (2007). How to sustain the customer experience: An overview of experience components that co-create value with the customer. *European Management Journal, 25*(5), 395-410. https://doi.org/10.1016/j.emj.2007.08.005

21. Grady, R. B. (1992). *Practical Software Metrics for Project Management and Process Improvement*. Prentice Hall.

22. Grootendorst, M. (2022). BERTopic: Neural topic modeling with class-based TF-IDF. *arXiv preprint arXiv:2203.05794*.

23. Hair, J. F., Black, W. C., Babin, B. J. & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th ed). Cengage Learning.

24. Halvadia, N., Halvadia, S. & Purohit, R. (2022). *Using text mining to identify key dimensions of service quality for the Indian public sector banks' mobile banking apps*. https://doi.org/10.21203/rs.3.rs-1536236/v1

25. Hammouri, Q., Almajali, D. A., Nusairat, N. M. & Saraireh, S. A. M. (2020). Determinants of users' satisfaction with mobile apps. *International Journal of Advanced Science and Technology*, *29*(3), 14613-14624.

26. Hassenzahl, M. & Tractinsky, N. (2006). User experience – a research agenda. *Behaviour & Information Technology*, *25*(2), 91-97. https://doi.org/10.1080/01449290500330331

27. Hoehle, H. & Venkatesh, V. (2015). Mobile application usability: Conceptualization and instrument development. *MIS Quarterly*, *39*(2), 435-472. https://doi.org/10.25300/MISQ/2015/39.2.08

28. Hussain, A., Abubakar, H. I. & Binti Hashim, N. (2014). Evaluating mobile banking application: Usability dimensions and measurements. In *Proceedings of the 6th International Conference on Information Technology and Multimedia* (pp. 136-140). *IEEE.* https://doi.org/10.1109/ICIMU.2014.7066618
29. Islam, K. M. A., Islam, S., Karim, M. M., Haque, M. S. & Sultana, T. (2023). Relationship between e-service quality dimensions and online banking customer satisfaction. *Banks and Bank Systems, 18(1), 174-183.* https://doi.org/10.21511/bbs.18(1).2023.15
30. ISO (2010). *ISO 9241-210 – Ergonomics of human-system interaction – Part 210: Human-centred design for interactive systems*. International Organization for Standardization.
31. ISO/IEC (2011). *ISO/IEC 25010:2011 – Systems and software engineering – Systems and software Quality Requirements and Evaluation (SquaRE) – System and software quality models*. International Organization for Standardization.
32. Iswani, S. (2023). Literature Review of M-Banking Experience in Generation X, Y, and Z: Study of Antecedents and Outcomes. *Cakrawala Repositori IMWI*, *6*(3), 307-323. https://doi.org/10.52851/cakrawala.v6i3.360
33. Jiang, H., Ma, H., Ren, Z., Zhang, J. & Li, X. (2017). What Makes a Good App Description? *arXiv preprint arXiv:1703.02227.* https://doi.org/10.48550/arXiv.1703.02227
34. Jun, M. & Palacios, S. (2016). Examining the key dimensions of mobile banking service quality: An exploratory study. *International Journal of Bank Marketing*, *34*(3), 307-326.
35. Keith, M. J., Babb, J. S., Jr., Furner, C. P. & Abdullat, A. (2011). The role of mobile self-efficacy in the adoption of location-based applications: An iPhone experiment. In *Proceedings of the 44th Hawaii International Conference on System Sciences* (pp. 1-10). IEEE. https://doi.org/10.1109/HICSS.2011.430
36. Khabour, S. M., Mustafa, D. & Althebyan, Q. (2023). Arabic sentiment analysis of mobile banking services reviews. In *Proceedings of the 2023 Tenth International Conference on Social Networks Analysis, Management and Security (SNAMS).* IEEE. https://doi.org/10.1109/SNAMS60348.2023.10375427
37. Kim, Y.-J. & Kim, H.-S. (2022). The Impact of Hotel Customer Experience on Customer Satisfaction through Online Reviews. *Sustainability, 14*(2), 848. https://doi.org/10.3390/su14020848
38. Kubrusly, J., Neves, A. & Marques, T. (2022). A Statistical Analysis of Textual E-Commerce Reviews Using Tree-Based Methods. *Open Journal of Statistics*, *12*(3), 357-372. https://doi.org/10.4236/ojs.2022.123023
39. Liu, B. (2012). *Sentiment Analysis and Opinion Mining.* Morgan & Claypool Publishers. https://doi.org/10.2200/S00416ED1V01Y201204HLT016
40. Liu, Y., Lu, X., Zhao, G., Li, C. & Shi, J. (2022). Adoption of mobile health services using the unified theory of acceptance and use of technology model: Self-efficacy and privacy concerns. *Frontiers in Psychology, 13*, 944976. https://doi.org/10.3389/fpsyg.2022.944976
41. Mwakisoba, V. A. & Meela, D. (2024). The influence of electronic banking on customer satisfaction in the Tanzanian banking sector: A case of NMB Bank branches in Morogoro Region, Tanzania. *Asian Journal of Economics, Business and Accounting*, *24*(3), 1-12. https://doi.org/10.9734/ajeba/2024/v24i101511
42. Nisha, N. (2016). Acceptance of mobile banking in Kerala: An extended UTAUT2 perspective. *Rajagiri Management Journal*, *10*(2), 35-47.
43. Oh, Y. K. & Kim, J. M. (2022). What improves customer satisfaction in mobile banking apps? An application of text mining analysis. *Asia Marketing Journal*, *23*(4), 75-95. https://doi.org/10.53728/2765-6500.1581
44. Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, *17*(4), 460-469. https://doi.org/10.1177/002224378001700405
45. Oliver, R. L. (1997). *Satisfaction: A Behavioral Perspective on the Consumer*. McGraw-Hill.

46. Orehovački, T., Blašković, L. & Kurevija, M. (2023). Evaluating the Perceived Quality of Mobile Banking Applications in Croatia: An Empirical Study. *Future Internet*, *15*(1), 8. https://doi.org/10.3390/fi15010008

47. Oyekunle, R. A., Danjuma, Y., Balogun, N. A. & Adedoyin, A. (2023). Online Customer Reviews and their Effect on the Download of Mobile Applications. *Journal of Information Technology and Computing*, *4*(2), 39-52.

48. Öztürk Birim, Ş. (2024). *Product Insights from Customer-Generated Data Using Topic Modeling with BERTopic and Sentiment Analysis with XLM-T: An Experiment on Turkish Reviews. Research Square.* https://doi.org/10.21203/rs.3.rs-3981153/v1

49. Parasuraman, A., Zeithaml, V. A. & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, *64*(1), 12-40.

50. Parasuraman, A., Zeithaml, V. A. & Malhotra, A. (2005). E-S-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of Service Research*, *7*(3), 213-233. https://doi.org/10.1177/1094670504271156

51. Ranjitha. P. K, Agarwal, S. (2024). Enhancing Customer Satisfaction Through Mobile Apps Intelligence: A Study on Wellness Apps. *Educational Administration: Theory and Practice*, *30*(5), 19-25. https://doi.org/10.53555/kuey.v30i5.2762

52. Sällberg, H., Wang, S. & Numminen, E. (2022). The combinatory role of online ratings and reviews in mobile app downloads: An empirical investigation of gaming and productivity apps from their initial app store launch. *Electronic Markets*, *32*(1), 1-17. https://doi.org/10.1057/s41270-022-00171-w

53. Sangaraju, V. R., Bolla, B. K., Nayak, D. K. & Kh, J. (2022). Topic Modelling on Consumer Financial Protection Bureau Data: An Approach Using BERT Based Embeddings. *arXiv preprint arXiv:2205.07259.* https://doi.org/10.48550/arXiv.2205.07259

54. Shaikh, A. A. & Karjaluoto, H. (2015). Mobile banking adoption: A literature review. *Telematics and Informatics, 32*(1), 129-142. https://doi.org/10.1016/j.tele.2014.05.003

55. Shankar, A., Datta, B., Jebarajakirthy, C. & Mukherjee, S. (2020). Exploring Mobile Banking Service Quality: A Qualitative Approach. *Services Marketing Quarterly*, *41*(2), 182-204. https://doi.org/10.1080/15332969.2020.1742982

56. Sharma, G. & Malviya, S. (2011). Exploring the Dimensions of Mobile Banking Service Quality. *Review of Business and Technology Research*, *4*(1), 187-196.

57. Sharma, N., Sharma, M. & Singh, T. (2024). Mobile banking app experience of generation Y and Z consumers. *Asia Pacific Journal of Marketing and Logistics*, *36*(8), 2008-2027. https://doi.org/10.1108/APJML-08-2023-0793

58. Squillaro, R. (2021). Digital Norms and Their Place in a Tech-Based Future. *Penn Journal of Philosophy, Politics & Economics*, *16*(1), 1-13.

59. Sugiono, O. D., Dewi, C. K. & Madiawati, P. N. (2025). The influence of service failure on mobile banking usage and its relation to user satisfaction. *Journal of the Community Development in Asia*, *8*(1), 62-79. https://doi.org/10.32535/jcda.v8i1.3672

60. Vargas-Calderón, V., Moros Ochoa, A., Castro Nieto, G. Y. & Camargo, J. E. (2021). *Machine learning for assessing quality of service in the hospitality sector based on customer reviews. arXiv preprint arXiv:2107.10328*. https://doi.org/10.48550/arXiv.2107.10328

61. Venkatesh, V. & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

62. Wu, S. & Dredze, M. (2019). Beto, Bentz, Becas: The Surprising Cross-Lingual Effectiveness of BERT. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics. https://doi.org/10.18653/v1/D19-1077

63. Zeithaml, V. A., Berry, L. L. & Parasuraman, A. (1993). The Nature and Determinants of Customer Expectations of Service*. Journal of the Academy of Marketing Science*, *21*(1). https://doi.org/10.1177/0092070393211001
64. Zhang, W., Wang, Q., Li, J., Ma, Z., Bhandari, G. & Peng, R. (2023). What makes deceptive online reviews? A linguistic analysis perspective. *Humanities and Social Sciences Communications*, *10*, 769. https://doi.org/10.1057/s41599-023-02295-5
65. Zhou, Q., Yu, H., Xu, G., Ren, X., Liu, D., Wang, X., Mai, X. & Xu, H. (2021). A study on factors affecting service quality and loyalty intention in mobile banking. *Journal of Retailing and Consumer Services, 60*, 102424. https://doi.org/10.1016/j.jretconser.2020.102424
66. Zhu, Q., Lo, L. Y.-H., Xia, M., Chen, Z. & Ma, X. (2022). Bias-Aware Design for Informed Decisions: Raising Awareness of Self-Selection Bias in User Ratings and Reviews. In *Proceedings of the ACM on Human-Computer Interaction, 6*(CSCW2), 386. https://doi.org/10.1145/3555597
67. Zimmermann, V., Gerber, N. & Volkamer, M. (2022). That depends -- Assessing User Perceptions of Authentication Schemes across Contexts of Use. *arXiv preprint arXiv:2209.13958*. https://doi.org/10.48550/arXiv.2209.13958