“The impact of security and privacy perceptions on cryptocurrency app evaluations by users: A text mining study”

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THE IMPACT OF SECURITY AND PRIVACY PERCEPTIONS ON CRYPTOCURRENCY APP EVALUATIONS BY USERS: A TEXT MINING STUDY

Abstract

This study examines how perceived security and privacy influence user ratings of cryptocurrency applications, which are critical for adoption and satisfaction amid the growing popularity of blockchain technologies and rising concerns over information security in online platforms and mobile apps. The study focuses on mobile applications from the Android app market. It used text mining methods to investigate over 64 thousand text-based user reviews and star ratings of over 140 cryptocurrency-related mobile applications available in the Google Play store. Using a partially supervised machine learning approach, this study first identified reviewer sentiment related to privacy and security, then employed ordinal regression analysis to examine the data to reveal the relationship between perceived security threats, privacy concerns, and app ratings. This study found that crypto apps average 3.84 out of 55 stars, which is higher than Productivity apps (3.46) but lower than FinTech (4.29) and Banking (4.25) apps. Ordinal regression analysis revealed security and privacy threats negatively impact ratings, while robust security measures improve them, with a model Pseudo R^2 of 0.25. These results have implications for both cryptocurrency app developers and platform managers, offering insights for enhancing user experiences and informing future research endeavors in this domain. It contributes to the literature by integrating the Protection Motivation Theory with sentiment analysis and provides a structured framework for developing an understanding of user behavior in the context of cryptocurrency apps.

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INTRODUCTION

During the last twenty years, online platforms and mobile applications have transformed daily life (Arruda-Filho et al., 2010). Mobile applications, accessible to users anytime and anywhere, have become part of users' daily routines (Azfar et al., 2016; Abramova & Böhme, 2016). This influence has also affected areas of financial applications, specifically digital assets like cryptocurrencies, by facilitating access to tools for monitoring, storing, and exchanging cryptocurrencies and using them in local or global transactions (Chopdar et al., 2018). Along with the increasing value of cryptocurrency and widespread adoption of digital assets, and among developers and users' variety of new mobile applications assisting them in making prompt decisions regarding alternative investments and trading options became also popular (Dahlberg et al., 2015). Understanding user perceptions is vital for developers aiming to enhance app adoption and satisfaction. However, studies reveal significant user concerns regarding the security and privacy of such apps, directly impacting satisfaction (Daradkeh, 2019; Herskind et al., 2020; Tam et al., 2020; Westin, 2003; Krebs & Duncan, 2015). The extensive personal data collection by apps has also intensified security and privacy concerns for both consumers and suppliers (Menon & Sarkar, 2016). Security and privacy are fundamental to sustaining trust and satisfaction in cryptocurrency apps (Gan & Lau, 2024; Sentana et al., 2023; Hsu & Lin, 2016). Despite their importance, empirical studies on how these perceptions influence user ratings are limited. Thus, there is a need to address this gap by examining the factors driving the adoption and satisfaction of cryptocurrency apps, focusing on privacy and security concerns, exploring how these concerns affect app ratings, the sentiment and subjectivity of user reviews, and the broader implications for developers and the digital marketplace.

1. LITERATURE REVIEW AND HYPOTHESES

Ratings and reviews are two commonly used indicators of user satisfaction of mobile apps and significantly influence the continued success of apps. Negative reviews can typically deter potential users and future purchases, therefore, negatively impacting an app's overall market performance (Salminen et al., 2020). Analyzing app reviews involves examining key aspects such as subjectivity, sentiment, and polarity. Subjectivity in reviews reflects opinions, emotions, and speculation, while sentiment analysis relates to determining the overall sentiment orientation in the text (Ahmed et al., 2018; Tan et al., 2017; Banfield, 2014; Wilson et al., 2009). Understanding the factors influencing reviewers' intentions to use or recommend apps is important for users and developers alike. Research across various domains, including food and beverages (Chahuneau et al., 2012), movies (Joshi et al., 2010), healthcare (Fu et al., 2017), and airline (Korfiatis et al., 2019) shows that user reviews and sentiment impact purchasing and usage decisions. Studies on app reviews and ratings (Dou et al., 2024; Fagernäs et al., 2021; Chatterjee, 2020) further emphasize the role of review length, sentiment, and polarity in shaping user intentions and app adoption. This highlights the value of understanding how review signals influence decision-making, as supported by information search theories.

User trust plays an important role in app adoption and continued use, particularly when security and privacy are at stake. In cryptocurrency apps, addressing these concerns effectively leads to higher user ratings, reflecting greater satisfaction (Chennamaneni & Gupta, 2023). However, developers often release new features without thorough testing, which can compromise security and privacy. Despite pre-admission checks for malicious activity, uncertainty remains about developers' efforts to safeguard apps (Taylor & Martinovic, 2017). Security concerns, influenced by app requirements and practices, affect user satisfaction (Tuch et al., 2012), while poor integration and interoperability hinder adoption (Dehzad et al., 2014). Apps with lower ratings struggle to survive, whereas those with higher ratings and positive reviews tend to dominate the market (Fu et al., 2017).

A wide range of studies (see Appendix Table A1), utilizing diverse methodologies and theoretical frameworks, have explored factors such as user behavior, trust, security, and privacy concerns, offering insights into how different variables influence app adoption, satisfaction, and continued use across various contexts. For instance, employing consumer culture theory and automated text analysis tools, Berger et al. (2020) investigated the meanings, norms, and values shaping consumer behavior in markets. Al-Natour and Turetken (2020) investigated how review sentiment aids consumers in focusing on pertinent information, suggesting that sentiment analysis scores can sometimes surpass star ratings in decision-making contexts. Pinochet et al. (2024) showed that productivity apps are tied to utility features and meeting user expectations, highlighting the importance of functionality in driving user satisfaction. In contrast, Kesgin and Murthy (2019) utilized selective perception and attribution theories to show how social currency influences online ratings and promotes long-term consumer loyalty, emphasizing the power of social dynamics in shaping user behavior and app success. Additionally, Banerjee and Chua (2019) examined information-processing behaviors concerning titles and descriptions, emphasizing the importance of considering review polarity alongside the evaluated service for a comprehensive understanding. Together, these

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studies illustrate the interplay between functionality, social influence, and review sentiment in shaping app ratings and adoption.

Studies on finance apps offer diverse perspectives on user-perceived risks and benefits. Users' motivation to adopt personal financial management apps increases with perceived usefulness and ease of use (Yen & Wu, 2016; Bitrián et al., 2021). Lee (2017) further demonstrated these factors, along with user satisfaction, significantly influence users' use and continuation use of apps within financial technology (FinTech). By proposing a machine learning-based approach to identify untrusted users, Mittal et al. (2021) emphasized the importance of trust in financial app usage, proposing a machine learning-based approach to identify untrusted users. These findings highlight the critical need for robust data security measures, as vulnerabilities in financial and non-financial apps can expose users to increased risks. The proliferation of mobile banking services has transformed financial access for millions worldwide, with many users relying on mobile money accounts. However, a large segment of the global population still does not have access to conventional banking services. Cryptocurrency emerges as a potential solution, offering individuals greater flexibility and accessibility in managing finances digitally (El Amri et al., 2021; Kshetri, 2023). This shift highlights the evolving landscape of digital finance, where mobile accessibility and digital options play pivotal roles in financial inclusion efforts.

The landscape of FinTech is evolving rapidly, with traditional apps like mobile banking coexisting alongside emerging crypto apps that operate on decentralized cryptocurrency platforms (Nikkel, 2020). Unlike traditional FinTech apps, which typically deal with centralized monetary systems, crypto apps operate within decentralized financial ecosystems. This fundamental difference in governance translates into varying levels of control, with traditional finance apps offering more centralized control compared to the decentralized nature of crypto apps. Moreover, cryptocurrencies facilitate low-cost global transactions, expanding financial accessibility beyond geographical boundaries traditionally limited by local currency usage (Sentana et al., 2023; Chen & Bellavitis, 2020). However, adopting crypto apps also introduces unique security and privacy considerations. While cryptocurrencies are designed with security in mind, users must navigate potential risks associated with using cryptocurrency wallets, digital wallets, or exchange providers. Security and privacy concerns are paramount for individuals engaging with cryptocurrencies, highlighting the need for robust protective measures (Nikkel, 2020; Wu et al., 2020).

Addressing the crypto app literature gap concerning security and privacy and their effect on user experience, this study employs the Protection Motivation Theory (PMT) (Rippetoe & Rogers, 1987; Rogers, 1975). This theory rationalizes how individuals react to perceived risks and motivate protective behavior. In this paper, negative perceptions of security and privacy act as barriers, lagging the cryptocurrency app use. On the contrary, effective security measures implemented by app providers serve as coping mechanisms, positively influencing app use and increasing trust in the platform. By extending PMT, this paper incorporates the subjective opinions and judgments of reviewers to further understand user perceptions. By considering the subjectivity of reviews, this study aims to capture various aspects of user experiences and perceptions regarding security and privacy in crypto app usage. This comprehensive approach enables the investigation of the factors affecting user attitudes and behaviors when considering app usage. Furthermore, crypto app evaluation, measured through star ratings, and users' app review sentiment serve as crucial indicators of crypto app adoption and the intention to continue usage.

The rapid growth of FinTech has prompted the widespread adoption of crypto apps, enabling users to store, transfer, and exchange cryptocurrencies. This surge is driven by increasing interest in cryptocurrency investments and transactions. However, rising cybersecurity incidents have heightened user concerns about data security and privacy (Bauer et al., 2020). Crypto apps collect various user data, some of which may involve sensitive information requiring explicit consent. The lack of assurances about data use exacerbates these concerns, impacting user trust and adoption (Fu et al., 2017). Product quality is a key determinant of customer adoption, with online reviews significantly influencing user decisions. DeLone and McLean's models (1992; 2003) emphasize the importance of system and information quality in shaping user intentions and system success. Moreover, emerging AI tools now assist in evaluating cryptocurrency apps as service software, where development quality directly affects user satisfaction (Jumah, 2023; Lu et al., 2023).

Privacy and security concerns influence the adoption and perception of cryptocurrency apps, focusing on different aspects of user trust. Privacy concerns involve the control and confidentiality of personal data, where users worry about unauthorized use or sharing of their information without consent, undermining trust (Rath & Kumar, 2021; Gu et al., 2017). Conversely, security concerns address protecting data from external threats like hacking, breaches, and theft, with users prioritizing technical safeguards to ensure safety (Gu et al., 2017). Although privacy and security concerns are intertwined, users often prioritize security measures over privacy worries (van der Schyff & Flowerday, 2021). Negative perceptions of security vulnerabilities frequently lead to unfavorable app reviews and lower star ratings, directly impacting adoption rates (Alnsour & Juma'h, 2023, 2024). Mobile devices, which are central to cryptocurrency app usage, amplify privacy concerns due to their extensive data collection practices. While data collection can enhance user experiences, it raises apprehensions when done without explicit consent (Rath & Kumar, 2021). Privacy concerns often stem from users' desire for autonomy over their information and are influenced by cultural and demographic factors (Tronnier & Biker, 2022). Cryptocurrency apps, requiring user data for functionality, heighten privacy apprehensions, potentially hindering adoption (Gu et al., 2017). Addressing privacy concerns through solutions such as enhanced transparency and user control can bridge the intention-behavior gap, encouraging adoption and trust in digital currencies (Sheeran & Webb, 2016). By integrating robust privacy and security measures, cryptocurrency apps can foster greater user confidence, ultimately driving broader acceptance of these technologies.

Security measures in mobile applications, including crypto apps, are critical controls implemented by developers to safeguard information (Jain & Shanbhag, 2012). This study expands on Yang et al.'s (2005) framework by incorporating security and privacy concerns specific to crypto apps, focusing on how these measures influence user perceptions, ratings, and adoption. Users' confidence in the adequacy of security measures directly impacts their willingness to engage with crypto apps and affects app ratings. Concerns about the safety of digital assets and personal information remain paramount, with robust security protocols enhancing trust and reliability (Fabian et al., 2016). Effective measures also contribute to smoother user experiences, leading to higher satisfaction and more favorable reviews. By addressing security concerns, crypto app developers can mitigate user apprehensions, fostering adoption and strengthening user confidence. This interplay between perceived security and adoption highlights the importance of prioritizing robust security measures to ensure both user trust and app success.

Based on the above literature review and analysis, the research hypotheses are as follows:

H1: *Negative perceptions regarding security threats adversely affect the evaluation and adoption of the crypto app, as evidenced by star ratings.*

H2: *Negative perception concerning privacy threats negatively impact the evaluation and the adoption of the crypto app, as evidenced by the star rating.*

H3: *Positive perception about security measures positively impacts the evaluation and the adoption of the crypto app, as evidenced by the star rating.*

2. METHODS

To meet the study's objectives, cryptocurrency applications from the Google Play Store were analyzed. Data were collected over a five-year period between 2014 and 2020, using a web crawler, yielding an initial dataset of around eighty-five thousand user reviews. This dataset over a long period provided good foundation for examining general trends and user perceptions. After a filtering pro-

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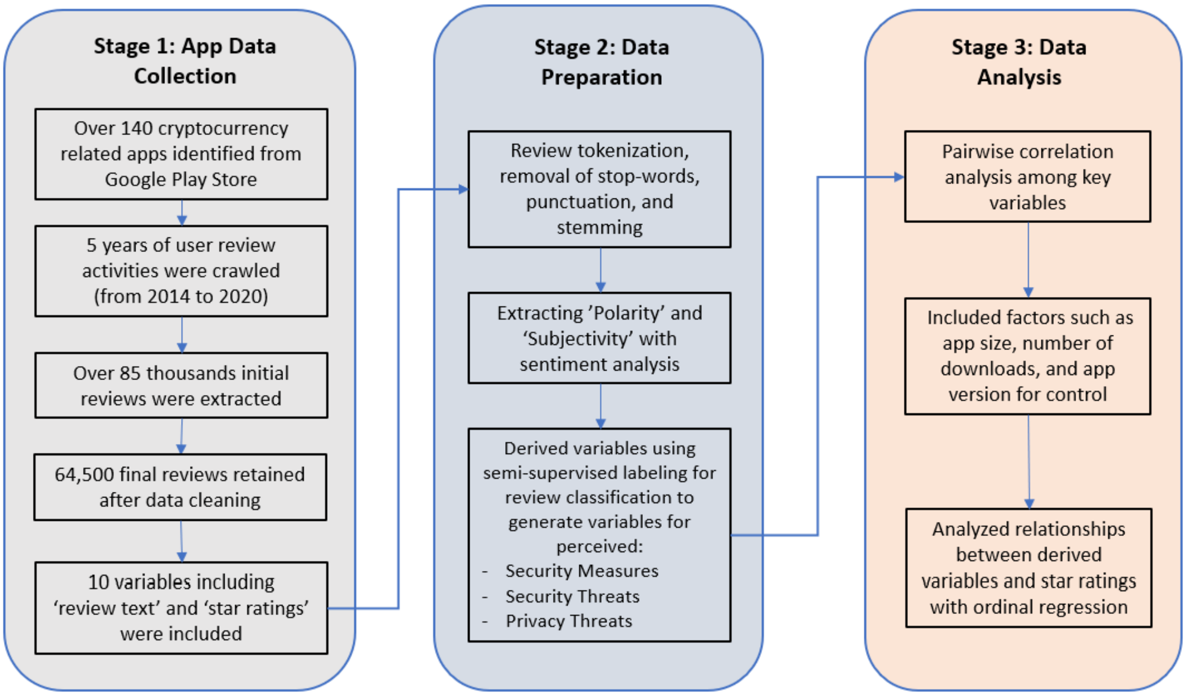

Figure 1. Data collection, preparation, and analysis process

cess to remove reviews with insufficient content, a refined dataset of over sixty-four thousand reviews was obtained along with the 5-point Likert-scale ratings of the apps.

In addition to the text content of the reviews and user ratings, the crawler captured various other app attributes including the time after the last update, the number of downloads, and the size and version numbers of the apps. See Figure 1 for the illustration of the data collection, preparation, and analysis process. This study focused its analysis on the subset of apps that collected both reviews and ratings, identified over 140 cryptocurrency apps, including popular digital currencies (e.g., Bitcoin, Ethereum, Bitcoin Cash, and Litecoin).

The data preparation followed a multi-step methodology. The crawled and filtered data were processed through tokenization step, followed by removal punctuation and stopping words. Then, stemming step reduced the words to their base forms to make the data ready for a sentiment analysis using Python libraries for natural language processing (NLTK and TextBlob). This provided review assessments for polarity and subjectivity for the content of the reviews.

While manual examination of textual content of the reviews may still offer valuable insights into users' perceptions, it inherently lacks scalability to accommodate the expanding volume of reviews and users. Recognizing this limitation, this study adopted a semi-supervised approach to extract meaningful variables on app features, similar to prior research (Hande et al., 2021; Çelik & Yıldırım, 2020; Gunasekara & Nejadgholi, 2018).

For analyzing text and unstructured data, Natural Language Processing (NLP) is an important technique (Zhang et al., 2021). Techniques like sentiment analysis, lemmatization, and entity recognition are common, however, subjective word meanings pose challenges to identify (Van Looy, 2022). Deep learning approaches that map words to vectors for richer language representations, such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs) address some of these challenges but require significant computational resources (Li et al., 2020; Salehan & Kim, 2016).

As an alternative to manual or end-to-end deep learning approaches, semi-supervised learning offers a more convenient and balanced approach between supervised and unsupervised methods, reducing the need for extensive labeled data and extensive computational resources while providing great accuracy. It begins with a labeled dataset, uses high-confidence pseudo-labels for unlabeled data, and refines the model iteratively (Ouali et al., 2020). Such approaches have shown to be effective in tasks like review classification and toxic content detection (Palomba et al., 2018; Gunasekara & Nejadgholi, 2018).

In this study, a subset of reviews was manually labeled to train a semi-supervised machine learning model aimed at extracting key variables reflecting users' perceptions of security and privacy. The focus was on three variables: perceived privacy threats, perceived security threats, and perceptions of security measures by app developers. The perceived privacy threats variable captures user concerns about improper handling of information privacy, with a value of 1 for identified concerns and 0 for none. Similarly, perceived security threats reflect concerns about inadequate information security, with 1 indicating issues and 0 indicating none. And the last one, perceptions of security measures by app developers indicate whether users recognized such measures, with 1 for acknowledgment and 0 for none. These binary variables were derived using the semi-supervised model's analysis of textual reviews.

The semi-supervised model iteratively generated pseudo-labels for unlabeled data, refining its accuracy to exceed 0.90. This approach made the classification of security and privacy-related perceptions across all reviews possible, providing valuable insights without the need for complete human assessment or extensive computational resources associated with deep learning. This balanced the need for accuracy with efficiency, ensuring the scalability of our analysis.

In the Appendix, Table A2 provides detailed definitions and measurements for the terms and concepts utilized throughout this study. This serves to ensure clarity and consistency in understanding the variables under investigation. This study conducted pairwise correlation analyses to examine the interrelationships between the key variables. Subsequently, in the Appendix, Table A3 presents the outcomes of these correlation analyses, highlighting the significance of the relationships observed. Utilizing a correlation matrix, a commonly employed technique for scrutinizing independent variables, helps assess the degree of association among them. Notably, the examination did not reveal any concerning correlations among the independent variables, as documented by previous studies (Greene, 2024). Also, the Variance Inflation Factor (VIF) resulted in less than ten, a widely accepted threshold indicating the absence of significant collinearity concerns within the study dataset (O'brien, 2007).

Regression analysis is a widely used technique for exploring the factors influencing a particular variable and its interpretability. In the context of analyzing text-based reviews, regression analysis has proven valuable for extracting meaningful insights. For example, Ren and Hong (2019) employed regression analysis to examine how emotions like fear and sadness, derived from textual reviews influence the perceived helpfulness of the reviews. Similarly, Liang et al. (2015) used regression analysis to study the relationship between sentiment expressed across multiple topics and an app's ranking. In line with the literature, this study uses ordinal regression to analyze star ratings (1 to 5), as it aligns well with the ordinal nature of the dependent variable. So, we can benefit from flexibility, interpretability, and statistical efficiency in capturing the relationships between variables (Greene, 2024; MacKay & Oldford, 2000). Equation (1) describes the Ordinal Regression model:

$$Y_i = \beta_0 + \beta_i X_i + \varepsilon_{it}, \tag{1}$$

where Y denotes the explained variable, denoted as App Star Rating$_i$, is influenced by a set of independent variables represented by X_i. β_i denotes the related parameters, while ε_{it} represents the error associated with each observation, reflecting the individual review's deviation from the model's predictions. The regression models are supplemented with a selection of control variables, strategically integrated to mitigate potential confounding effects and illuminate the unadulterated causal pathways between explanatory and dependent variables. The inclusion of control variables serves as a methodological safeguard, effectively obstructing any unintended causal pathways and ensuring the purity of the estimated effects of the explanatory variables

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(MacKay & Oldford, 2000). Contrary to the substantive interpretation accorded to primary variables of interest, control variables are regarded by Hünermund and Louw (2020) as entities with limited direct interpretive significance in estimation results. Consequently, the emphasis lies in interpreting the effects of the primary variables of interest, with control variables primarily serving identification purposes. This study has included several characteristics of reviews as control variables, encompassing factors such as time after the last update, downloads of apps, rating number, size of apps, and Android version.

3. RESULTS

The study analyzed crypto app reviews, focusing on sentiment, topics, and user perceptions. About 39% of reviews expressed negative sentiments on information security, while 27% reflected positive views on information privacy, with the remainder being neutral. Most reviews discussed general cryptocurrency topics or Bitcoin, with mentions of other cryptocurrencies, such as Ethereum and Litecoin, being relatively rare. Overall, the average star rating was above average, and sentiment analysis revealed predominantly positive user sentiments, with review polarity averaging slightly positive. Reviews were generally subjective. Despite the prominence of security and privacy in broader discussions, these topics were infrequently mentioned in the reviews, with 943 addressing security concerns and 896 discussing privacy concerns. The results suggest that while users generally view crypto apps favorably, addressing the relatively low focus on security and privacy concerns in reviews could enhance user trust and satisfaction. See Table 1 for a statistical summary of key variables.

As individuals increasingly use cryptocurrencies for money transfers and managing digital assets, crypto apps play a crucial role in providing access to these services. However, risks associated with app usage significantly influence adoption. This study examines how crypto app users perceive security and privacy threats, as reflected in their reviews, and how these concerns impact their app ratings. The initial analysis revealed that, despite these risks, users generally report a positive experience, with an average rating of 3.84/5.00 stars, which surpasses the average for other app categories like Productivity, where the average is 3.46/5.00 (Sefferman, 2016). Yet that number is still lower than the average star rating of FinTech apps (according to Sefferman (2021), the average star rating in 2020 was 4.29 for Android), Banking (4.25), and Insurance (3.88). For variables on a five-point scale, values below three are considered unfavorable, and above three favorable (Ho-Dac et al., 2013). While finance apps are generally prone to negative sentiment (Sefferman, 2021), the study results indicate crypto apps, on average, exhibit positive sentiment, indicating that most reviews were favorable. Additionally, the average number of downloads for a crypto app exceeds 800,000, suggesting strong user interest in adopting these apps.

Using ordinal regression analysis, the study initially focused on exploring the relationship be-

Table 1. Key variable statistics

	Variable	Average	Standard Deviation	Minimum	Maximum
1	Star rating	3.838	1.587	1	5
2	Security measures	0.029	0.158	0	1
3	Security concerns	0.011	0.111	0	1
4	Privacy concerns	0.010	0.061	0	1
5	Polarity	0.291	0.362	–1	1
6	Subjectivity	0.521	0.292	0	1
7	High Risk App	0.642	0.483	0	1
8	Time after Last Update (in days)	286	1,272	1	6,320
9	Size of Apps (in Megabyte)	29	23	1	100
10	Downloads of Apps (in thousands)	802	1,570	0.01	10,000
11	Version of Android	5	1	1	8
12	Ratings number (thousand)	31	62	1	319

Note: Observations = 64,500.

tween users' negative perceptions of app security and their sentiments, alongside the numerical evaluations of app performance (see Appendix, Table A4). In column 6, the coefficient for security threats is –0.62 ($p < 0.01$), indicating a significant negative impact on app ratings, supporting *H1*. Similarly, the coefficient for privacy threats is –0.52, also significant ($p < 0.01$), demonstrating that concerns over privacy affect star ratings, supporting *H2*. Conversely, the coefficient for security measures is positive and significant ($p < 0.01$), suggesting that effective security practices enhance user ratings, supporting *H3*. These findings hold true both when security and privacy concerns are considered individually (models 1 to 5) and collectively (model 6), where the Pseudo R^2 value is about 25%, indicating the model's strength in explaining variance in app ratings.

4. DISCUSSION

The study's findings align with existing literature, affirming the strong relationship between review sentiment and app star ratings (Noei et al., 2019). The results also reveal that polarity influences yearly average ratings more significantly than subjectivity, suggesting that the sentiment expressed in reviews plays a critical role. Additionally, reviewer characteristics, such as risk aversion, appear to affect their app ratings. This aligns with Albizri (2020), who argued that reviewers' beliefs and behaviors shape their decisions, and Tronnier and Biker (2022), who found that cultural and demographic factors are pivotal in shaping privacy concerns.

Blockchain and cryptocurrency technologies are still in their early stages of development, and many users remain skeptical about adopting them. Concerns around security, privacy, and the volatile nature of these technologies contribute to this hesitation, highlighting the need for further advancements and trust-building measures to drive wider acceptance (Li & Juma'h, 2022; Juma'h & Li, 2023, 2020; Nguyen et al., 2021). Analysis of crypto app reviews revealed that 39% of reviews expressed negative sentiment, primarily around information security, while 27% reflected positive views on privacy, and the rest were neutral. This skepticism aligns with the tendency of users to focus on negative issues, as evidenced by the higher percentage of negative sentiment in reviews.

Interestingly, the study found that, despite user concerns, the average star rating for crypto apps was higher than categories such as Productivity but still lower than FinTech and Banking apps. These findings highlight both the growing interest in crypto apps, reflected by an average download count exceeding 800,000, and the necessity to address security and privacy issues more prominently to enhance trust and satisfaction among users. Ordinal regression analysis further revealed that perceptions of security and privacy significantly influence user ratings, confirming their negative impact on star ratings. Conversely, effective security measures positively impacted ratings. These findings suggest that users reward apps with robust security features, which can offset concerns about privacy and risk.

Also, while review polarity exhibited a declining trend, indicating growing negativity, average subjectivity has increased. This shift suggests that users are increasingly sharing personal opinions in their reviews, focusing on individual experiences rather than objective assessments. Interestingly, broader topics like general cryptocurrency and Bitcoin dominated reviews, with limited mentions of other cryptocurrencies such as Ethereum and Litecoin.

This study offers valuable managerial and practical insights. Security and privacy are critical to user adoption and app success, emphasizing the need for robust features and transparency. Developers should leverage user reviews as feedback to address concerns and build trust. While this research enriches the understanding of security and privacy perceptions in cryptocurrency apps, limitations such as potential biases in online reviews and lack of direct user engagement highlight areas for future research. Examining specific app features, reviewer characteristics, and cryptocurrencies across diverse contexts, languages, and user bases will provide a more comprehensive understanding of user behavior and app performance.

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CONCLUSION

This study investigated how user perceptions of security and privacy influence their evaluations of cryptocurrency apps. By analyzing user-generated reviews from the Google Play Store, the research uncovered valuable insights into the factors shaping app ratings in this growing yet underexplored market. The findings demonstrate that users' concerns about security and privacy have a significant negative impact on app ratings, while effective security measures positively influence user evaluations. The study also highlights the critical role of sentiment in reviews, revealing that polarity influences app ratings more than subjectivity. Additionally, the increasing focus on personal opinions in reviews suggests a shift toward more individualized user feedback. These results show the importance of addressing security and privacy issues to enhance user trust and satisfaction, which are essential for succeeding in the competitive app marketplace. Crypto app developers and stakeholders must prioritize these areas to foster greater user confidence, improve ratings, and ultimately drive the adoption of blockchain technologies. By providing a detailed analysis of user sentiment and its impact on app ratings, this study contributes to the broader understanding of consumer behavior in the context of cryptocurrency apps and offers actionable insights for app developers striving to meet user expectations.

AUTHOR CONTRIBUTIONS

Conceptualization: Ahmad Juma'h, Yazan Alnsour, Hasan Kartal.
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Formal analysis: Ahmad Juma'h, Yazan Alnsour, Hasan Kartal.
Investigation: Ahmad Juma'h, Yazan Alnsour, Hasan Kartal.
Methodology: Ahmad Juma'h, Yazan Alnsour, Hasan Kartal.
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Supervision: Ahmad Juma'h.
Validation: Ahmad Juma'h, Yazan Alnsour, Hasan Kartal.
Writing – original draft: Ahmad Juma'h, Yazan Alnsour.
Writing – review & editing: Ahmad Juma'h, Hasan Kartal.

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APPENDIX A

Table A1. Summary of studies related to NLP techniques and customer intention to use based on user reviews

Study	Year	Contribution Area	Highlighted Findings	NLP Techniques Used	Data Source
Menon & Sarkar	2016	Privacy and security in mobile apps	Privacy and security perceptions are crucial for app adoption and user satisfaction.	Sentiment analysis, text classification	Mobile app reviews
Fabian et al.	2016	Privacy awareness in blockchain networks	Emphasized the need for enhanced privacy awareness in blockchain networks.	Text mining, privacy analysis	Blockchain network reviews
Gu et al.	2017	Privacy concerns in mobile app downloads	Privacy concerns negatively influence the intention to download apps.	Sentiment analysis, elaboration likelihood model	Mobile app reviews
Banerjee & Chua	2019	Online reviews trust	Polarity impact on user trust in online reviews	Sentiment analysis, polarity scoring	Hotel reviews
Korfiatis et al.	2019	Unstructured data and service quality	Extracting service quality dimensions using reviews.	Sentiment analysis and topic modeling	Airline passenger reviews
Al-Natour & Turetken	2020	Sentiment analysis in consumer reviews	Found that sentiment analysis scores can sometimes surpass star ratings in influencing consumer decisions.	Sentiment analysis, star rating correlation	Online product reviews
Chatterjee	2020	Helpfulness of reviews	Sentiment analysis and mining impact the perceived helpfulness of reviews.	Sentiment analysis, emotion mining	Hotel reviews
Wu et al.	2020	User trust and app security	Examined how security features in apps influence user trust and app adoption.	Sentiment analysis, emotion detection	Mobile app reviews
Fagernäs et al.	2021	User perceptions of VR relaxation apps	Identified key user perceptions and issues with VR relaxation apps using mixed methods.	Sentiment analysis, topic modeling	User reviews of VR apps
Sentana et al.	2023	Security and privacy issues.	Analyzed privacy and security risks in cryptocurrency apps.	Sentiment analysis, topic modeling	Cryptocurrency app reviews

Table A2. Variables and concept definitions

No	Item	Definition
1	App star ratings	Ranging from 1 to 5, were collected using a web crawler from user submissions in the digital marketplace.
2	Perceived privacy threats	User perception of improper handling of information privacy was extracted from reviews using a semi-supervised ML model. A value of 1 indicates the reviewer identified privacy concerns, while 0 indicates no mention of such issues.
3	Perceived security threats	User perception of inadequate information security was extracted from reviews using a semi-supervised ML model. A value of 1 indicates the reviewer found the app lacking in security, while 0 indicates no mention of security concerns.
4	Perception of security measures by app developers	User perceptions of developer-implemented security measures were extracted from textual reviews using a semi-supervised ML model. A value of 1 indicates the reviewer recognized security measures in the app, while 0 indicates no mention of security measures.
5	Review polarity	The polarity of the textual review, ranging from –1 (most negative) to +1 (most positive), with 0 indicating neutrality, was extracted using a natural language processing API.
6	Review subjectivity	The subjectivity of the review, ranging from 0 (highly objective) to 1 (highly subjective), was extracted using a natural language processing API.
7	High-risk app	Apps that deal with financial information and data. Apps that may store banking, credit card, and tax-related information.
8	Days before app update	Time in days after last update.
9	Size of Apps	The size of an app is measured in megabytes (MB).
10	Downloads of Apps	Counts of downloads of apps (in the app store)
11	Version of Android	Refers to the specific release of the app’s software identified by a version number.
12	App ratings total number	Refers to the cumulative count of user-submitted ratings for an app displayed in the app store

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Table A3. Pairwise correlation of the variables used

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1 Star rating	1											
2 Security measures	0.41*	1										
3 Security threats	–0.37	–0.80*	1									
4 Privacy threats	–0.11	–0.34*	–0.13*	1								
5 Polarity	0.65*	0.39*	–0.34*	–0.14*	1							
6 Subjectivity	0.33*	0.24*	–0.23*	–0.01	0.35*	1						
7 High–risk app	0.09*	0.17*	–0.12*	–0.08*	0.10*	0.05*	1					
8 Last update in days	0.06*	0.04*	–0.03	–0.03	0.07*	0.02	–0.03	1				
9 Size of Apps	–0.01	–0.02	0.01	0.03	–0.04	0.03	–0.14*	–0.53*	1			
10 Downloads	–0.24*	–0.09*	0.15*	–0.08*	–0.18*	–0.06*	0.07*	–0.15*	0.01	1		
11 App version	0.10*	0.07*	–0.06*	–0.02	0.07*	0.07*	0.11*	–0.16*	0.20*	–0.06*	1	
12 Total number of ratings	–0.21*	–0.11*	0.16*	–0.08*	–0.16*	–0.05*	0.03	–0.06*	0.06*	0.95*	–0.02	1
13 Android OS version	0.21*	0.19*	–0.17*	–0.02	0.16*	0.14*	0.29*	–0.37*	0.30*	–0.19*	0.49*	–0.10*

Note: * denotes $p < 0.05$.

Table A4. Results of ordinal regression models (star rating)

Variables	Models					
	1	2	3	4	5	6
Security measures	0.72***					0.52***
	(0.05)					(0.06)
Security threats		–0.92***				–0.62***
		(0.07)				(0.07)
Privacy threats			–0.93***			–0.52***
			(0.13)			(0.13)
Polarity				3.67***		3.64***
				(0.03)		(0.03)
Subjectivity					1.67***	0.04*
					(0.03)	(0.03)
High risk app	–0.25***	–0.27***	–0.24***	–0.31***	–0.25***	–0.31***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Last update in days	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size of Apps	0.00	–0.00	0.00	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Downloads	–0.00*	–0.01**	–0.00	0.01***	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Android OS version	0.10***	0.10***	0.12***	0.05***	0.07***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Total reviews	0.72***	0.67***	0.71***	0.72***	0.71***	0.72***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Chi–squared	4057***	4048***	3928***	25960***	7900***	26132***
Pseudo R–squared	24%	23%	23%	25%	24%	25%

Note: Observations = 64,500. Standard errors in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1. Years fixed effects are included in all models.