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Why Are Egyptian Mobile Banking Users Dissatisfied? An Exploratory Text Mining Analysis

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Abstract

This research aims to explore the main mobile banking service quality dimensions that lead to shaping customer dissatisfaction in the Egyptian banking sector. This research was conducted on the top ten Mobile banking applications in Egypt, according to Statista (2023). Data were collected from Google Play Store as reviews covering the period from January 2020 to May 2024 were extracted from the mobile banking application's URL using Python code applied on Google Colab. Topic modeling was used to explore the main dimensions causing dissatisfaction by applying the Latent Dirichlet Allocation (LDA) method through Orange data mining software, analyzing 4,634 negative user reviews to uncover the latent dimensions of mobile banking service quality. The findings support that the main dissatisfiers were ranked from highest to lowest importance: customer support, login problems, faulty updates, and security. The implications of this study are to support the improvement of mobile banking services and help banks develop more effective digital marketing strategies that fix the main customer dissatisfaction factors, and deliver high-quality services based on the findings, which can serve as a competitive advantage for banks. This study contributes to the literature by understanding mobile banking dimensions in the Egyptian market depending on analyzing thousands of real customer reviews and ranking their importance according to their MTP in the corpus.

Keywords Mobile Banking Applications, Service Quality Dimensions, Text Mining Approach, Latent Dirichlet Allocation (LDA), Online Customer Reviews (OCR).

1. Introduction

The accelerated improvements in mobile devices and their capabilities have created several opportunities for mobile-based services to adapt faster to customers increasing requirements and preferences (Kushwaha & Agrawal, 2016); (Mittal & Agrawal, 2022). With the rising usage of smartphones and the Internet, digital servitization has become a common trend, especially in the finance sector (Manser Payne, Dahl, & Peltier, 2021).

Furthermore, the COVID-19 pandemic has accelerated global digitization, particularly in the banking sector. As a result of the epidemic, Customers have been increasingly hesitant to visit bank branches, fearing infection with COVID-19. Therefore, an increasing number of clients have switched to depend intensively in using online and mobile banking as alternatives for the traditional offline bank services (Mondres, 2020). Financial sector professionals argue that the pandemic has facilitated the adoption of digital banking technology. In response to the crisis, around 65% of banks in the United States increased their technology capabilities (Mondres, 2020). Thus, traditional banks have to cope with the growing need for non-face-to-face transactions while also ensuring customer satisfaction and loyalty through mobile banking services (Shankar, A.; Tiwari, A. K.; Gupta, M., 2022).

According to (Zhou, 2012), mobile banking refers to the use of mobile devices to access banking services. Mobile banking allows users to access a variety of financial services, including balance inquiries, bill payments, card management, fund transfers, and peer-to-peer payments. According to (Shankar, A.; Datta, B.; Jebarajakirthy, C.; Mukherjee, S., 2020), mobile banking applications are the most popular of all mobile applications. Similarly, (Barnes & Corbitt, 2003); (Shaikh & Karjaluoto, 2015) defined mobile banking as a channel through which consumers can access banking services. On the other hand, the International Telecommunication Union (2011) describes mobile banking as the execution of financial services and transactions using mobile communication techniques and mobile devices.

One of the biggest explanations for interest in mobile banking is the benefits it provides for both banks and consumers. On the one hand, mobile banking is one of the most cost-effective and efficient platforms for providing banking services to both banks and customers (Shankar, Datta, & Jebarajakirthy, 2019). On the other hand, (Karimi & Liu, 2020); (Verkijika & Neneh, 2021) emphasized that mobile banking has grown in popularity due to its numerous benefits for both consumers and businesses (e.g., convenience, faster processing times, cashless and widespread transactions, smooth handling of bulk transactions, etc.) and contribution to

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improved consumer experience. As financial services become increasingly digitized, banks are seeking methods to offer value to their consumers (Manser Payne, Dahl, & Peltier, 2021).

In Egypt, mobile payments have grown significantly recently in response to international and domestic markets and technological advances. Egypt has considerable potential for mobile banking expansion due to the wide adoption rate of handsets. By December 2022, mobile subscriptions in Egypt had climbed to 99.38 million (Portal, 2023). According to the (DataReportal, 2023) report, almost 93.9% of Egyptians use mobile phones to access the Internet. Furthermore, 13.3% of those users access a banking, investing, website, or mobile app every month, which indicates that the percentage of mobile banking applications is likely to continue to grow in the coming years.

The (Ministry of Communications and Information Technology. (n.d.))(MCIT) COVID-19 recovery tactics research points out that the pandemic was a catalyst for increasing client demand for digital solutions. The use of e-wallets, internet banking, and mobile banking has increased exponentially. By early 2020, 28 of Egypt's 38 banks had been given mobile banking licenses. The MCIT report additionally stated that banks are working right now on improving digitalization.

2. Research Question

According to the previously mentioned facts, there is a strong need to analyze customer reviews, using one of the most popular topic modeling methods, which is the Latent Dirichlet Allocation (LDA) algorithm, to explore the most significant service quality dimensions of mobile banking applications in Egypt, by extracting latent themes from Google Play users' reviews. The objective of this research can be summarized by the following research question.

RQ1: What are the main service quality dimensions that shape customer dissatisfaction mentioned in OCR?

The contributions of this study are fourfold. First, this study is one of the few studies that explores service quality dimensions in the Egyptian banking sector using Text-mining approaches. Second, this study uses the inductive method by exploring the main dimensions from online customer reviews, which contrasts with many previous studies that depended on the deductive method by predetermining the drivers of customer satisfaction or dissatisfaction.

Literature Review

3.1 Service Quality in Mobile Banking from Conventional Studies

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Service quality dimensions in mobile banking applications have been studied extensively in the conventional literature, depending on questionnaires and surveys. In the following table (1), the researcher illustrated a sample of previous survey-based studies.

Table (1) Reviewing Service Quality Dimensions in Survey-based Studies.

Study	Objective & Method	Dimensions	Key Findings
(Asfour & Haddad, 2014)	The Impact of Mobile Banking on Enhancing Customers' E-Satisfaction. Method: 360 customers of Jordanian mobile banking apps, analyzed using Structural Equation Modeling (SEM).	• Reliability • flexibility • privacy • accessibility • ease of navigation • efficiency • safety	significant impact of the overall dimensions of mobile banking service on customer E-satisfaction Reliability, flexibility, privacy, accessibility, ease of navigation, efficiency, and safety are important dimensions. Privacy and accessibility were found to be the most influential dimensions.
(Jun & Palacios, 2016)	This study focuses on uncovering the key dimensions of m-banking service quality and their associated sub-dimensions specific to the context of m-banking. Method: 900 customer comments from USA banks users were analyzed using NVivo through	M-Banking Application Quality • Security • Convenience • Ease of Use • Content • Accuracy • Speed • Diverse Mobile Application Service Features • Aesthetics M-Banking Customer	The analysis reveals a total of 17 dimensions of m-banking service quality five dimensions, such as mobile convenience, accuracy, diverse mobile application service features, ease of use, and continuous improvement, are considered as the main sources of customer satisfaction/dissatisfaction

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	Structural Equation Modeling (SEM)	Service Quality • Courtesy • Reliability • Understanding the Customers • Responsiveness • Credibility • Continuous Improvement • Competence • Access • Communication	
(Arcand, PromTep, Brun, & Rajaobelina, 2017)	This study aims to examine the impact of mobile banking service quality (security/privacy, practicity, design/aesthetics, enjoyment and sociality) on customer trust and satisfaction. Method: 375 respondents were collected through an online survey and analyzed through Structural Equation Modeling (SEM).	• Security and privacy, • practicality, • design/aesthetics • enjoyment • sociality	– Findings confirm that trust significantly and positively impacts commitment/satisfaction. There is a significant relationship between security and privacy, practicality (regarded as utilitarian factors), enjoyment, sociality, and customer satisfaction. insignificant interface design and either trust or commitment/satisfaction
(Mostafa, 2020)	This paper attempts to investigate the potential effect of mobile banking (m-banking) service	• Perceived ease of use • perceived usefulness • security and privacy • perceived enjoyment	Perceived enjoyment, perceived usefulness, perceived security and privacy, and perceived ease

	quality dimensions (ease of use, usefulness, security/privacy and enjoyment) on customers' value co-creation intention (CVCCI) in the banking sector Method: 301 respondents from Egypt, and analyzed through Structural Equation Modeling (SEM)		of use The empirical evidence confirms the potential role of m-banking service quality dimensions, the ATT-m-banking, and customer trust in developing CVCCI. In addition, the mediation effect of ATT-m-banking in the m-banking service quality dimensions and CVCCI link was demonstrated. Interestingly, trust was not found to have a moderating effect between the ATT-m-banking and CVCCI.
(Haq & Awan, 2020)	This study aims to empirically explore e-banking service quality and its impact on e-banking loyalty through a mediating effect of e-banking satisfaction, mediating effect of e-banking satisfaction between privacy & Security and e-banking loyalty Method: 976 responses in Pakistan, and analyzed through Structural Equation	• Reliability • Security and privacy • website design • customer service	privacy and security, and e-banking loyalty were proved as fully mediated by e-banking satisfaction; however, the indirect effect of the reliability and website design on e-banking loyalty was partially mediated

	Modeling (SEM)		
(Yusfiarto, 2021)	This study aims to investigate the impact of mobile banking service quality on building customer loyalty in Islamic banking Method: 273 respondents from Indonesian Islamic banks, and analzyed through Structural Equation Modeling (SEM)	• Efficiency • fulfillment • Privacy • System availability	m-banking service quality has a positive and significant effect on attitudinal and behavioral loyalty, and e-satisfaction The keys to mobile banking service quality are Efficiency and system availability.

3.2 Service Quality in Mobile Banking from Text-mining Studies

On the other hand, service quality dimensions in mobile banking applications have been studied rarely using text-mining techniques, and the most used text-mining algorithm from all previous studies was the Latent Dirichlet algorithm (LDA). In the following table (2), the researcher illustrated a sample of previous text-mining-based studies.

Table (1) Reviewing Service Quality Dimensions in Text-Mining-based Studies.

Study	Objective	Dimensions	Findings
(Leem & Eum, 2021)	The study aims to measure mobile banking service quality. Method: 3,359 comments of Korean users were extracted from the Google Play Store, analyzed	• Reliability • Flexibility • Privacy • Accessibility • Ease of • Navigation • Efficiency • Safety	Practicality, enjoyment, and security/privacy are the most important mobile bank service quality dimensions.

	using LDA		
(Verkijika & Neneh, 2021)	Determine the factors that could influence recommendations for mobile payment applications.	M-Banking Application Quality: • Security • Convenience • Ease of Use • Content • Accuracy • Speed • Diverse Mobile Application Service Features • Aesthetics M-Banking Customer Service Quality: • Courtesy • Reliability • Understanding the Customers • Responsiveness, Credibility • Continuous Improvement • Competence • Access • Communication	13 factors are influential in fostering users' positive and/or negative recommendations of mobile payment systems. • Ease of use • Usefulness • Convenience • Security • Reliability • Satisfaction • Transaction speed • Time saving • Customer support • Output quality • Perceived cost • Usability • Trust
(Oh & Kim, 2022)	To identify factors that improve customer satisfaction with the mobile banking application service.	• ease of use • usefulness • security and privacy • enjoyment	Security and convenience are the most influential factors in customer satisfaction with mobile financial services.

	Method: 96,140 reviews from Google Play Store and App Store across 4 banks in the USA between 2019 to 2021, using Latent Dirichlet algorithm (LDA)		
(Hussain, Hannan, & Shafiq, 2023)	To identify the dimensions of mobile banking service quality. Method: 58,290 reviews from the Google Play Store across 24 banks in Pakistan. using Latent Dirichlet algorithm (LDA)	• Content • Convenience • Ease of use • Cost • Customer support • Efficiency • Interactivity • Privacy and security • Usefulness • User identification	Positive reviews indicate the following dimensions: security, convenience, ease of use, continuous improvement, usefulness, and app attributes. Negative reviews indicate the following dimensions: system availability, responsiveness, faulty updates, login problems, and reliability.
(Dey, Islam, & Rana, 2023)	To identify customer perceptions of mobile banking applications.	• Reliability • security and privacy • website design • customer service & support.	Convenience, security, client service, ease of use, speed, high perceived usefulness, and ease of connectivity of the applications.
(Sally, 2023)	To discover dissatisfaction reasons of mobile banking applications	• Customer service • Functionalities and updates • Operational failure	Unstable recent updates, bad customer support, and functional and nonfunctional errors.
(Okatan & Çam, 2024)	To analyze customer reviews of digital	• Ease of use • Convenience • fees	Usefulness, convenience, and service fees of digital banking applications are the Key factors

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	banking services		impacting customer satisfaction.

3.3 The Role of Online Customer Reviews

Nowadays, Web 2.0 technologies play a cornerstone role in the rapid increase of a massive amount of text data in social media through allowing to users to share their experience easily through their User-generated (UGC) and become a content creator for this textual data and share this content on various platforms (Calli, 2016); (Çallı & Clark, 2015).

UGC is defined as media content, such as text, audio, or video, that is generated by the public for sharing on online platforms using a user-centric model. This type of content includes valuable information, such as customer attitudes, opinions, and experiences (Daugherty, Eastin, & Bright, Journal of Interactive Advertising); (Liu, Jiang, & Zhao, 2019). According to (Park, Gu, Leung, & Konana, 2014), UGC is a crucial source for exploring client demands, as it provides rich textual data at a low cost, unlike customer surveys or interviews. (Park, Gu, Leung, & Konana, 2014) categorized UGC into different types, including online customer reviews, blogs, and social media. This study mainly depends on Online Customer reviews (OCR), which are one of the most important sources for assessing customer response (Ho Dac, Carson, & Moore, 2013).

One of the platforms that users use to share their OCR is mobile app stores, which enable users to rate the app on a scale of perceived satisfaction and express their positive or negative opinions. This gave the bank an advantage in enhancing service quality by identifying complaints early and understanding service failures (Leem & Eum, 2021); (Susanto, Chang, & Ha, 2016). OCR reflect customer feedback in two ways. The first is an overall rating where consumers can write about their positive/negative experiences with a product or brand and its features. Second, while writing their reviews, they are asked to rate their overall level of satisfaction on a five-point scale during an individual review (Qiu, Pang, & Lim, 2012). According to (Tsao, Chen, Campbell, & Sands, 2020), this scale is equivalent to the Likert scale, where 1 expresses high dissatisfaction and 5 expresses high satisfaction. Moreover, according to (Chatterjee & Mandal, 2020); (Heng, Gao, Jiang, & Chen, 2018), there is proof in the literature that these evaluations and ratings are real and reliable.

In mobile banking applications, an extensive literature review found that few studies have considered online customer reviews (OCR) in the context of m-banking service quality (Shankar, A.; Datta, B.; Jebarajakirthy, C.; Mukherjee, S., 2020); (Shankar, A.; Tiwari, A. K.;

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Gupta, M., 2022); Leem & Eum, 2021); (Oh & Kim, 2022); (Mittal & Agrawal, 2022); (Halvadia, Halvadia, & Purohit, 2022); (Hussain, Hannan, & Shafiq, 2023). Most of this research relied on Google Play Store online reviews. Also, several previous studies on mobile applications showed that OCR from mobile app stores can be used to extract numerous findings (Tavakoli, Zhao, Heydari, & Nenadić, 2018); (Hatamian, Serna, & Rannenberg, 2019); (Jha & Mahmoud, 2019). For Example, (Tavakoli, Zhao, Heydari, & Nenadić, 2018) demonstrated that these reviews can provide valuable information and requirements (such as problem reports, feature requests, updates, costs, and suggestions) for app development and marketing. (Jha & Mahmoud, 2019) investigated 6,000 user reviews from the iOS app store and found that 40% of them had at least one non-functional recommendation. Similarly, (Hatamian, Serna, & Rannenberg, 2019) observed that app reviews can reveal user privacy issues regarding mobile applications.

Despite all the previously mentioned benefits of user-generated content and their massive volume, which presents a great chance to understand the real customer experience, it was discovered through an academic literature review that insufficient attention was given to such user-generated data Leem & Eum, 2021); (Shankar, A.; Tiwari, A. K.; Gupta, M., 2022).

According to the previously stated, this research applies content analysis of online customer reviews (OCR) for mobile banking applications. OCR offers many advantages. First, online customer reviews (OCR) are a type of user-generated content that customers rely on to impact their purchasing or adoption decisions (Ansari & Gupta, 2021); (Park, Gu, Leung, & Konana, 2014). Second, analyzing customer reviews allows mobile payment organizations to gain a better understanding of their consumers' preferences and how to improve their services (Oh & Kim, 2022). Third, the open-ended nature of online customer reviews (OCR) helps researchers to explore several new dimensions that influence customers.

3.4 The Role of Topic Modeling in Analyzing Online Customer Reviews

Today, large amounts of User-Generated Content are produced daily, including a massive number of customer reviews, which is very hard to scan and analyze all these reviews manually (Heng, Gao, Jiang, & Chen, 2018). According to that, using topic modeling techniques becomes very needed and applied in a lot of fields to analzye Online Customer reviews (OCR).

Topic Modeling (TM) is a method that depends on the frequency of terms appearing in a document to extract topics that consist of a combination of particular phrases. This method has been used for analyzing content in several research fields. The result of the topic modeling method is a group of topics, each composed of word clusters from a document based on a specific pattern (Jacobi, van Atteveldt, & Welbers, 2015). Many researchers find this method useful in identifying significant features found in a large amount of unstructured text data (Tirunillai & Tellis, 2012).

Many topic modeling methods exist, including Correlated Topic Model (CTM), Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA), Latent Semantic Indexing (LSI), and Probabilistic Latent Semantic Indexing (PLSI) (Abdelrazek, Eid, Gawish, Medhat, & Hassan, 2023). Despite this, Latent Dirichlet allocation (LDA), a form of unsupervised machine learning clustering method originally proposed by Blei et al. (2003), is employed in this study. The most popular LDA (Latent Dirichlet Allocation) technique will be used to extract the main topics and related terms from the Google Play Store reviews of the scraped users.

In this study, the orange data mining software, which was developed especially for scholars and researchers by a team of researchers and developers at the Bioinformatics Laboratory of the Faculty of Computer and Information Science, University of Ljubljana, Slovenia, is used to employ the latent Dirichlet Allocation (LDA) topic modeling technique. For several reasons, latent Dirichlet allocation (LDA) was selected. First, compared to non-probabilistic topics produced by other topic modeling methods like Latent Semantic Analysis, the topics generated by LDA are probabilistic (Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990). Second, it makes it possible to determine the weight that each topic in the corpus reflects, in addition to detecting hidden themes (Abdelrazek, Eid, Gawish, Medhat, & Hassan, 2023). Third, previous studies on mobile banking in different countries (e.g., (Cheng & Sharmayne, 2020); (Omotosho, 2021); (Verkijika & Neneh, 2021); Leem & Eum, 2021); (Oh & Kim, 2022); (Dey, Islam, & Rana, 2023); (Hussain, Hannan, & Shafiq, 2023) have depended mainly on LDA as the main topic modeling technique to analyze customer reviews.

4 Methodology

4.1 Research Design

The major goal of this study is to explore the main service quality dimensions that shape customers' dissatisfaction in the Egyptian mobile banking sector. To achieve this, the study identifies an ideal method for analyzing Google Play store reviews, see Fig. 1. This research consists of four distinct primary phases: (1) Data Collection, (2) Data Preprocessing, (3) Topic Modeling, and (4) Data Visualization by Orange (3.35).

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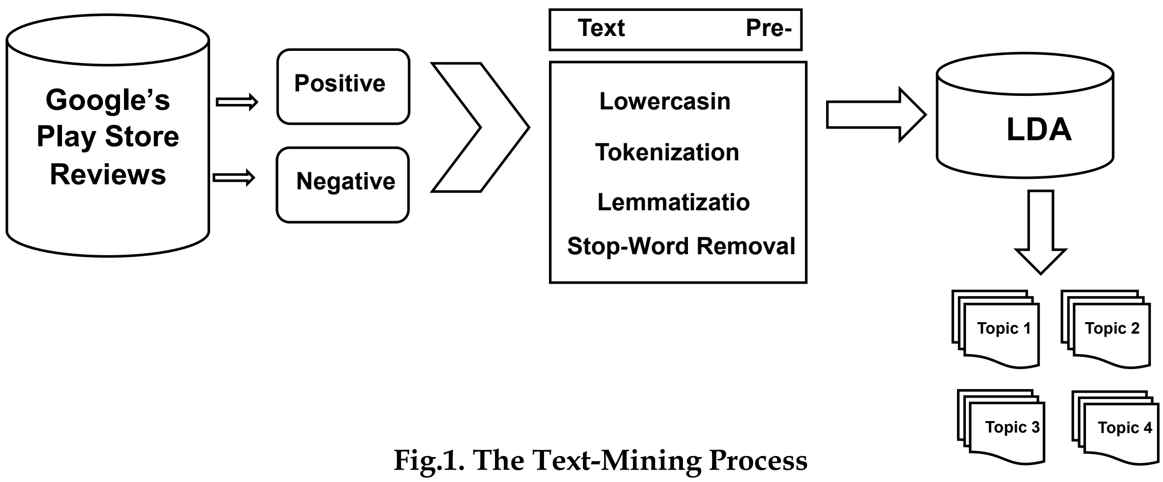

Fig.1. The Text-Mining Process

Some previous studies relied on sentiment analysis to categorize customer reviews as positive, negative, or neutral before applying LDA. However, in this study, sentiment analysis was not employed, as the users' overall ratings were available and attached to each review, which directly measured customer satisfaction or dissatisfaction. Also, sentiment analysis has a limitation that sarcasm leads to misleading sentiment evaluation (Maynard & Greenwood, 2014).

4.2 Data Collection and Cleaning

This study collected 12,460 negative reviews posted on the Google Play Store by users of the top 10 mobile banking applications operating in the Egyptian market. These banks' mobile banking apps ranked among the leading banks operating in Egypt, based on Statista's (2023) rankings. The data was collected from the period of 2020 till May 2024, and classified into 3 public banks and 7 private banks.

4.3 Pre-processing of data

Next, the data pre-processing where the unstructured textual data converted into structured data, which results from the analyzed text quality. The study applied the following steps to transform unrestructured text, i.e. converting characters to lowercase and removing URLs; it also implements tokenization and normalization. Moreover, all punctuation, special

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characters, and extra whitespaces were removed. Finally, lemmatization was performed to convert all words to their main base, and stop words like "I", "an" were removed through the preprocessing widget in Orange 3.29 data mining software. After the preprocessing, the total number of reviews was reduced to 4,634.

4.4 Topic modeling on data

After that, the topic modeling widget was applied using the Latent Dirichlet Allocation (LDA), and the optimal number of topics was determined using the Multidimensional Scaling MDS widget in Orange software. The selection was determined based on achieving the minimal word overlap between topics Multidimensional Scaling (MDS) visualization. (Jamadar, Karnik, Birari, & Patil, 2024) stated that MDS visualization relies on similarities and differences, where similar items appear closer together, while dissimilar ones are farther apart.

Once the topics were extracted, the top ten keywords within each topic were reviewed. Their weights were considered to identify the dominant service quality dimensions represented by each topic. To validate the reliability of customer dissatisfaction determinants, two researchers were asked to label the topics for randomly chosen samples, and reliability was calculated based on the responses.

5 Results and Discussion

5.1 Analysis of Users' Rating

The total number of extracted reviews was 18,233, divided into positive, neutral, and negative. The negative reviews were 12,460, and after data cleaning and preprocessing, became 4,634.

Table 1. Number of user reviews by banks.

Sr.	Bank Application	Total Extracted Reviews	Type
1	NBE Mobile	2576	
2	BM Online	3737	State Bank
3	BDC Mobile Banking	327	
4	CIB Mobile Banking App	3067	
5	AAIB Mobile	215	
6	QNB Egypt Mobile Banking	4898	Private Bank
7	Faisal Online	760	
8	HDB Mobile Banking	170	

9	ALEXBANK Mobile Banking	513
10	NBK Mobile Banking	1970
	Total	18,233

Source(s): Author's Work

5.2 Selecting the number of topics

To determine the optimal number of topics, the default number of Topic Modelling widget in Orange 3.35 was used; first, Topic modeling using LDA was performed with k set to 10, but a strong similarity between topics was observed. Therefore, LDA was also run with different k values. At k = 4, minimal overlap between topics was observed, indicating that four is the optimal number of topics.

As shown in Figure 2, the Multidimensional scaling (MDS) widget shows that the four topics have a decent space between each other, which means that these topics are quite different (Jamadar, Karnik, Birari, & Patil, 2024). which means that the extracted topics have the lowest possible overlapping rate. Furthermore, there is a connecting line between Topics 2 and 4, which means that there is a connection between the two dimensions.

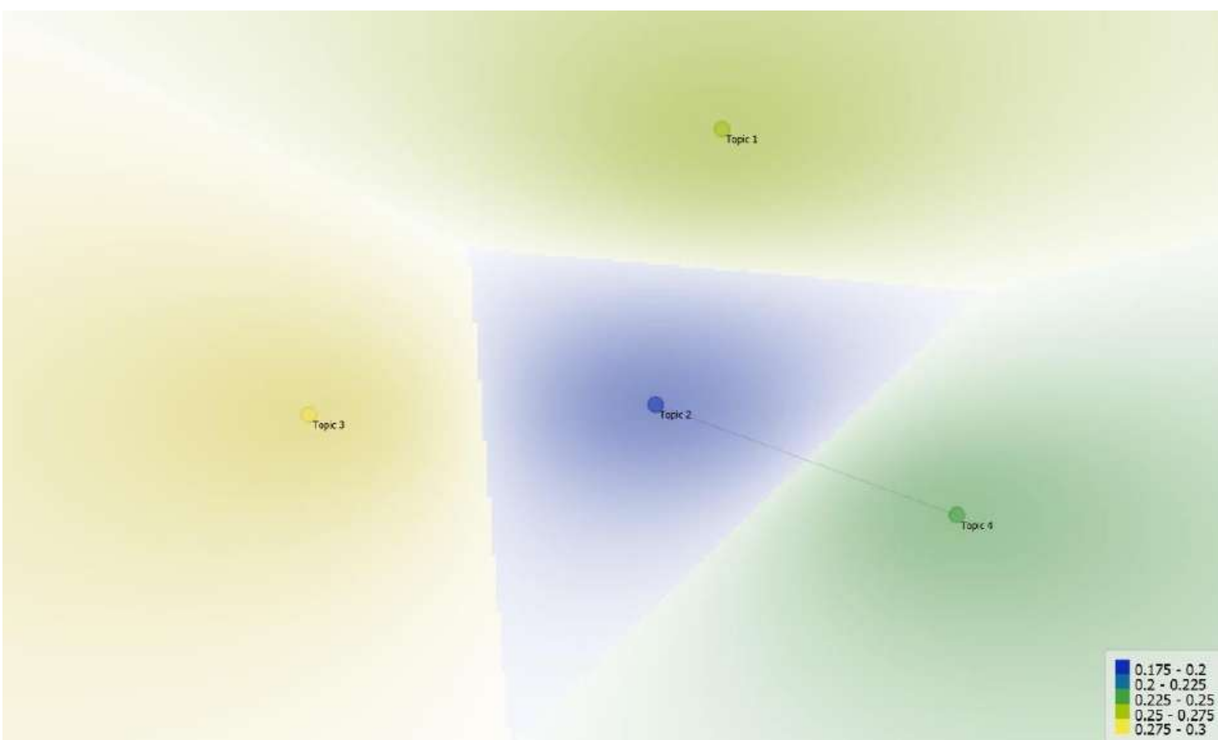

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Fig. 2. Multidimensional Scaling (MDS) projects Service quality dimensions.

5.3 LDA Result

The result of the LDA topic modeling algorithm is presented in the following table (4), including the top topics discovered and assigned dimensions for each topic.

Table 4. LDA result and assigned dimensions corresponding to marginal topic probability.

Topics Number	Assigned Dimension	Marginal Topic Probability	High-weighted Words	weights
Topic 1	Login Problems	0.275	Login	0.0719
			Password	0.0298
			Update	0.0256
			fix	0.0255
			Error	0.0196
			Message	0.0158
			Fingerprint	0.0152
			Server	0.0144
			Issue	0.0121
			Log	0.0081
Topic 2	Security	0.194	Update	0.0315
			Error	0.0132
			Pdf	0.0129
			Slow	0.0114
			Bug	0.0112
			Old	0.0108
			Access	0.0105
			Fix	0.0091
			Load	0.0086
			Screen	0.0072
Topic 3	Customer Support	0.300	Worst	0.0479
			Slow	0.0472
			Service	0.0402
			Poor	0.0308
			Experience	0.0279
			Customer	0.0268
			Useless	0.0099
			Call	0.0098
			Service	0.0086
			Chat	0.0052
Topic 4	Faulty updates	0.231	Update	0.1058
			Version	0.0216

	Stopped	0.0145
	Old	0.0126
	Latest	0.0115
	Error	0.0101
	Biometric	0.0092
	Access	0.0086
	Crash	0.0081
	Transfer	0.0068

As shown in Table 2, the Topic modeling widget cluster service quality dimensions from negative reviews into 4 main topics, which are login problems, security, customer support, and faulty updates, according to marginal topic probability. Seeking to shed light on the "marginal topic probability" service quality dimensions, on the one hand, the highest probability of a topic goes to the customer support topic (30%), and this high probability comes from different words, such as worst, slow, service, poor, experience, customer, useless, call, services, and chat. which means that customer support dimensions are one of the most important dimensions that shape customer dissatisfaction.

In addition, the topic of login problems comes second in the dissatisfiers dimensions with a probability (27.5%) from all topics. Many login terms appear frequently, and the highest term weights were "Login", "Password", "Update", "Fix", "Error", "Message", "Fingerprint", "Server", "Issue", and "Log" have the most importance.

After that, the faulty updates dimension come in the third number with topic probability (23.1%), this topic presented in users reviews using the following terms "Update", "version", "Stopped", "Old", "Latest", "Error", "Biometric", "Access", "Crash", and "Transfer", These terms reflect that users are dissatisfied with the recent update, which may be caused by poor testing before launching the updated version.

Finally, the fourth topic is security, which is according to Fig. 2 of MDS, appears connected to the faulty updates dimension. In other words, most security issues appeared after recent wrong updates. On the other hand, the other topics, Login problems and customer support, did not show any significant association together. Thus, each of them has an independent dimension not affected or attached to any other dimension.

Security dimension come in the fourth number with topic probability (19.5%) this topic presented in users reviews in the following words: "Update", "Error", "Pdf", "Slow", "Bug", "Old", "Access", "Fix", "Load", and "screen" have the most importance.

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In the previous table, the listed words are the high-probability words from the LDA result, and each topic probability from the total corpus is represented by MTP, which is the Marginal topic probability.

5.3 Topics Ranking

Based on MTP, topics can be arranged according to their probability percentage within the corpus. In Table 5 below, the topics are presented along with their assigned dimensions, marginal topic probability percentages, and the number of reviews in which each dimension predominantly appears.

Table 5: Mobile Banking Service Quality Dimensions Ranking.

Dissatisfaction Dimensions	Number of Reviews	MTP	Reviews Sample
Topic 3: Customer Support	1390	30	• Calling customer services for an answer and being on hold for a long time, that is not the service I was looking for. • I will close my account due to no customer support. • Bad Customer service, stating the same response without any valuable solution.
Topic 1: Login Problems	1274	27.5	• 3 weeks ago, it refused to log in, and I had to change the password, and each time I try to change it, the app refuses to accept and shows invalid login. • I am trying to log in with my credentials on the application, but it refuses with an error message • Login Issue since the most recent update, I can't log in to my

Topic 4: Faulty updates	1066	23	• The new update does not have a field to enter a value amount for creating a certificate. • The old version was quite OK, but this new one is crashing each time I use it. • The app is horrible since the latest update, especially the language display.
Topic 2: Security	904	19.5	• Screenshots are not allowed on Android, but work well on IOS What is the security issue with it? • The screen is blinking many times till the App is open. • Opening the app now redirects to downloading a PDF file in the browser
Total Negative reviews	4,634	100%	

6. Future Research Directions:

This section outlines important gaps and suggests potential areas for future studies.

- Expanding the sample of the research to examine all mobile banking applications in the Egyptian Market.
- Conduct a cross-cultural analysis by comparing all African banks.
- Analyze Arabic online customer reviews.
- Examine each bank individually to explore detailed service quality dimensions.

5. Conclusion

This research has a deep dive into analyzing Egyptian banks users reviews and to know more about the main dimensions that lead to their dissatisfaction, from the analysis the Most of the Egyptian mobile banking application users are very dissatisfied with a rating 1 90% percentage, and dissatisfied users with rate 2 are only 10% percentage, which means that there are very vital dimensions that cause these customers to be very dissatisfied, and banks in Egypt must work on enhancing their mobile services.

The most important service quality dimensions that shape users' dissatisfaction are Customer support across all channels, phone, chat and email, so the Egyptian banks should work on increasing the customer representative numbers, ensure 24/7 support, hire well-trained employees, and make strong KPIs for the customer service team. Secondly, the IT department in banks should work on solving Login problems that users face and enhance the biometric authentication methods to make application access easier and user-friendly. Finally, Faulty updates have a strong connection with security problems that users frequently face security issues following updates. Therefore, banks must test each update extensively and ensure that all user scenarios have been tested to minimize post-update problems.

In conclusion, Egyptian banks need to accelerate the improvement of their mobile banking services to keep pace with the digital era, where everything around us can be done with a phone touch. Additionally, they must also listen more to their users' opinions and work on developing solutions to deal with their pains.

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