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RESEARCH ARTICLE

Identification of Key Service Features for Evaluating the Quality of Metaverse Services: A Text Mining Approach

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ABSTRACT Recent advances in the metaverse have revolutionized the way services are experienced, creating a virtual world that seamlessly blends real-life and digital experiences. While research on metaverse services has traditionally focused on technological advancements, recent efforts emphasize the need for a customer-oriented approach to evaluating service quality. However, few studies have explored this customer-oriented approach. To address this gap, this paper identifies and prioritizes nine service features that significantly influence customer satisfaction in metaverse services from a customer-oriented perspective. In particular, this study analyzed 437,527 online customer reviews of Roblox, Bitmoji, and VRchat by employing text mining and machine learning algorithms, such as topic modeling, sentiment analysis, and logistic regression. As a result, the 'co-experience' feature emerges as a crucial factor, closely aligned with user objectives when engaging with metaverse services. These findings provide valuable insights for service managers to enhance their offerings effectively, positioning them favorably in the evolving metaverse landscape.

INDEX TERMS Metaverse, service quality, text mining, sentiment analysis, topic modeling.

I. INTRODUCTION

The metaverse, derived from the fusion of "meta" (which signifies transcendence) and "universe," encompasses a three-dimensional virtual realm where avatars actively participate in a range of political, economic, social, and cultural activities [1]. Recently, the advancement of the metaverse has transformed the traditional ways of experiencing services because such technology can be used to create a virtual world based on daily life where both the real and the digital coexist [2]. Service customers are no longer constrained by temporal or spatial limitations when experiencing services through the provision of metaverse services [3]. In addition, the traditional customer culture that revolved around face-to-face transactions is shifting toward a zero-contact service culture, leading to increased activity in online service across various industries [4]. For example, in the tourism industry, customers now utilize metaverse to create travel plans; seek destination information; and even experience products, services, or places before reaching their destination [5].

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Whereas research on metaverse services primarily focused on technological advancements in the past [6], recent efforts emphasize the necessity of a fundamental shift toward a customer-oriented approach to evaluating the quality of metaverse services [7], [8]. The customer-oriented approach has been employed to characterize customers' perceptions and reactions arising from the utilization or anticipated utilization of a product, system, or service [9]. Studying the customer-oriented approach to quality evaluation for metaverse services also requires examining key elements, including the experience across multiple platforms (e.g., mobile devices, personal computers (PC), augmented reality (AR) devices, or virtual reality (VR) devices); real-time communication with other customers; and the creation of a substantial volume of images, texts, and videos through avatars for expressing their own ideas, sharing those ideas with others, and participating in daily activities that closely resemble reality. In short, identifying the characteristics and level of the elements in the customer perspective will be essential, and further suggestions based on the findings could enhance the now outstanding aspects and promptly address areas for improvement [10].

However, relatively few studies have explored the customer-oriented approach for quality evaluation thus far. A shortage of a universally accepted concept and dedicated research persists on this matter [11], despite the growing research interest in recent years regarding the quality of experience in metaverse services. Furthermore, the existing studies have primarily focused on only a few metaverse platforms for quality evaluation, such as VR services (e.g., [12], [13]) or mobile metaverse services (e.g., [4], [14]), despite the importance of comprehending the complete range of metaverse services to facilitate quality evaluation. Identifying the service features based on actual customer experiences is crucial for evaluating the quality of metaverse service experiences, as the success of future metaverse services relies on the management of these experiences [15].

To address this challenge, this study utilized a text mining approach to analyzing online reviews as a potential strategy for effectively assessing service quality [16], [17], [18]. Analyzing online reviews can be considered an evaluating quality of metaverse services from a customer-oriented perspective, given that the reviews represent the needs, requirements, and complaints from customers who actually use metaverse services [19], [20]. Based on the analysis, this study identified key service features for evaluating the quality of metaverse services and determined the importance of service features which can be used to prioritize the points in service quality management and improvement. This study collected 437,527 online customer reviews covering three prominent metaverse services that incorporate mobile, VR, and AR technologies. These services, namely Roblox, Bitmoji, and VRChat, were selected to ensure a comprehensive assessment. By using machine learning algorithms, this study identified nine key service features for evaluating the quality of metaverse services and analyzed the relationships among them and the overall customer satisfaction. The relationship was used to determine the importance of key service features.

The management of quality of experience could be the key success factor of metaverse services, and securing a high level of understanding in terms of literacy for the metaverse from the customer's perspective can be inferred a necessity [21]. To identify service features and determine key service features for evaluating quality of experience, this study used a text mining approach to estimate accurately the extent to which focal service features of metaverse services affect customer satisfaction using online review data. The findings contribute to the academic discussion toward a successful metaverse service development and evaluation. This study is unique in the sense that a text mining approach is applied to understand better the service features of metaverse services. Such approach enabled us to address the gap between existing research on metaverse service quality evaluation by considering various platforms of metaverse services, ranging from mobile, PC, AR, and VR. The above is the distinct contribution of our paper among existing studies conducted on metaverse services (e.g., [12], [13]), and our work illustrates a strong potential of the text mining approach as a new research methodology for management and business studies.

The remainder of this paper is organized as follows. Section II describes related studies on metaverse service quality and importance estimation using online reviews. Section III describes the text mining approach and the results of text analysis. Section IV discusses the results of analysis for metaverse service improvement. Finally, Section V provides the concluding remarks and presents future research directions.

II. RELATED WORKS

A. QUALITY OF METAVERSE SERVICES

Metaverse services can be defined into the following four primary scenarios: augmented reality, lifelogging, virtual worlds, and mirror worlds [2]. This categorization is based on whether the implemented space is reality- or virtual-centered and whether the implemented information is centered on the external environment or individuals [22]. In previous studies, the metaverse service primarily concentrated on the virtual world's structure, such as game and education; more recently, however, it is often depicted as a platform that fosters content-driven exchanges and social interactions [2]. Customers can engage in real-time communication and encourage active participation on this platform by generating substantial amounts of content through avatars. It closely resembles real-life interactions through various exchanges facilitated by technologies such as VR, AR, mixed reality, and extended reality, which enable the creation of digital spaces that closely resemble the real world or are entirely unique (e.g., [23]). In summary, the success of metaverse services depends on active customer participation, highlighting the importance of evaluating the quality of metaverse services from a customer-oriented perspective.

Several studies attempted to propose the measurements for evaluating the quality of metaverse services from the customer-oriented perspective. Porcu et al. [24] emphasized the importance of Quality of Experience (QoE) in metaverse services from a customer perspective, which measures the level of satisfaction or dissatisfaction of users when engaging with immersive media experiences. They introduced the following two dimensions for evaluating the QoE of metaverse services: the social dimension, encompassing customer behavior, customer attitudes, and customer interactions; and the economic dimension, covering aspects related to financial considerations and employment opportunities. This study is limited in that the technical aspects of metaverse services, such as device characteristics (e.g., hardware specification) and issues related to cybersickness caused by devices, were not considered.

Zhou et al. [8] explored the utilization of metaverse technological features for assessing QoE across various metaverse contexts. They presented eight key contexts within the metaverse services landscape, encompassing metaverse-based education, commerce, gaming, project team management, museum exhibitions, brand management, tourism, and digital government. They also identified that each context has different design objectives, resulting in varying technological features and their respective importance through literature review. For example, efficiency, interactivity, and real-time collaboration between teachers and students stand out as critical factors in assessing QoE in metaverse-based education. Meanwhile, in the realm of metaverse commerce, interactivity and vividness have been identified as factors that positively influence purchase intention and indirectly affect behaviors through psychological outcomes, including cognitive and affective outcomes.

Vlahovic et al. [13] proposed a QoE assessment for VR services with a focus on human, technological, and contextual aspects. They employed ITU-T Recommendation G.1035, which categorizes influence factors into the following three main types: human traits, system attributes, and contextual elements. These influence factors encompass human characteristics such as expectations and expertise, immersion, cybersickness, vision, and hearing. System attributes include hardware, network/transmission, media/coding, and content; while contextual elements involve task, social, temporal, and physical factors.

Baker et al. [25] carried out user interviews to pinpoint 13 factors that influence customers' comprehensive perceptions of VR services within the tourism industry. They categorized these factors into the following three distinct groups: those associated with the presentation of VR content, those pertaining to the content itself, and those related to the functionality of hardware and software. The presentation category pertains to the delivery of virtual experiences, encapsulating customers' perceptions of presence, immersion, and authenticity. The content category reflects customers' experiences when utilizing VR services, encompassing aspects such as entertainment value, diversity of content, and the type of guide employed. Lastly, the functionality category provides insights into the practicality and usability of VR devices, considering factors such as video resolution, comfort level of the head mounted display, and overall operational convenience.

The aforementioned studies share a commonality in extracting various quality features to evaluate the QoE of metaverse services from a customer perspective. However, research rarely investigates how the extracted quality features influence the overall satisfaction of metaverse services. Zhou et al. [8] suggested the important technical factors for different metaverse contexts. However, these findings were derived from a literature review rather than quantitative analysis, which represents a limitation of this study. Furthermore, the aforementioned studies either did not consider the technical factors of metaverse services (e.g., [24]) or focused exclusively on specific technologies, such as VR (e.g., [13]). To address these limitations, this study utilized a text mining approach for the analysis to extract features for the QoE assessment of metaverse services encompassing various devices, such as VR, AR, and mobile devices. In addition, this study used machine learning algorithms to identify key service features for evaluating the quality of metaverse services and analyzing the relationships among the service features and the overall customer satisfaction.

B. TEXT MINING APPROACH FOR SERVICE QUALITY EVALUATION

Understanding and analyzing customer perceptions of a specific service is crucial for identifying the necessary features to evaluate and improve service's quality [26]. Parasuraman et al. [27] introduced the SERVQUAL model which consists of five dimensions to understand and analyze customer perceptions of service quality. Many studies have made efforts to identify service features that influence customer satisfaction using the SERVQUAL dimensions, such as personalization, localization, and information quality for mobile location services (e.g., [28]). In addition, feature importance is considered a crucial determinant for prioritizing improvements to strategically enhance customer satisfaction, as it has a direct impact on the overall customer satisfaction [29], [30]. To estimate the feature importance, numerous studies primarily used the methods of surveys and interviews as data containing customer perceptions [31], [32]. For instance, Heo and Kim [28] utilized exploratory and confirmatory factor analyses to identify factors that affect user satisfaction based on collected survey data. Furthermore, they assessed the importance of these factors using a structural equation model.

Constructing features and estimating their importance for service evaluation through surveys and interviews can be a resource-intensive and time-consuming process, even when conducted meticulously [33]. To overcome these limitations, online reviews are gaining popularity as a method for evaluating service quality from a customer-oriented perspective as they provide readily available data, are free to access, and reflect collective opinions [19]. Moreover, customer satisfaction, emotions, and intentions related to services, which are closely linked to service performance (e.g., the intention to reuse a service), can be gathered from online reviews [34]. Previous research has often employed ratings of customer reviews (e.g., star rating in hotel application) and the quantity of reviews to gauge the traffic or popularity of the provider [35].

Many studies have endeavored to incorporate text data into their research efforts owing to the potential of utilizing text data in service quality evaluation. Ding et al. [36] and Korfiatis et al. [37] gathered online reviews and employed topic modeling algorithms to identify key service features for the hotel and tourism industries, respectively. Chakrabarti et al. [38] analyzed online reviews to investigate the relationship between SERVQUAL dimensions and customer satisfaction for the three largest private banks in India, utilizing logistic regression as the analytical method. They utilized lexicon-based sentiment analysis to estimate sentiment scores for SERVQUAL dimensions as independent variables. Additionally, they employed user overall rating (i.e., customer satisfaction) as the dependent variable. In the studies mentioned above, analyzing text data is a suitable approach because online reviews contain customer satisfaction viewpoints.

Despite the potential of text mining for service quality evaluation, research has inadequately focused on metaverse services. Therefore, this study aimed to evaluate the quality of metaverse services. Specifically, an integrated framework was employed to analyze online reviews, encompassing feature identification, sentiment analysis, and feature importance estimation. By contrast, previous studies often conducted these processes separately (e.g., [36], [38]).

III. TEXT MINING APPROACH TO ANALYZING ONLINE REVIEWS OF METAVERSE SERVICES

This study employed text mining and machine learning algorithms to identify service features of metaverse services and estimate the importance values of the features from online reviews. Figure 1 shows the overall process and used algorithms of the text mining approach. The approach comprises the following four steps: (1) collecting and preprocessing data, (2) identifying service features for quality evaluation, (3) analyzing the sentiments of service features, and (4) estimating the importance of service features. Sections A to D outline the objectives of these steps and provide a detailed account of how the author applied these procedures in examining online reviews.

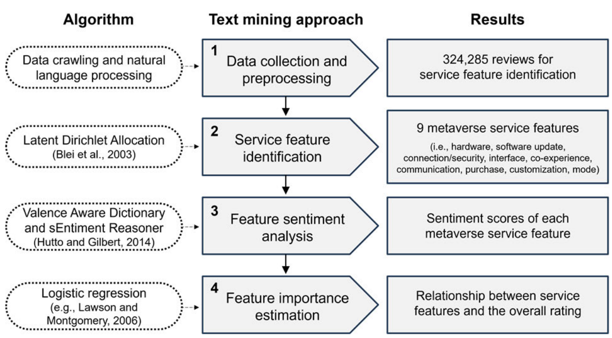

FIGURE 1. Overall process of the text mining.

A. COLLECTING AND PREPROCESSING DATA

Step 1 involves the collection and preprocessing of online customer reviews from a well-known review website or application, such as Google Playstore, Apple Appstore, and Steam. The content and rating of the reviews are collected along with information such as title, date, overall rating, and review comments. Duplicate reviews in the collection are removed by checking the reviewer ID, date, comments, and overall rating. In addition, the online reviews are structured into preprocessed words with a part-of-speech (POS) tagging and original sentences with emojis, emoticons, and punctuations. Text preprocessing with POS tagging proceeds as follows [39]. Uppercase letters are converted to lowercase, punctuation and stop words are removed, words are lemmatized, and words that occurred either very frequently or very rarely are removed.

This study collected a total of 437,527 online reviews for the U.S. version of three applications using the Selenium web crawler library in Python. Reviews for Roblox (235,755) and Bitmoji (79,600) were collected from Google Playstore platform, while VRChat reviews (122,172) were collected from Steam platform. This study chose these applications to identify service features that can reflect the characteristics of various metaverse platforms, especially various hardware characteristics, in the quality of experience. Roblox is a widely recognized metaverse application that offers access and gameplay across various devices, including tablets, mobile phones, and PCs. Bitmoji is another notable metaverse service that leverages AR technology. By contrast, VRChat is a prominent metaverse application primarily tailored for use with VR devices such as Oculus Rift, HTC Vive, and Valve Index.

The collected data include both structured items, such as review date, reviewer ID, overall rating, and unstructured items, such as comments, and preprocessed content information. In overall rating, Roblox and Bitmoji use a 1–5 point scale, while the VRChat records recommendations as either True or False. With respect to the review content, the Natural Language Toolkit (NLTK) in Python—which is a suite of libraries and programs for natural language processing for text written in English—was used for deleting duplicate reviews, tokenization, stop word removal, lemmatization, and POS tagging. Furthermore, review contents with fewer than 10 words were excluded from the analysis due to their limited content, which was considered insufficient for identifying service features. Consequently, 324,285 reviews were transformed into preprocessed word with POS and original sentences as shown in Figure 2.

B. IDENTIFYING SERVICVE FEATURES OF METAVERSE SERVICES

Step 2 involves identifying service features which can be used for quality evaluation of metaverse services. The service features that customers frequently mention in the online reviews are identified using Latent Dirichlet Allocation (LDA). The method has been employed in various studies to extract feature words from online reviews [40], [41]. LDA is a robust probabilistic topic model that extracts latent topics from extensive textual data. In the LDA model, each review is assumed a combination of a set of topic probabilities, and each topic is a combination of a set of words. To prepare the input for LDA, review-noun matrix is generated, as service feature words are presumed to be nouns [18], [42]. Coherence of topics is used to determine the number of topics in LDA. The topics are comprehended and labeled by manually interpreting nouns within each topic. The label of each topic can be regarded as a service feature for quality evaluation [18], [40], [43]. In addition, the nouns associated with each feature

No.	App	ID	Date	Rating	Review Comments	Preprocessed review comments with POS tagging
1	Roblox	8b339XX	2023-06-24	5	Perfect App! Though, There are a few problems sometimes. I'll be in the character creator and I will choose an animation but it will combine with the previous animation. Overall, Great game. Edit There's a bug where I'll be in a game and it just crashes completely, no lag spikes or anything, and it just logs me out. While I have no problem getting back in, this bug/glitch is a little annoying and interrups my gameplay. Still love it!	('perfect', 'JJ'), ('app', 'VBZ'), ('though', 'IN'), ('problem', 'NN'), ('sometimes', 'RB'), ('character', 'JJ'), ('creator', 'NN'), ('choose', 'JJ'), ('animation', 'NN'), ('combine', 'VBP'), ('previous', 'JJ'), ('animation', 'NN'), ('overall', 'RB'), ('great', 'JJ'), ('game', 'NN'), ('edit', 'NN'), ('bug', 'NN'), ('game', 'NN'), ('crash', 'NN'), ('completely', 'RB'), ('lag', 'JJ'), ('spike', 'NN'), ('anything', 'NN'), ('log', 'NN'), ('problem', 'NN'), ('getting', 'VBG'), ('back', 'RB'), ('little', 'JJ'), ('annoying', 'VBG'), ('interrups', 'NNS'), ('gameplay', 'NN'), ('still', 'RB'), ('love', 'VB')
...	...	...	...	...	...	...
227,332	Roblox	990aeXX	2022-06-14	3	I love the game there's a bunch of games and its the best free to play game in my opinion.	('love', 'VB'), ('game', 'NN'), ('bunch', 'JJ'), ('game', 'NN'), ('best', 'JJS'), ('free', 'JJ'), ('play', 'NN'), ('game', 'NN'), ('opinion', 'NN')
227,333	Bitmoji	2ad81XX	2023-09-30	4	I like creating a Bitmoji and sending, but I don't like bitmoji keyboard. The experience was not smooth after you choose an image. It would ask me what contact to send it to even when I was in a chat and then it'd be duplicated and then close the window. Something's up there. The original sharing usage from the app is pretty good and I'll continue to use it!	('like', 'IN'), ('creating', 'VBG'), ('bitmoji', 'JJ'), ('sending', 'VBG'), ('like', 'IN'), ('bitmoji', 'JJ'), ('keyboard', 'NN'), ('experience', 'NN'), ('smooth', 'VBD'), ('choose', 'JJ'), ('image', 'NN'), ('would', 'MD'), ('ask', 'VB'), ('contact', 'JJ'), ('send', 'VB'), ('even', 'RB'), ('chat', 'RB'), ('duplicated', 'VBD'), ('close', 'JJ'), ('window', 'NN'), ('something', 'NN'), ('original', 'JJ'), ('sharing', 'NN'), ('usage', 'JJ'), ('app', 'JJ'), ('pretty', 'RB'), ('good', 'JJ'), ('continue', 'NN'), ('use', 'NN')
...	...	...	...	...	...	...
269,590	Bitmoji	88673XX	2023-06-20	5	I like the fact that I can say alot just using a pic.for the Occasion. Love it !!!!!	('like', 'IN'), ('fact', 'NN'), ('say', 'VBP'), ('using', 'VBG'), ('occasion', 'NN'), ('love', 'NN')
269,591	VRChat	60372XX	2017-02-28	TRUE	Such a fun experience, meet some fun and interesting people and have had a lot of laughs. Excited to see this evolve and become even better. If you're looking for some great social interaction this is the place to get them.	('fun', 'NN'), ('experience', 'NN'), ('meet', 'NN'), ('fun', 'NN'), ('interesting', 'VBG'), ('people', 'NNS'), ('lot', 'VBP'), ('laugh', 'IN'), ('excited', 'JJ'), ('see', 'NN'), ('evolve', 'VBP'), ('become', 'VB'), ('even', 'RB'), ('better', 'RBR'), ('looking', 'VBG'), ('great', 'JJ'), ('social', 'JJ'), ('interaction', 'NN'), ('place', 'NN'), ('get', 'VB')
...	...	...	...	...	...	...
324,285	VRChat	65456XX	2019-02-27	TRUE	Basically replaced the loneliness I was feeling in real life, even met a few friends on it, all and all it's fun and enjoyable and probably the best game I've played in a while.	('basically', 'RB'), ('replaced', 'VBN'), ('loneliness', 'NN'), ('feeling', 'VBG'), ('real', 'JJ'), ('life', 'NN'), ('even', 'RB'), ('met', 'VBD'), ('friend', 'NN'), ('fun', 'NN'), ('enjoyable', 'JJ'), ('probably', 'RB'), ('best', 'JJS'), ('game', 'NN'), ('played', 'VBD')

FIGURE 2. Part of the customer review database.

can be expanded by incorporating synonyms using resources, such as word embedding techniques [44].

In this study, the Gensim library in Python was employed to use LDA for identifying service features and word2vec for expanding nouns within each topic. A review–noun matrix (324,285–55,299) was prepared as the input matrix for LDA. The number of topics was tested from 1 to 30, following the observation that the maximum value of topic coherence occurred at a cluster number of nine as shown in Figure 3. Next, keywords obtained from the LDA were manually reviewed to understand and name each topic to define service features of metaverse services. Only the keywords that effectively described non-duplicate terms and well-represented service feature were extracted to distinguish among the features. Lastly, the keywords for each service feature were expanded by incorporating synonyms using word2vec.

Table 1 shows the results of the representative keywords of each topic. The identified features are as follows: four (''hardware,'' ''software update,'' ''connection/security,'' and ''interface'') address the technological enablers of metaverse services which include functionality and usability of metaverse services, while the remaining five (''co-experience,'' ''communication,'' ''purchase,'' ''customization,'' and ''mode'') pertain to the service experience and purpose of metaverse customers.

The four features on service enablers are as follows: Hardware (f_1) encompasses the experiences related to the equipment required to use metaverse services. Various devices such as mobile, PC, VR, and AR can be used to experience metaverse services, and customers engage with the service using these devices. The experience of the service can vary on the bases of the hardware specifications. To illustrate, the resolution specification of the device being used can affect the level of immersion in the experience. Software update (f_2) encompasses the experiences related to bug resolution, error fixing, and service process optimization resulting from version changes in metaverse service applications. However, the potential of this feature to

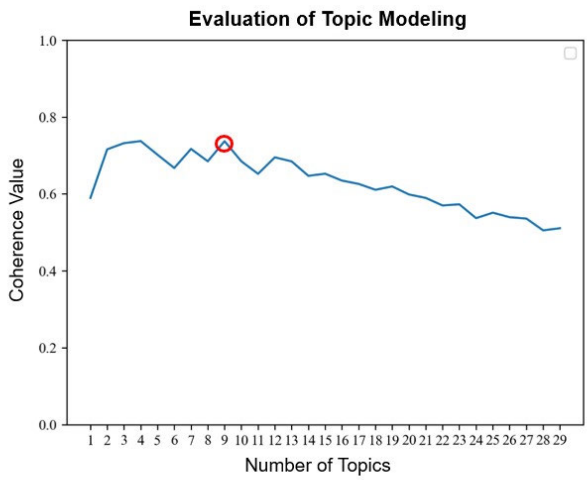

FIGURE 3. Changes in topic coherence values according to the number of topics.

cause customer dissatisfaction underlines the crucial need to continuously monitor the feature and to respond promptly. Consequently, service providers consistently strive to identify and address dissatisfaction stemming from software updates. Connection/security (f_3) pertains to the network-related experiences such as Internet connectivity, privacy, and account login encountered during the use of metaverse services. This feature represents the customer's environment for accessing and using the metaverse service and serves as a fundamental technological enabler. Interface (f_4) encompasses the experiences related to the point of human-computer interaction and communication in a device, such as display screens, keyboards, and VR devices. The feature also includes guidance for the first-time experience of metaverse services including icons, assistance from surrounding non-player characters, and any software user interface elements that help customers achieve their goals within the metaverse services.

The five features of service experience and purpose are as follows: Co-experience (f_5) represents the experience of

TABLE 1. Metaverse service features for evaluating the quality of experience.

Category	Service feature	Keywords (by LDA and word2vec)	Number of reviews (ratio to the total reviews)
Service enabler	Hardware (f_1)	pc, phone, computer, device, tablet, control, mobile, button, xbox, ipad, …	37,428 (12%)
	Software update (f_2)	update, bug, fix, version, problem, glitch, mess, optimization, crash, error, …	75,981 (23%)
	Connection/Security (f_3)	wan, discord, server, internet, lag, connection, download, freeze, account, id, …	113,065 (35%)
	Interface (f_4)	text, image, language, sign, message, app, button, icon, menu, click, …	66,898 (21%)
Service experience and purpose	Co-experience (f_5)	family, kid, friend, cat, dog, school, home, play, work, relax…	98,114 (30%)
	Communication (f_6)	talk, meet, chat, interaction, communicate, express, conversation, share, emotion, hangout…	35,054 (11%)
	Purchase (f_7)	buy, money, robux, pay, worth, purchase, gift, card, refund, spend, …	31,100 (10%)
	Customization (f_8)	avatar, face, clothing, character, hair, clothes, style, outfit, customization, edit, …	53,432 (16%)
	Mode (f_9)	player, devs, platform, creator, simulation, mode, tycoon, minecraft, theme…	30,186 (9%)

mirroring people's daily lives within the metaverse services, particularly engaging in co-experiences with family, friends, colleagues, and more. People engage in activities such as doing, playing, working, relaxing, and others through these activities, they can feel emotions such as love, friendship, and familial bonds. In essence, this feature represents the purposes for which metaverse services are used, projecting real-life experiences into the metaverse environment to achieve those purposes. Communication (f_6) pertains to the experiences related to communication with other individuals within the metaverse services, as it is one of the most common and vital aspects of metaverse environments. Given its importance in satisfying customers (e.g., [45]), service providers need to consider how to facilitate effective communication. For example, in Roblox, they enhance users' communication experiences by providing various means of emotional expressions, effects, and emojis when utilizing avatars.

Purchase (f_7) encompasses the experiences related to spending money to buy items, engage in mode experiences, or make transactions with others within the metaverse services. To illustrate, in Roblox, transactions between individuals happen using the currency "Robux," rendering the experience of purchasing Robux essential. This process includes experiences such as buying Robux and using it to purchase other items. As these experiences may vary depending on the platform (e.g., mobile and PC), service providers need strategies for purchase-related experiences across different platforms. Customization (f_8) encompasses the experience of decorating or personalizing one's avatar within the metaverse services. Customers express themselves within the metaverse by changing aspects of their avatars, such as clothing, face, style, and hair. This experience also extends to customizing accompanying items such as pets and various accessories. Lastly, mode (f_9) encompasses the experiences related to the multiple modes offered within the metaverse services. Depending on the objectives within the metaverse service, different modes are provided, allowing customers to engage in various experiences. For example, within Roblox, existing mode includes simulation and tycoon, and customers participate in these modes to enjoy content and interact with other customers, thereby experiencing the metaverse environment.

Among the nine metaverse service features, connection/security (f_3) represents the largest portion of the customer reviews which play an essential role as enablers for using metaverse services. Co-experience (f_5) denotes the second most reviewed, which signify the importance of daily living and interacting with other users within the metaverse. The connection/security feature has a strong correlation with the "functionality" and "immersion" concepts, while the co-experience feature is closely associated with the concept of "presence" as previously discussed in studies such as that of Vlahovic et al. [13]. By contrast, mode (f_9) is mentioned in less than 10% of the reviews, suggesting that in metaverse services, prioritizing specific experiences may be more important than offering a variety of activities through modes.

C. ANALYZING THE SENTIMENTS OF SERVICE FEATURES

Step 3 involves the analysis of the sentiments associated with the service features. These sentiments are subsequently used to estimate the importance of these service features in Step 4. Valence Aware Dictionary and sEntiment Reasoner (VADER) is employed for sentiment analysis, and it is an unsupervised machine learning model that relies on lexicons and rules to gauge the sentiments expressed in social media texts [46]. This algorithm performs well, even with short messages such as customer reviews, because VADER's sentiment lexicon is finely tuned to sentiment in microblogs such as Twitter [47]. Furthermore, this algorithm can be used to various service sectors without the need for supplementary information, as VADER is a rule-based method that does not require any training data [48], [49].

Customer reviews are linked to specific service features using a string-matching technique that verifies whether the customer reviews contain keywords of service features illustrated in Table 1. Next, the affective lexicons and their intensities in each sentence are assigned values based on well-established sentiment word banks and five generalizable heuristics in VADER. The compound score is computed by averaging the scores of all affective lexicons, which are then normalized to a scale between −1 (most extreme negative) and 1 (most extreme positive). For example, in the sentence, "while I have no problem getting back in, this bug/glitch is a little annoying and interrupts my gameplay," the compound score of "software update" feature is −0.04 each based on the VADER sentiment analysis. Lastly, the compound scores of the service features mentioned in a review are determined by averaging the compound scores of the sentences discussing those specific features.

This study calculated the sentiment scores of the metaverse service features using the VADER library in Python. Table 2 displays the outcomes of the sentiment analysis, which is employed to estimate feature importance. The overall ratings of Roblox and Bitmoji have been transformed into a binary format, where 0 represents negative ratings (1, 2, and 3 ratings) and 1 represents positive ratings (4 and 5 ratings). This conversion was applied because using the original five scale ratings led to lower prediction model performance [18]. Similarly, the overall ratings of VRChat have been converted into binary format, with 0 denoting "False" and 1 representing "True."

TABLE 2. Sentiment analysis results and dataset for feature importance estimation.

No.	Service features					Overall rating
	f_1	f_2	…	f_8	f_9	
1	0.00	-0.06	…	0.61	0.38	1
2	0.00	0.32	…	0.00	0.00	1
3	0.00	0.39	…	0.59	0.00	0
…	…	…	…			…
324,284	0.73	0.00	…	0.00	0.73	0
324,285	0.49	0.00	…	0.00	0.49	1

D. ESTIMATING THE IMPORTANCE OF SERVICE FEATURES

Step 4 involves analyzing the relationship between service features and the overall rating (i.e., overall customer satisfaction), which indicates the estimation of the importance of metaverse service features. A logistic regression is used to estimate the importance values of the identified service features on the ratings. Logistic regression has been widely employed to identify the features that influence overall rating or customer satisfaction of products and services [50]. The sentiment scores assigned to the identified service features serve as input variables, while the overall rating is used as the output variable to construct a prediction model for estimating feature importance in Table 2.

In this study, the importance of the metaverse service features in relation to overall ratings was estimated using the statsmodels library in Python for logistic regression. Table 3 shows the results of the logistic regression. All service features are statistically significant, as all values in the fifth column (i.e., P > |z|) converge to zero. In short, all service features are the most influential attributes that highly impact the overall satisfaction of the metaverse services. In addition, the values of β (i.e., the second column) represent the impact on user satisfaction with metaverse services. Among the nine service features, co-experience is generally more important than the other features.

TABLE 3. Importance values of nine metaverse service features.

Service features	β (coefficient)	SE(β)	z	P>|z|	Exp(β) (odds ratio)
f_1	1.28	0.03	39.84	0.00	3.59
f_2	0.82	0.02	38.74	0.00	2.27
f_3	1.55	0.02	83.94	0.00	4.72
f_4	1.96	0.02	80.87	0.00	7.07
f_5	2.36	0.02	117.57	0.00	10.56
f_6	0.69	0.03	23.93	0.00	2.00
f_7	1.57	0.04	44.58	0.00	4.81
f_8	1.60	0.03	58.66	0.00	4.95
f_9	-0.22	0.03	-7.94	0.00	0.80

The exponential of β (i.e., the last column in Table 3) represents the odds ratio, which is useful for interpreting feature importance. The odds ratio is defined as the probability of the outcome event occurring divided by the probability of the event not occurring [51]. It measures how the odds of the outcome change when the value of a predictor variable is increased by 1 unit. If the odds ratio is greater than 1, it indicates an increase in the odds of the outcome; but if it is less than 1, it signifies a decrease in the odds. The odds ratios of co-experience (f_5) and interface (f_4) suggest that these two service features are 10.56 and 7.07 times more likely to result in user satisfaction than dissatisfaction, respectively. By contrast, the odd ratios of mode (f_9) is 0.8 times, indicating that customers are more likely to be satisfied rather than dissatisfied. In summary, strengthening service features related to co-experience and interface is important to enhance the service quality of the metaverse while maintaining service quality feature related to mode.

IV. DISCUSSION: USE THE IDENTIFIED SERVICE FEATURES FOR SERVICE IMPROVEMENT

This section describes the use of the identified metaverse service features framework for service improvement. The

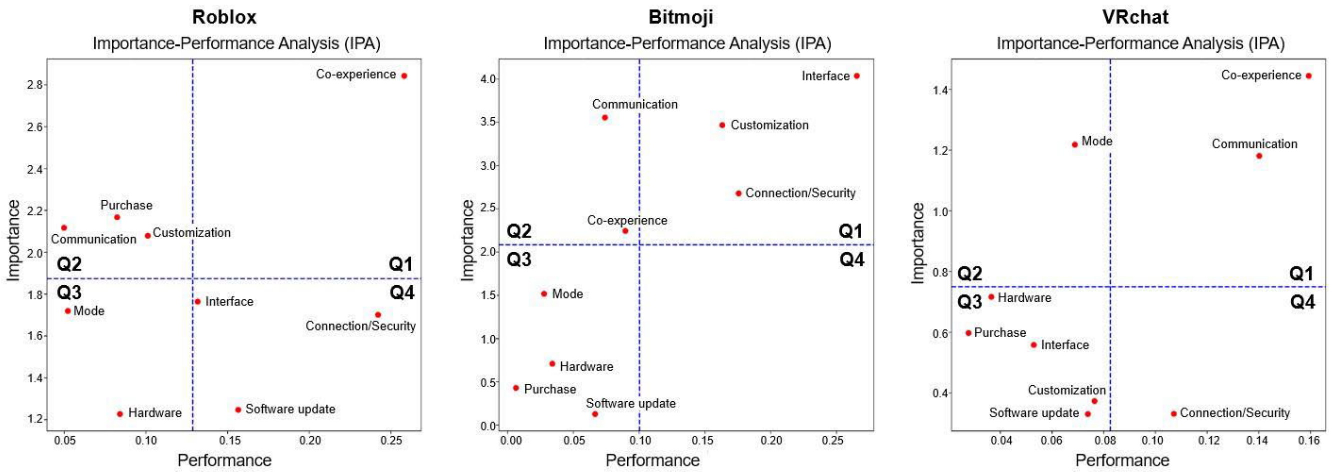

FIGURE 4. IPA of the Roblox, Bitmoji, and VRChat.

identified features can be employed for conducting an importance-performance analysis (IPA), a commonly used technique for gaining insights into customer satisfaction and formulating strategies for service enhancement [29]. An IPA offers strategic guidance through four quadrants, categorizing features based on their performance and importance levels as depicted in Figure 4. Quadrant 1 (Q1) suggests ''keep up the good work,'' where features are considered major strengths and competitive advantages due to their high performance and importance. Quadrant 2 (Q2) advises to ''concentrate here,'' as features in this quadrant are major weaknesses, having lower performance but higher importance. Quadrant 3 (Q3) provides ''low priority'' recommendations, with features seen as minor weaknesses due to their low performance and importance. Quadrant 4 (Q4) offers ''overkill'' guidance, indicating that features in this quadrant are minor strengths, boasting high performance but low importance.

In this study, data collected from Roblox, Bitmoji, and VRChat were segregated and analyzed separately to create their IPA to assess the distinctive differences in metaverse service characteristics as illustrated in Figure 4. This study utilized the identified nine service features and logistic regression to compute the importance and performance of service features. The importance is determined by the absolute coefficient of logistic regression for feature importance estimation (i.e., $|\beta|$), while the performance is calculated on the basis of the average value of sentiment scores of each feature (i.e., sentiments in each feature divided by the total review size of each feature) [18]. The cross-hair of the IPA is established by considering the importance and performance values of metaverse service features, and this approach exhibits strong discriminative capabilities among the features [52].

In the IPA of Roblox (i.e., the left side of Figure 4), co-experience (f_5) was placed in Q1, indicating that the feature comprises major strengths and competitive advantages that should be maintained through sustained investment. This result shows that Roblox customers primarily put value on experiencing activities and everyday experiences they enjoy within the service. Communication (f_6), purchase (f_7), and customization (f_8) were positioned in Q2, while functionality-related features (e.g., hardware, software update, and interface) were located in Q3 or Q4. This result indicates that Roblox customers prioritize the experiential aspects of interacting with other customers and personalizing their experiences within Roblox over functional aspects. The functionality-related features were previously considered the key success factors of Roblox (e.g., [10]), but they are currently in a lower priority category, suggesting that Roblox has been effectively managing these features, such as various interfaces and numerous updates for bug fixes. In summary, the results indicate the need for the development of various strategies to enhance customer experience rather than focusing on functional aspects.

Bitmoji (i.e., the middle side of Figure 4) primarily focuses on using AR for interactions with people, highlighting the importance of uninterrupted communication with others, which is why connection/security (f_3), user-friendly interface (f_4), and customization (f_8) were positioned in Q1. Co-experience (f_5) and communication (f_6) were positioned in Q2, indicating a need for more focused support and improvement. All other features were positioned in Q3, indicating that enhancing these service functions may not be a priority for Bitmoji.

In the case of VRChat (i.e., the right side of Figure 4), co-experience (f_4) and communication (f_5) was positioned in Q1, emphasizing communication with friends or family members through this application. In addition, mode (f_9) was positioned in Q2, indicating the need for immediate investment and attention to effectively manage the features. VRChat offers a variety of worlds (modes), but satisfaction with these worlds does not seem to be very high. This finding indicates the need to support customers in creating and experiencing other worlds to improve their satisfaction.

V. CONCLUSION

This paper introduces a methodology for assessing the quality of metaverse services by extracting service features from online reviews using text mining techniques. Specifically, the approach utilizes LDA for identifying service features relevant to metaverse service quality evaluation. Additionally, sentiment analysis and logistic regression are employed to estimate the importance of sentiment-related service features in influencing overall customer satisfaction. The identified features offer valuable insights for service managers, enabling them to allocate resources effectively for service enhancement. Among these features, co-experience emerges as a crucial factor for improving metaverse service quality, warranting focused attention from the company. The feature is deemed important owing to their strong relevance to the primary purposes for which users engage with metaverse services.

From a theoretical perspective, this study advances the field of service quality evaluation by demonstrating the practical application of online reviews in assessing metaverse service quality. Despite the significance of online reviews in evaluating metaverse services, limited efforts have been done to harness their potential for quality evaluation. This research profoundly enhances our understanding of the multifaceted dimensions involved in evaluating metaverse service quality through online reviews. Our findings and outcomes will benefit future studies related to service evaluation using online reviews and provide a foundation for data-driven service innovation in today's data-rich economy. From a practical standpoint, this study has identified service features that can assist service developers in evaluating the existing metaverse services or designing new metaverse services. These features have valuable implications for companies interested in metaverse services. In particular, the company can utilize the identified service features to conduct an IPA, enabling them to evaluate their strengths compared with competitors and to pinpoint areas that need improvement as discussed in Section IV.

This study has several limitations that can be addressed in future research. First, the findings are contingent on the available data. Changes in data source or data collection time frame could potentially yield different results. This study relied on data from the Google Playstore and Steam platforms. Future research might consider expanding or narrowing the scope and using different data sources, such as social media databases and expert interviews, depending on their research objectives. Second, the results obtained through text mining should be integrated with insights from actual metaverse research and evaluation projects involving service designers. Collaborating with such projects can enhance our understanding and promotion of metaverse service quality evaluation. Third, machine learning models are continually evolving and improving. Future studies can leverage more advanced models to identify metaverse service features and estimate their importance.

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