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Online Review Analysis from a Customer Behavior Observation Perspective for Product Development

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Abstract: Observing customers is one of the methods to uncover their needs. By closely observing how customers use products, we can indirectly experience their interactions and gain a deep understanding of their feelings and preferences. Through this process, companies can design new products that have the potential to succeed on the market. However, traditional methods of customer observation are time-consuming and labor-intensive. In this study, we propose a method that leverages the analysis of online customer reviews as a substitute for direct customer observations. By correlating a customer journey map (CJM) with online reviews, this research establishes a verb-centric analysis that produces a CJM based on online review data. Various text analysis techniques were utilized in this process. When applying online retail site review data, our method of customer observation required one week. This proved to be more efficient in comparison with traditional customer observation methods, which typically need at least one month to complete. Additionally, we observed that the customer behavior-based VOC (voice of customer) identified during the CJM mapping process offers broad insights that are distinct from traditional product feature-centric review analyses. This behavior VOC can be effectively utilized for product improvement, new product development, and product marketing. To verify the usefulness of the behavior VOC, we asked product development experts to evaluate the quantitative analysis results of the same reviews. The experts evaluated the CJM as useful for product conceptualization and selecting technology priorities.

Keywords: online review analysis; customer journey map; customer observation; text mining; customer behavior

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1. Introduction

Competitive and innovative product design requires a deep understanding of the customer. Currently, companies are making efforts to understand customers and design products from their perspective. However, customer understanding is impossible without empathy for the customer [1]. To achieve this, companies use techniques such as customer observation and interviews to gain insight into their customers. However, due to the constraints of time and space, and lack of diverse information, companies face difficulties in this endeavor. Online product review analysis can overcome these problems by allowing companies to observe customers in their natural environment. With the development of smartphones and the internet, companies can easily obtain customer feedback on their products. Online product review analysis has the potential to observe customer behavior without the constraints of time and space [2]. Furthermore, due to the diverse range of users evaluating the products, there is a high potential for diversity in the information gathered. This paper proposes an online review analysis approach that can overcome the limitations of traditional customer observation methods. To accomplish this, the customer journey map (CJM) tool was applied to product review analysis to facilitate the text analysis process.

In addition, to infer customer emotions and opinions from their product usage, text analysis techniques were comprehensively applied to derive customer behavior-based voice of the customer (VOC). This technique was applied to the product data of TWS earbuds to compare the differences between VOC derived from customer behavior observations and the results of traditional product review analyses. The validity and effectiveness of the approach was verified through expert interviews.

2. Related Work

2.1. Customer Observation and Product Design

To identify customer needs, companies should examine the product from the customer's perspective [3]. A product design that satisfies customers can be achieved by empathizing with customer behavior and thoughts [4–6]. To achieve this, customer observation and interview techniques can be used to determine customer characteristics and gather detailed information on product users and their preferences [7]. These customer observation techniques have evolved into ethnographic methodologies. This approach, which originated in anthropology, introduces a fundamental approach to closely observe and gain insight into customer behavior by entering their world for product design [8,9]. Through customer observation, companies make efforts to understand the customer's thoughts and behaviors by accessing their world. As a result, companies can develop products that better fulfill customer needs, which is directly linked to the success of new product development [10].

However, there are several issues in applying this methodology to product development. First, there are the constraints of time and space. Selecting customers for interviews and customer observation requires substantial effort and time [6,11,12]. However, product release cycles continue to get shorter, demanding short-term customer analysis [11–13]. Additionally, in the case of customer observation, spatial constraints may arise depending on the product. Spatial circumstances may make it difficult for companies to observe customers using portable products while on the move.

Lastly, there is a diversity issue in the information acquired. Existing customer observation methodologies have limitations in the number of participating customers, resulting in a lack of diversity in the information obtained, and a tendency towards heavy biases in the analysis results of the analysis subjects [11,13,14].

2.2. Customer Review Analysis and Product Design

The introduction of smartphones and the internet has led to an increase in customer reviews on online commerce and social network platforms. This has been highlighted as a new source of finding the VOC [15]. Customer reviews are written with the purpose of providing information to potential buyers who are considering purchasing the product [16]. Reviews that describe detailed usage experiences of the product have sufficient value for companies [2].

Research identifying product features from customer reviews has persisted for an extended period [17–19]. In line with this trend, studies analyzing quantitative VOC based on sentiment analysis of product features have been conducted [20–25]. Customer reviews provide a wealth of unstructured customer feedback information. Therefore, they not only include feedback on product features but also encompass various customer behaviors that can assist in customer observation. To explore the targeted data from such, it is important to define the direction of review analysis and design an appropriate method [26]. In this regard, efforts have been made to find useful information for product development [23,27].

If enough customer review data are available, valuable insights into customer behavior can be obtained in a short period with less effort compared to approaches such as customer interviews and observations. Additionally, the contribution of diverse customers to the review data helps to overcome the issue of information bias encountered in traditional customer observations [28].

To find insights into customer observation from customer reviews, a customer journey map (CJM) can be used as an analytical tool. The CJM is a tool that tracks the customer journey and analyzes interactions between service providers and customers to explore customer experiences [29]. CJMs are usually created through direct observation or interviews with customers. They can also be derived from customer review data. This allows us to understand product usage behavior and discern the VOC, also known as behavior VOC. Unlike traditional product feature-based review analysis, behavior VOC captures the needs and feelings of customers as they interact with the product. With such an approach, we can obtain reviews that more vividly reflect customer behaviors, thereby acquiring information that can contribute to the development of new products.

2.3. Customer Journey and Mapping

Customer observation is the act of recording product usage space, customer behavior, events, time, goals, feelings, etc., for a company so that it can offer competitive products and services [30]. In line with this perspective, the CJM observes customers' service usage behavior and tracks their thoughts, evaluations, and emotions step-by-step, conveying them to the service providers. The CJM is a two-dimensional matrix with two axes. The horizontal axis consists of the actions, situations, and procedures that customers encounter while using the service, arranged according to their temporal flow. These elements are the touchpoints through which customers interact with the service. The CJM then analyzes the emotions, thoughts, and experiences they have while using the service [31]. The vertical axis is where the service provider selects the topics they want to obtain information about regarding the customers at the touchpoints. The service provider can change the topic according to the analysis objectives and select the emotions, thoughts, opinions, etc., of the customers at the touchpoints to analyze.

In this study, we will use the behavior of customer product usage at the touchpoints and place them on the horizontal axis. We aim to extract the behavior VOC and product usage environment information related to the touchpoints from the review data. These elements will then be placed on the vertical axis. Finally, we will apply text data analysis techniques to find information that corresponds to the two axes set in the customer reviews.

To explore information related to customer behavior by applying text mining techniques to the CJM, we need to solve one problem. In traditional review analysis, customer feedback was identified by focusing on frequently used noun-centered keywords. These keywords were then used to identify critical product features, followed by each customer's qualitative and quantitative analysis. We will explore the background and customer product usage behavior shown by the CJM using text mining techniques. Nouns related to product features are typically expressed in one or two words and are used as keywords for analysis. However, analyzing behaviors requires considering various verbs with the same meaning. We plan to group these verbs for our analysis. By focusing more on customer behaviors and verbs than product features and nouns, we expect to find new insights from product reviews. Further details of the analysis method will be discussed in the next chapter.

3. Research Model

3.1. Creating a Customer Journey Map from the Perspective of Product Usage

We aim to apply the CJM used in services towards products to derive behavior VOC through customer product usage observation. To achieve this, we will examine the key elements of the CJM in previous studies and apply them to customer product usage behavior.

The core elements of the CJM define the service usage process and the customer's needs and emotions as observed during interactions between service providers and customers [32]. In the case of a product CJM, the service usage process can be defined as the product usage process, while the customer's needs and emotions can be defined as behavior VOC. To design this in detail, we referred to previous research on CJM realization. The researchers categorized the horizontal axis into pre-use, during-use, and post-use periods of customer service usage, while the vertical axis was based on customer requirements and data collected at the touchpoints they aimed to gather [30]. From a product perspective, the interaction in the CJM can be divided into stages of customer product usage behavior, which can be analyzed in a step-by-step manner. These steps can be divided into three stages: the installation and maintenance stage before the customer uses the product, the stage where the customer uses the product, and the last stage, where the product malfunctions after the customer uses it. This classification is based on previous research [33,34].

Once all the CJM elements from the product development perspective are defined, they are classified in detail using text data analysis techniques and judged as touchpoints of the CJM. The CJM overall map is then created with the touchpoints on the horizontal axis and background, and the behavior VOC on the vertical axis. The creation of the entire map is carried out in two stages. First, customer product usage behavior is explored from review data to identify CJM touchpoints, and then it is segmented into stages (Process). Next, VOC and environment information are derived from the touchpoints. The completed CJM map is used as a guide for review data analysis and is also used to summarize analysis results in a table, as shown in Figure 1.

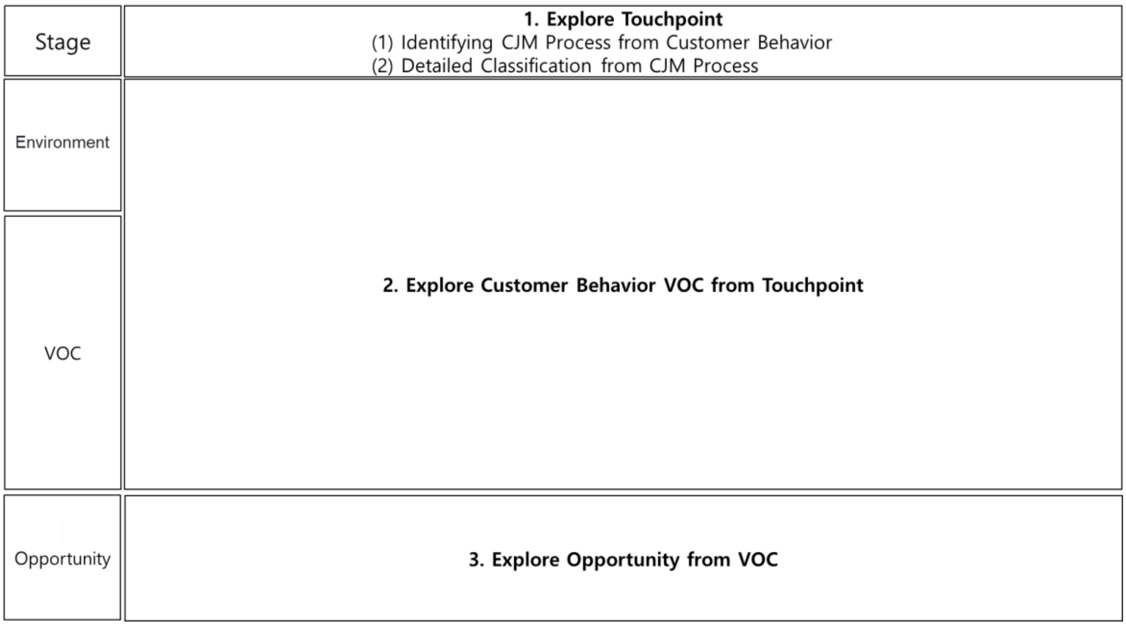

Figure 1. Components and Derivation Stages of the CJM.

3.2. Model for Customer Review Analysis through Product CJM

3.2.1. Data Acquisition

Customer review data can be collected from channels such as SNS and online commerce. This study collected and analyzed customer reviews from online retail sites. Because online retail sites do not impose a character limit, unlike social media, they allow for more detailed reviews and serve a clear purpose of sharing product evaluations among customers [16]. The review data were collected using Web Parser and followed the process: (1) Start with the online review URL of the target product. (2) From the target URL, review contents and actual product purchase verification, along with other items provided by the site, can additionally be collected for analysis interpretation. (3) The collected data are saved in a file format suitable for analysis software.

3.2.2. Data Preparation

To facilitate review analysis, data preprocessing is performed. In this study, three preprocessing steps were conducted: fake review filtering, text preprocessing, and part-of-speech (POS) tagging.

Fake review filtering is a process of removing intentionally biased or exaggerated reviews, which can have a negative impact on product purchasing decisions, from the collected reviews. In this process, we filtered fake reviews using a word arrangement analysis-based machine learning classifier [35]. Then, we conducted text preprocessing on the filtered review data to remove unnecessary special characters and convert all characters to lowercase. Finally, we reduced the text data volume by selecting only the parts of speech that matched the analysis objective using the POS tagging method [36]. In this study, we included verbs in addition to commonly used nouns and adjectives because the analysis focused on customer behavior.

3.2.3. Touchpoint Exploration

In the preprocessed data, we identified touchpoints by analyzing customers' product usage behavior in a step-by-step process. In this process we (1) explored the touchpoints in the CJM from the perspective of customer product usage and (2) broke down the product usage process at the touchpoints. When determining the touchpoints from customer behavior, various verbs that convey the same meaning must be taken into consideration. Hence, to include more reviews on customer behavior in the analysis, it is essential to consider not just individual words but also groups of words with the same meaning. This approach sets our method apart from previous latent Dirichlet allocation (LDA)-based review analysis-related studies [22,37]. Therefore, we grouped similar verbs to determine touchpoints. To group words, we used word embedding to calculate the vector value of the position of words in a sentence and used clustering based on this [38,39]. Word embedding was applied using the CBOW algorithm of word2vec, which allows for efficient analysis in large review datasets [40]. This technique is suitable for identifying homonyms through clustering because it can determine synonyms based solely on words, without considering the context. Additionally, k-means clustering was employed to group words with vector values, as it enables grouping based on vector coordinates and offers good computational efficiency in large review datasets [41]. After the word grouping was completed, we evaluated the meaning of each group to identify touchpoints and processes. We determined whether each word group belonged to the stage of product use before, during, or after the touchpoint. Then we examine whether it can be further separated into a product use process.

3.2.4. Behavior VOC Exploration from Touchpoint

To identify the touchpoints of the CJM and product usage stages, the behavior VOC and product usage context were explored at each stage. To facilitate exploration, keyword groups matched to each stage were employed to select related reviews from the entire review dataset. The selected reviews were then analyzed for keywords-related behavior VOC using the LDA technique [42].

Prior to selecting the reviews, they were segmented into sentence-level units. This approach was taken to prevent the LDA results from becoming overly concentrated on dominant words frequently used when analyzing entire review paragraphs. The simplicity of the CJM mapping process is illustrated in Figure 2.

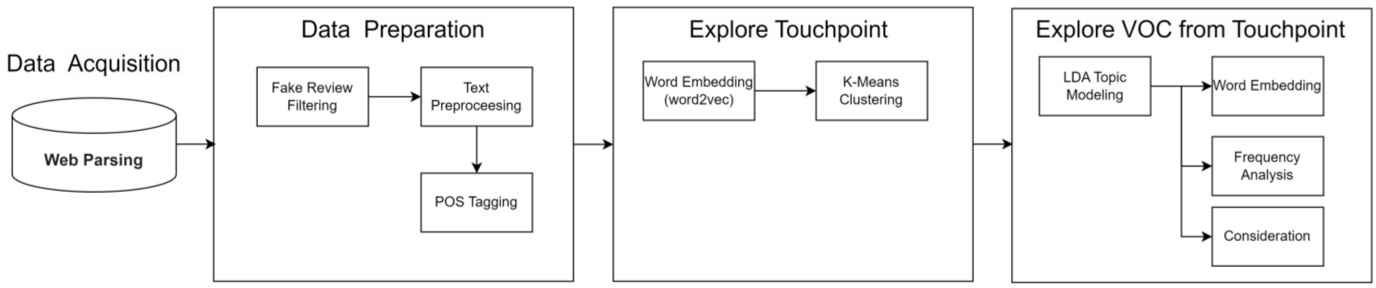

Figure 2. CJM Mapping Process.

4. Empirical Study

4.1. Data Acquisition from Online Retail Site

A web parser was developed in Python to collect reviews of TWS (true wireless stereo) earbuds (a small earphone that is inserted in the ear) product from the online retail website, Amazon (www.amazon.com, accessed on 19 August 2020).

At the time of the research, TWS earbuds were still in the early stages of product maturity, with varying prices and quality across different products. Therefore, we anticipated finding a wealth of information on customer behavior through the diversity of online reviews. Amazon is one of the world's leading retail sites, offering a wide variety of TWS products and a vast number of customer reviews. Hence, we collected diverse product reviews of TWS earbuds from Amazon customers. Data were collected for 93 TWS earbuds products with more than 300 reviews each. The data collection period spanned from August to September 2020, yielding a total of 225,241 reviews. The data categories included release year, actual product purchase verification, product classification, and review content.

4.2. Acquired Data Preparation

To eliminate deliberately misleading fake reviews that could cause confusion, we applied a filtering technique using the support vector machine (SVM) algorithm from the Python sklearn library [43]. A pre-determined Amazon review dataset was used as the training data [44]. Out of the total 225,241 reviews, fake reviews were removed, leaving 179,165 reviews for analysis.

To alleviate the computational burden of review analysis and to analyze customer behavior centered on verbs as parts of speech, each word was tagged and selected according to the part of speech it represented. This process utilized the Penn Treebank tag set from the NLTK library in Python. [45]. Since customer behavior is key for review analysis, we selected the following parts of speech: verbs, adjectives, and nouns.

4.3. Touchpoint Exploration of the Use of TWS Earbuds

In the refined online review data, key elements of customer product usage were identified to explore the touchpoints. Customer behavior is expressed through various verbs, so we grouped the similarities of word vector values using clustering to identify elements of customer product usage behavior. To assign vector coordinate values to words based on their position within a sentence and to group words with similar meanings, we employed the Continuous Bag of Words (CBOW) algorithm from word2vec, applied using the Python gensim library [46]. During the implementation of the algorithm, words with a frequency of fewer than 100 were excluded. The vector size was set to 100, with a window size of 5. K-means clustering from the Python sklearn library was then employed to group words with similar coordinate values. Due to the configuration of the window size in word2vec being set to 5, the number of fitting words within each cluster was accordingly determined to be the same. From the word groups, the touchpoints of the CJM were determined and the product usage stage—before use, product use, or after use—was identified. For example, the words ['charge', 'charging', 'charged', 'charger', 'power', 'charges', 'recharge', 'plugged', 'recharging', 'recharges'] can be considered as part of the before-use stage, representing the customer activity of charging the product. Using this approach, nine groups related to customer behavior were selected from 527-word groups, with the results shown in Table 1 on the following page. Detailed information about the word groups and their constituent words can be found in Appendix A Table A1.

The customer touchpoints identified in Table 1 included the before-use Setup and Charge groups, while the product-use touchpoints were listening to music, watching videos, playing games, walking, using transportation, making phone calls, and engaging in sports activities, with breakdowns occurring after use. From the number of words associated with each touchpoint, we were able to determine the relative importance of customer behavior elements. During the product usage phase, listening to music, making calls, and sports activities were the most important, in that order. This information enables developers to assess the importance of product usage from the customer's perspective and set development priorities accordingly.

We can now identify the key elements of product usage behavior for customers using TWS earbuds at each stage. Two stages were identified in the before-use stage: customers installing the product and charging it. During the product use stage, six stages were identified based on various situations in which customers used the product. In the after-use stage, behavior associated with product malfunction was identified.

Table 1. Word groups related to the touchpoints mapped to the CJM.

Name		Number of Words
Before Use	Setup	46,678
	Charge	40,597
Product Use	Music	32,148
	Video	7644
	Game	796
	Move	5367
	Phone Call	20,151
	Sports	27,724
After Use	Failure	84,109

4.4. Behavior VOC Exploration from TWS Earbuds Touchpoints

The 179,165 reviews were divided into 647,015 sentences, and the sentences were selected using the constituent words of the behavior-focused word groups as keywords. By applying the LDA to the selected sentences, the main topics mentioned in the sentences could be identified. In this study, we applied the LDA algorithm included in the gensim library of Python [47,48]. These then became the behavior VOCs for those keywords. In the LDA analysis process, the optimal number of topics was determined for each group of selected texts where the perplexity was low and the coherence was at its maximum. The number of words output was set to 5 in order of contribution. Table 2 below presents the results of extracting review sentences using the word group from the previously derived listening-to-music touchpoint and applying LDA to explore the behavior VOC and context. Through this, we could achieve the objective of our research: to observe the experiences of users employing TWS earbuds through online reviews. They listen to music while using YouTube, podcasts, and Pandora audiobooks. Additionally, users have dual needs. They desire to listen to music at high volumes to focus solely on the music while also wanting to hear external sounds and engage in conversations or phone calls. Furthermore, for prolonged music sessions with TWS earbuds, users consider long battery life and comfort to be crucial.

Each word group could be further analyzed for behavior VOC by applying frequency analysis and word2vec. For example, in the music-listening stage, customers evaluated items related to bass and treble. To determine whether customers were more interested in the bass or the treble, the importance of h′ighs′, which was used synonymously with t′reble′ was evaluated using word2vec. Mentions of b′ass′ were found 15,904 times, and those of treble frequencies t′reble′ and h′ighs′ totaled 3854 occurrences (1154 and 1700, respectively). Based on these results, it can be inferred that customers consider bass the most important, followed by treble.

By repeating this process, behavior VOC based on the CJM framework can be mapped. First, touchpoints belonging to the before-use, product-use, and after-use stages are arranged in the horizontal rows. Here, the touchpoints include Setup and Charge in the before-use stage, and Music, Video, Game, Phone Call, Sports, and Move in the product-use stage, as well as Failure in the after-use stage. Next, information related to the product usage environment associated with the touchpoints is placed at the top of the vertical columns. Below that, the thoughts and feelings customers have while using the product are described as the VOC based on their behavior. The completed CJM framework-based behavior VOC is shown in Figure 3.

Table 2. Behavior VOC while listening to music.

Topic Modeling Result	Voice of Customer
‘0.092*″ears″ + 0.075*″fit″ + 0.060*″music″ + 0.043*″sounds″ + 0.039*″perfect″’	— Sound quality — Ear fit
‘0.119*″sound″ + 0.094*″good″ + 0.085*″music″ + 0.082*″quality″ + 0.074*″bass″’) ‘0.061*″played″ + 0.056*″review″ + 0.049*″music″ + 0.040*″streaming″ + 0.037*″treble″’),	— Sound quality evaluation for bass — Sound quality evaluation for treble
0.119*″pause″ + 0.102*″play″ + 0.051*″control″ + 0.040*″cut″ + 0.037*″touch″’	— Touch controls while listening to music
0.270*″sounds″ + 0.081*″hear″ + 0.034*″volume″ + 0.028*″loud″ + 0.028*″sound″	— High volume
‘0.145*″time″ + 0.083*″hours″ + 0.045*″music″ + 0.042*″charge″ + 0.036*″get″’)	— Battery life while listening to music
0.153*″pandora″ + 0.055*″music″ + 0.040*″used″ + 0.039*″getting″ + 0.038*″audiobooks″’) ‘0.112*″music″ + 0.088*″love″ + 0.049*″youtube″ + 0.040*″etc″ + 0.035*″videos″’),	— Used in Pandora audiobooks — Listening to music from streaming services such as YouTube
‘0.051*″music″ + 0.041*″airpods″ + 0.038*″made″ + 0.035*″walking″ + 0.029*″conversations″’	— Possibility of external conversation while listening to music
′0.123*″phone″ + 0.122*″music″ + 0.112*″calls″ + 0.069*″listened″ + 0.056*″sound″	— Using the call function while listening to music

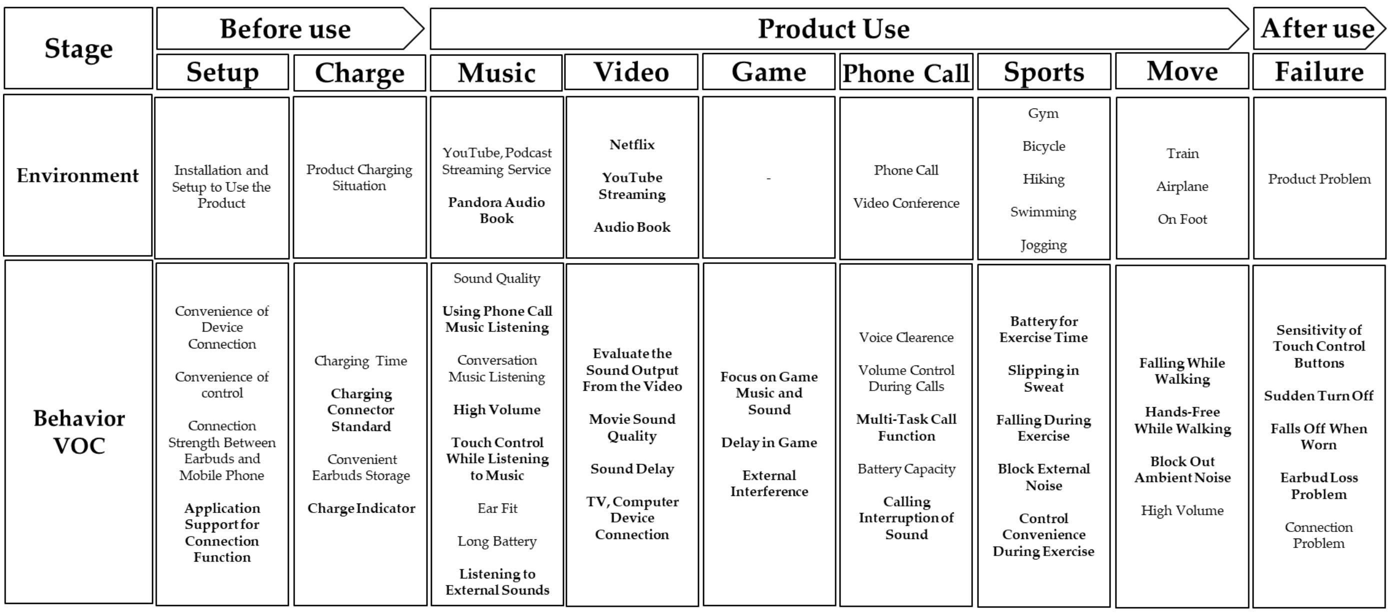

Figure 3. CJM for TWS Earbuds Customer Observation.

Furthermore, the product usage environment was clarified for each customer behavior stage. The environment includes the purpose of use, related smartphone apps, and additional descriptions of usage behaviors. This information helps product developers understand customer behavior better. In the VOC items, emotions and thoughts experienced by customers at each stage are expressed as VOC. Online reviews contain customer product evaluations and judgments based on their product usage behaviors. The previously mentioned behavior VOC along with background information allow for indirect observation of customer actions.

It was found that collecting and analyzing data took approximately one week, excluding the development of the analytical algorithm. Although the time required may vary depending on the situation and objectives, direct customer observation in this case required 3 months [49]. The customer interview method through surveys took at least 1 month to collect questionnaires [50]. In comparison with these methods, this project was able to explore customer observation information within a shorter period. Furthermore, fewer personnel were involved in understanding the meaning of word groups and identifying the behavior VOC from the LDA analysis results. This demonstrated that fewer human resources were utilized in comparison with traditional customer observation methods, where long-term customer behavior must be closely monitored and analyzed in real time, as indicated in [51].

5. Discussion

In the previous section, we demonstrated that customer reviews of TWS earbuds allowed us to identify stages and touchpoints of customer product usage behavior, enabling customer observation with less time and effort. We aim to examine the uniqueness of the behavior VOC resulting from customer observation and validate its contribution to product development.

5.1. Uniqueness and Contribution

In this section, we examine the uniqueness and contribution of the online review analysis results. The unique feature of this study's online review analysis is the examination of customer behavior. By analyzing the customers' product usage behaviors, environments, and opinions, we acquire knowledge about the causes and processes leading to product evaluations. This online review analysis study offers unique information from a customer observation perspective.

In contrast, most of the previous research on online product reviews has primarily focused on identifying and analyzing the core product features evaluated by customers [17,18,21,52–56]. However, an analysis skewed toward product features is not suitable for gaining insights into the causes and processes that lead customers to evaluate products.

To verify this, the study first compares the qualitative VOC derived from traditional product feature analysis with the behavior VOC from this study. As a result, the unique aspects of this study in relation to product feature analysis are identified and its contribution to product development is considered. To identify differences, the same data set used in the research is employed to locate product feature elements and compare them with the results of this study. Previous research focused on identifying core product features by concentrating on nouns, whereas this study emphasizes the understanding of product usage behavior through verbs. Therefore, while previous research focused on understanding customers' direct needs through evaluations of the product's core features, this research centers on analyzing customer product usage behavior to derive the reasons and processes behind their product evaluations.

The analysis revealed that previous research identified core product features evaluated by customers, such as Sound Quality, Battery, Ear Fit, Case, Charging, Noise Cancellation, Waterproof, Connection, Phone Call, and Equalizer. In contrast, this study derived elements of customer product usage behavior, such as Setup, Charging, Listening to Music, Watching Videos, Gaming, Making Calls, Engaging in Sports, and Using While Moving. The difference becomes clear in the qualitative VOC identified through LDA analysis of online reviews using each word group as a keyword.

Comparing the VOC from the two analyses, the difference in the knowledge gained through online review analysis becomes clear. While previous research focuses on understanding customers' direct needs through evaluations of the product's core features, this study centers on analyzing customer product usage behavior to derive the reasons and processes behind their product evaluations. For instance, in the product feature analysis, the Connection VOC reveals that customers evaluate connection stability, but it is difficult to clarify why they consider it important. However, the results of this study show that customers are sensitive to sound delays while watching videos and playing games. As another example, customers in the product feature analysis evaluated the importance of battery capacity. However, this study reveals that customers assess battery capacity while listening to music, making phone calls, and engaging in sports. The specific differences in VOC can be seen in Figure 3 on the previous page 8 and in the product feature analysis Table 3, with unique behavior VOC highlighted.

Table 3. Product feature perspective VOC.

Product Feature	VOC
Sound	— Not only for music but also for movies and podcasts — Tendency to value bass — Clear relationship between noise cancellation and sound quality
Battery	— Displayed function for charging the battery — Battery charging time and life
Ear Fit	— Various ear tips give satisfaction when wearing — The size of the earphone unit affects the fit
Case	— Charging is vital — Both the case's battery capacity and size matter
Charging	— The need for wireless charging — Charging time
Noise Cancellation	— Noise canceling has a large effect on the overall sound
Waterproof	— Some people shower while listening to music
Connection	— Convenience of connection, connectivity while charging — The stability of the connection is important
Phone Call	— The sound quality of the microphone — Battery consumption when using the microphone
Equalizer	— Adjusting the equalizer through the sound app, mainly the bass

In this study, our work is differentiated from previous research by enabling the understanding of the product evaluation process through the analysis of customer behavior. This has a similar effect to observing and empathizing with customers. Empathy involves the willingness to understand and consider customers' needs and interests [57]. Customer empathy forms the basis for developing competitive products [10,58–60]. From a practical perspective, this research assists in determining the priorities for product development [61]. Examining the example of TWS earbuds, we can confirm from the frequency of appearance within customer behavior elements that improving the operation method is a high priority. Additionally, by specifically explaining the need for operational improvements during movement (walking and while using transportation) and sports, developers can enhance their understanding of customer experiences. This, in turn, allows developers to adjust the priorities for product improvement.

Furthermore, the findings of this study are useful for new product development. Traditional product feature analysis research focuses solely on customer requirements for already developed product features. This approach is useful for improving existing product features but is not suitable for developing new products [62–64]. In the context of new product development, analyzing online reviews from a customer observation perspective as conducted in this study is more appropriate and beneficial for developing new product concepts and assessing the value of applied technologies [65,66].

Additionally, this study can be effectively utilized in marketing. The CJM has long been used to capture user perceptions for customer brand management [67]. Building on previous research that applied the CJM in marketing, the marketing applications for this product's CJM include promotions and branding [68]. From a promotional perspective, understanding the context of customer product use can inform the development of promotional plans. For instance, in the case of TWS earbuds, promotions could involve collaborations with streaming platforms used by customers. From a branding perspective, analyzing product use behavior can help categorize target customer segments and enable strategic product development. For example, developing targeted products for sports enthusiasts could emphasize features such as water resistance, anti-sweat, noise cancellation, voice control, and long battery life based on the sports behavior VOC of customers.

In summary, this study reaffirms the potential of the knowledge embedded in online reviews. With the advancement of the internet and smartphones, the volume of customer reviews we can access is increasing. As the quantity of online reviews grows, so does the diversity of knowledge that can be acquired [69,70]. Our research extends traditional text analysis techniques by incorporating verb usage and review sentence classification to discover product development requirements from a customer observation perspective. This review analysis identifies product usage behaviors and related requirements that were not evident in traditional product feature reviews. Through this, we not only advance text analysis methodologies but also emphasize the importance of setting perspective for review analysis, choosing parts of speech, and combining text analysis techniques.

5.2. Validation

In this section, we aim to verify the practicality of the analysis results for product development. To verify the effectiveness, the same data were analyzed as a quantitative VOC for sentiment analysis based on existing product features. Then, TWS earbuds developers evaluated the results. Sentiment analysis enables researchers to quantitatively understand customer evaluations of product features. Various studies have been conducted in this area. Some studies focused on finding quantitative customer evaluations based on product features [20,54,71]. Other studies aimed to identify product weaknesses by comparing analysis results with those of competing products [72]. Some studies suggested a method to automatically identify positive and negative sentiments by finding similar words using word2vec and conducting sentiment analysis [73]. Each study shares a common goal of quantifying customers' positive and negative emotions toward products and determining their relative importance.

Sentiment analysis for this study was conducted using the unsupervised learning-based Senti-WordNet with the Python NLTK library [74]. The results from this analysis are tabulated in Table 4 on the following page. The categories resemble those of the previously mentioned qualitative VOC for product features. However, the results are presented as quantitative VOC by ranking positive sentiments and frequency.

To compare the differences between the analysis results, we interviewed TWS earbuds product development experts. The participants were three developers of LG Electronics' TWS earbuds. Interviews were conducted via an online survey, with questions from the Technology Acceptance Model perspective. The focus was on the usefulness and ease of use when developers utilize analysis results in product development [75]. In comparing the VOC of this study's customer behavior observation (Figure 3 on page 8) with the quantitative feature analysis (Table 4), experts positively evaluated the results of this study in terms of usefulness as helpful in acquiring information and developing product concepts for new product development. They found it easy to understand the customers' purpose of using the product and to comprehend detailed customer thoughts at each stage of use. In addition, they positively evaluated the ability to confirm TWS earbuds' product usage behavior and context. In particular, the use of the call function for conferences or meetings and the VOC in the sports category were considered useful information obtained from customer behavior observation analysis.

Table 4. Sentiment Analysis Results.

Product Feature	Sentiment Ratio		Positive Rank	Frequency Rank
	Positive	Negative		
Sound	0.84	0.16	1	1
Battery	0.77	0.23	4	3
Ear Fit	0.73	0.27	7	2
Case	0.74	0.26	6	4
Charging	0.76	0.24	5	6
Noise Cancellation	0.81	0.19	3	7
Waterproof	0.6	0.4	9	10
Connection	0.68	0.32	8	5
Phone Call	0.74	0.26	6	8
Equalizer	0.82	0.18	2	9

Regarding the ease of use, the study received good evaluations for understanding customer product usage behavior at each stage. However, in comparison with previous studies, it was considered insufficient for applying analysis results to product development from a product improvement perspective. This is because the existing product feature-centered quantitative VOC was much more intuitive in verifying customer evaluation results, receiving relatively higher ratings for the ease of use.

Lastly, the experts emphasized that while quantitative VOC is important for determining technology priority and the detailed product specifications of required technologies, this study's results are more useful for the refinement of new product concepts and technologies. Ultimately, they mentioned that despite the differences in results from evaluating the same data from different perspectives, it should primarily be utilized in product development.

Through the interview results, we confirmed that this study provides useful information that can be utilized complementarily with existing sentiment analysis research. Furthermore, it is significant that companies can both understand and empathize with customers, which is essential to the development of new products, by mapping customer behavior CJM from review data. The CJM in this study is geared toward observing and empathizing with customers in a phased manner. This approach is essential for developing new product development concepts. The CJM used in this review analysis study serves as a tool for exploring latent customer requirements and solutions [76]. This is why it receives positive evaluations from product developers for its contribution to new product development concepts.

5.3. Practical Recommendations for Industry Practitioners

Experts have identified the strengths of this study as the setting of product concepts and the prioritization of technology. Developers can assess and apply the importance of customer requirements by considering the behavior VOC and context of the product CJM from our research. To do this, developers need to collect online data related to the target product and carefully assess the importance of requirements from the behavior VOC and the context of the touchpoints.

In addition, we share detailed practical recommendations necessary for developers to apply our research. First, the Y-axis of the product CJM can be freely set. Developers can expand it to include items they deem necessary beyond the behavior VOC and context of this study, such as technologies and opportunities associated with touchpoints. Second, the more review data collected, the better. While customers clearly judge the positive and negative aspects of core features when writing reviews, related behaviors can vary widely. To discover a variety of behaviors associated with customer observations, it is beneficial to have as many online reviews as possible. Third, it is advisable to set the window parameter of word2vec to 5. Increasing the value may blur the boundaries between word groups and decreasing it may cause fragmentation. However, since this recommendation is based on our empirical results, we suggest adjusting the value to approximately 5 to find the appropriate touchpoints. The exploration of touchpoints and behavior VOC requires qualitative judgment, and accurate analysis results can be obtained through cross-verification by multiple individuals [10,77]. Lastly, it is effective not to focus solely on the words and characters within the product CJM but to envision the overall perspective of customers' thoughts and actions. If necessary, directly reproducing customer behaviors may be helpful.

6. Conclusions

In this study, we have aimed to define customer behavior inherent in review data, specifically focusing on customer product usage and consequently exploring the VOC through this observation. We utilized the CJM as a guide for investigating interactions between customers and products, enabling us to identify the behavior VOC. To accomplish this, we included verbs uncommonly used in conventional review analysis studies and employed techniques such as word2vec and clustering to group different verbs with similar meanings. Subsequently, we applied LDA around the keywords associated with these groups to identify the VOC related to customer behavior.

We have confirmed that our proposed method, when applied to TWS earbuds review data, allows for the identification of customer product usage behavior and VOC in a shorter time. This approach requires fewer resources compared to traditional customer observation methods such as interviews, filming, and surveys. This review-centric customer behavior observation approach can accommodate rapid product development cycles and is expected to be beneficial to individuals and developers in small-to-medium enterprises (SMEs), who may struggle with traditional customer observation.

From the perspective of customer behavior, review analysis uncovers information about the reasons and processes behind customers' product evaluations, which is difficult to find in traditional product feature-based review analysis. Through expert interviews, we validated the utility of review information from a behavior observation standpoint, confirming it as a valuable resource for product developers to understand customers, generate new product development concepts, and prioritize technologies.

Due to concerns about environmental pollution and global warming, sustainable product development plays a crucial role in meeting consumer demands and expectations. Today's consumers are interested not only in high-quality products but also in how these products are made and the impact their production processes have on the environment and society [78]. Therefore, companies can enhance brand loyalty and market competitiveness by developing sustainable products that meet these consumer expectations [67]. Consequently, the need for new product development that considers these factors has become more significant than ever. This requires deep insights into customer needs. Thus, the significance of our study lies in identifying customer behaviors and associated requirements that are not commonly found in traditional online review research.

In our future research, we plan to acquire customer text data not only from online retail sites, as utilized in this study, but also from social media platforms and online communities. This array of diverse customer data will enable us to provide valuable insights for product development. The writing intent, purpose, and context vary across each data source.

Therefore, by applying our methodology to each type of data, we anticipate discovering new knowledge regarding customer understanding.

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Appendix A

Table A1. Word groups related to customer behavior mapped to the CJM.

Product Usage	Cluster Number	Group of Words
Product Setup	18	[‘phone’, ‘connect’, ‘connection’, ‘pairing’, ‘iphone’, ‘device’, ‘connected’, ‘paired’, ‘bluetooth’, ‘devices’, ‘app’, ‘connectivity’, ‘sync’, ‘connecting’, ‘note’, ‘connects’, ‘android’, ‘laptop’, ‘setup’, ‘settings’, ‘computer’, ‘ipad’, ‘google’, ‘switching’, ‘cell’, ‘pixel’, ‘windows’, ‘tablet’, ‘pc’, ‘link’, ‘synced’, ‘mobile’, ‘ios’, ‘macbook’, ‘ipod’, ‘fire’, ‘mac’, ‘kindle’]
Charge	6	[‘charge’, ‘charging’, ‘charged’, ‘charger’, ‘power’, ‘charges’, ‘recharge’, ‘plugged’, ‘recharging’, ‘recharges’]
Music	10	[‘music’, ‘listening’, ‘listen’, ‘audio’, ‘playing’, ‘podcasts’, ‘listened’, ‘rock’, ‘podcast’, ‘audible’, ‘radio’, ‘hip’, ‘classical’, ‘hop’, ‘tunes’, ‘rap’, ‘jazz’, ‘listens’, ‘pandora’]
Video	10	[‘video’, ‘watch’, ‘watching’, ‘tv’, ‘videos’, ‘youtube’, ‘movies’, ‘movie’, ‘streaming’, ‘netflix’, ‘news’]
Game	10	[‘game’, ‘games’, ‘gaming’]
Move	25	[‘go’, ‘pocket’, ‘head’, ‘lose’, ‘walk’, ‘drop’, ‘move’, ‘room’, ‘signal’, ‘leave’, ‘break’, ‘feet’, ‘sitting’, ‘moving’, ‘distance’, ‘close’, ‘hand’, ‘losing’, ‘stable’, ‘closed’, ‘front’, ‘interference’, ‘bag’, ‘source’, ‘ft’, ‘breaking’, ‘reception’, ‘walked’, ‘floor’, ‘purse’, ‘ground’, ‘breaks’, ‘pockets’, ‘wall’, ‘moved’, ‘arm’, ‘pants’, ‘maintain’, ‘door’, ‘walls’, ‘outs’, ‘living’, ‘foot’, ‘rooms’, ‘wifi’, ‘strength’, ‘loosing’, ‘inches’, ‘table’, ‘backpack’, ‘kitchen’, ‘apartment’, ‘meters’]
Calling	36	[‘calls’, ‘call’, ‘talking’, ‘talk’, ‘conversation’, ‘conversations’]
Sports	22	[‘running’, ‘gym’, ‘run’, ‘walking’, ‘workouts’, ‘workout’, ‘exercise’, ‘wires’, ‘runs’, ‘exercising’, ‘worry’, ‘plan’, ‘jogging’, ‘mowing’, ‘walks’, ‘riding’, ‘activity’, ‘activities’, ‘morning’, ‘lawn’, ‘cords’, ‘sleep’, ‘ride’, ‘bike’, ‘plane’, ‘sweating’, ‘cleaning’, ‘flight’, ‘wore’, ‘trip’, ‘afraid’, ‘dog’, ‘yard’, ‘bed’, ‘sports’, ‘commute’, ‘road’, ‘school’, ‘treadmill’, ‘motorcycle’, ‘traveling’, ‘biking’, ‘train’, ‘grass’, ‘outdoors’, ‘miles’, ‘helmet’, ‘equipment’, ‘drive’, ‘busy’, ‘jumping’, ‘jog’, ‘shop’, ‘lifting’, ‘street’, ‘casual’, ‘public’, ‘outdoor’, ‘tangled’, ‘mile’, ‘sessions’, ‘jump’, ‘places’, ‘chores’, ‘covid’, ‘training’, ‘bus’, ‘weights’, ‘rides’, ‘laying’, ‘intense’, ‘fear’, ‘situations’, ‘safety’, ‘cycling’, ‘flights’, ‘eating’, ‘cardio’, ‘fitness’, ‘windy’, ‘basis’, ‘mow’, ‘indoors’, ‘session’, ‘weather’, ‘impact’, ‘city’, ‘commuting’, ‘crowded’, ‘worrying’, ‘asleep’, ‘budge’, ‘trips’, ‘tools’, ‘hiking’, ‘exercises’, ‘studying’, ‘bending’, ‘vigorous’, ‘classes’, ‘stationary’, ‘dogs’, ‘machines’]
Failure	19	[‘left’, ‘right’, ‘earbud’, ‘working’, ‘bud’, ‘issue’, ‘put’, ‘problem’, ‘issues’, ‘times’, ‘fine’, ‘turn’, ‘side’, ‘problems’, ‘reason’, ‘started’, ‘annoying’, ‘start’, ‘cut’, ‘disconnect’, ‘seconds’, ‘kept’, ‘turned’, ‘goes’, ‘gets’, ‘keeps’, ‘cutting’, ‘noticed’, ‘putting’, ‘static’, ‘cuts’, ‘frustrating’, ‘happened’, ‘turning’, ‘reconnect’, ‘holding’, ‘minute’, ‘happen’, ‘happens’, ‘constant’, ‘turns’, ‘disconnecting’, ‘wont’, ‘drops’, ‘starts’, ‘shut’, ‘disconnected’, ‘disconnects’, ‘dropping’, ‘stops’, ‘became’, ‘random’, ‘loses’, ‘randomly’, ‘channel’, ‘reconnecting’, ‘restart’]

Table A2. Word groups related to product features.

Product Feature	Group of Words
Sound	['sound', 'sound quality', 'music', 'songs']
Battery	['battery', 'battery life', 'batteries']
Ear Fit	['fit', 'fits', 'ear']
Case	['case']
Charging	['charging', 'recharge']
Noise Cancellation	['cancellation', 'cancelling']
Waterproof	['waterproof', 'water, 'proof']
Connection	['connection', 'connecting', 'sync', 'pairing', 'connectivity']
Phone Call	['voice', 'mic']
Equalizer	['eq', 'equalizer']

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