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Customer Satisfaction Model Based On Online Reviews

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Abstract. This paper explores the aspects of consumer interest in healthcare wearable devices and their influence on satisfaction, motivating businesses to enhance their offerings. The LDA model was used to identify customer happiness aspects and then integrated with machine learning methods to build a satisfaction model using 11,349 online review data from the well-known shopping website Amazon as a data set. By focusing on 13 product dimensions with seven integrated attributes, such as quality, service, functionality, usefulness, social, value, and ease of use, the satisfaction model built with the Multi-Layer Perceptron (MLP) has the best performance in predicting customer attention to products (F1 0.6534). While social, quality, and service attributes harm customer satisfaction and should be a priority for merchants for quality control and service enhancement, functionality is the most crucial product feature for customer groups. In the future, we will take incidents of false and malicious reviews into account while analyzing as we did not take into account the authenticity of the reviews. To provide organizations with deep management insights, this document collects the dimensions of customer attention to products, the features of satisfaction impact, and the objectives for improvement.

Keywords: Customer Satisfaction, Online Reviews, Healthcare Device, Topic Modeling, Machine Learning, Multi-Layer Perceptron.

1. Introduction

Customers like health monitoring wearable items because they can track the wearer's heart rate, sleep, and other physiological data and offer health recommendations as they become more conscious of their health status [1,2]. According to studies, the market for wearable health monitoring devices will expand quickly, with an average annual growth rate of 24.7% before 2026 [3]. Despite this expanding market, however, research by researchers on wearable health monitoring devices has largely concentrated on the factors that influence users' desire to use them [4,5] rather than raising significant issues about the needs and satisfaction of consumers with these goods.

We all know that the development of mobile Internet technology has made online shopping a common practice among consumers. A significant amount of unstructured text data is generated in the e-commerce platform as a result of customer groups commenting on the performance and functionality of products in comments. Also, these review data can be used as feedback to show how customers favour specific products and what they tend to buy [6, 7]. Customer reviews can be used to mine and acquire insight into consumption intents, enhance product competitiveness, and boost customer happiness in the context of developing natural language processing technologies. Conversions of purchases made possible. To continuously enhance and improve products and improve comparisons, this paper attempts to identify customer group concerns about products based on online comment text data. It also establishes a product satisfaction model to measure customer preferences, which will help merchants improve their services and marketing strategies to increase the conversion rate of product purchases and give merchants product management inspiration.

2. Related research

2.1. Satisfaction research on health wearable products

How to manage health care in a scientifically based manner has received more attention in recent years. The "National Fitness Plan (2021-2025)" of our nation, for instance, which was published in August 2021, emphasizes the significance of this problem. As a result of technological advancement, smart health wearables are essential for people to monitor their health. Based on the fundamental physical measurements tracked by smart health wearable devices (HWDs, healthcare wearable devices) and personal health objectives, people can create customized fitness plans. In order to motivate product improvement and functional improvement to satisfy customers' increasing health management needs, it is beneficial to comprehend the elements that influence consumer satisfaction with health wearable goods. According to Table 1, survey questionnaires are the primary research method to examine consumer satisfaction with health apparel goods. In the age of big data, using consumer online review data is the preferred option due to its low cost of collection and massive data volume as compared to the high time and financial costs of questionnaire surveys, difficulty in ensuring data reliability, and limited sample data [19,20,32-35]. The study also develops a satisfaction model using consumer online review data to advise priority tactics for enhancing health wearable devices. It also offers advice and research-based new ideas for businesses engaged in product demand gathering and improvement programs.

Table 1: Research status of HWDs

Author (Year)	Data Source Questionnaire	Data Source Online Review	Topic Model	Summarize Customers Focus on Dimensions/Attributes	Prioritized Product Improvement Strategy	Build Satisfaction Degree Model
Wu Jiang (2017)	√			√		√
Wu Jiang (2017)		√	√	√		
Dong (2018)	√			√	√	

Li Shuyun (2019)		√		√	√	
Kim (2021)	√			√		√
Liu (2022)	√			√	√	
Jeng My (2020)	√			√		√
Jeng My (2022)	√			√	√	
This Research		√	√	√	√	√

2.2. Dimensions of customer satisfaction based on online reviews

The consumer's perception of a product's attributes is called customer satisfaction. Internet reviews, which combine review content and ratings, are a significant medium for customers to express their satisfaction with products. Customers frequently base their ratings of items on their perceptions of such features, which are known as customer satisfaction dimensions (CSDs) [16,17]. Researchers' interest in the customer satisfaction influencing elements found in online reviews has increased recently [18–20], and topic modelling of review texts has taken over as the primary tool for analyzing consumer satisfaction dimensions and demand preferences. To find themes in enormous amounts of text data, topic models employ an unsupervised probabilistic model [21]. Both the Probabilistic latent semantic analysis (PLSA) and Latent Dirichlet Allocation (LDA) are often used algorithms in topic modelling and have been effectively employed for a variety of applications, including sentiment analysis [22], consumer behaviour analysis [17], prediction [23], and other activities. According to online reviews, the LDA algorithm is considered more appropriate for analysing product and service improvement [19,20,24,25]. For instance, Wang and Zhang used the LDA model to extract customer preferences from review data to analyse how to enhance products [26]. Ibrahim examined Twitter data using an LDA model and network analysis to determine how to enhance the platform's customer service. [27] Bi and Liu et al. used internet reviews to conduct LDA and IPA analysis to find product and service problems among different customer groups [19,20]. Via online reviews, MOU and Ren employed the LDA approach to better understand their clients' viewpoints and offer solutions for enhancing cross-border export e-commerce [28]. This study employs the LDA approach to extract consumer satisfaction characteristics from online evaluations.

2.3. Customer satisfaction model based on machine learning

Customer satisfaction is a consumer evaluation based on their expectations for a product or service and their actual use of it. It is a subjective psychological state. Customer satisfaction verification is essential for market analysis, client loyalty, and improvements to products and services [29–31]. The typical approach to building a customer satisfaction model is a questionnaire survey method, which involves interviewing clients to gather the quantitative data the model needs. Yet, questionnaire surveys demand a significant time and financial commitment [19,20,32–34]. Moreover, factors like the complexity of the questionnaire design, the respondents' subjective desires, and the sample representativeness frequently have an impact on the quality, reliability, and validity of questionnaire data [19,20,35,36]. Online evaluations that are affordable, simple to collect, and produced willingly by customers are certainly a better option than questionnaire surveys with high collection costs and unstable quality [37–39]. For instance, Tirunillai and Tellis extracted consumer satisfaction dimensions from online reviews using the hidden Dirichlet distribution topic model to offer businesses or retailers ideas for enhancing goods or services [17]. To model customer satisfaction in online reviews and determine the relative significance of each aspect of a good or service, Farhadlo et al. developed a Bayesian method [32]. To determine customer satisfaction in online product reviews, Xiao et al. suggested an econometric model [40]. Because the traditional measurement model must meet the normality assumption and because customer ratings are frequently imbalanced when used as satisfaction measurement indicators in the e-commerce industry, the research findings have theoretically advanced the construction of the satisfaction model, but there are still some limitations. Perhaps a bimodal distribution will probably cause the satisfaction model to depart from reality. In despite of imbalanced samples, data-driven machine learning algorithms perform well. It can more accurately characterise intricate connections, such as the nonlinear connection between independent and dependent variables [19,20].

3. Research framework

Customer satisfaction modeling and online review topic extraction are the two main components of this study. The first half consists of text preprocessing and LDA topic modeling; the second part builds a customer happiness model using a range of machine learning techniques and examines, through text mining, the variables that influence consumer satisfaction with wearable health monitoring technologies.

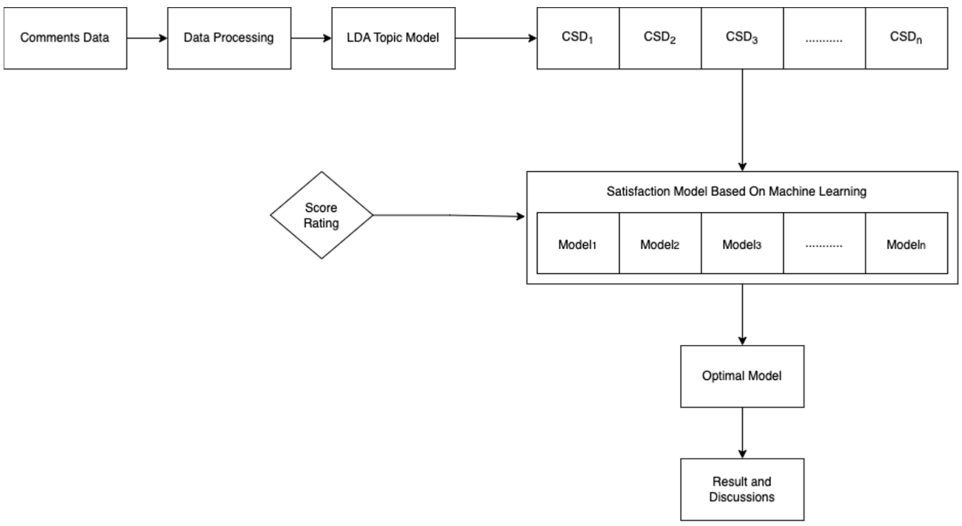

Figure 1: A research framework

3.1. Online review topic extraction

(1) Data Preprocessing

Preprocessing data is a fundamental part of text mining. Online review text data frequently has a lot of noise and useless information, which helps standardize subject modelling afterwards. In order to obtain consistent text data, this study preprocesses the Fitbit brand online review data using NLTK tools. This preprocessing includes eliminating symbols, stop words, special characters, and lowercase word restoration. The first stage in topic modelling is the vectorized expression of the text. Text vectorisation is the process of transforming textual data into numerical feature vectors. This study uses the TF-IDF text vectorization tool from Scikit-learn. Typically, vectorisation is based on word frequency or TF-IDF value. High-frequency words may only be present in a small portion of the review text in a big text corpus, making it impossible for word frequency to reflect a word's significance throughout the full text accurately. The TF-IDF value (Term Frequency-Inverse Document Frequency) includes the inverse text frequency index of terms based on word frequency, which can more accurately measure the significance of individual words throughout the full collection of text data. For mining the themes suggested by reviews, text vectors reflecting semantic importance in terms of TF-IDF values work well.

(2) Online Review Topic Modeling

In this study, possible topics are extracted from review text data using Latent Dirichlet Allocation (LDA), and topics are defined as aspects of customer satisfaction. In order to extract customer satisfaction aspects from online reviews, this paper uses the LDA topic model. Determining the ideal number of topics and the naming of topics is especially essential when utilizing topic models to extract customer satisfaction characteristics from review texts. This study used the grid search approach, using the consistency score, elbow rule, and Occam shaving to determine the ideal number of topics. The customer satisfaction dimension (hence referred to as CSD) is obtained by topic integration, and Knife is used to estimate the ideal number of topics in the topic model.

3.2. Customer satisfaction modelling

With ratings, customers express their measure of satisfaction with a product, and the reviews' content represents the elements that influence those ratings [16,19,20,25,27,33]. The model's output feature $y \in \{1,2,3,4,5\}$ is established using the division of Amazon's product rating scale into 1 to 5 stars. Traditional statistical models based on the assumption of normality are not applicable because product ratings in e-commerce scenarios frequently have a J-shaped distribution rather than a Gaussian distribution, whereas machine learning models have good learning ability for non-normally distributed data and excellent predictive performance. This research trains various classification satisfaction models using the "review-topic" probability distribution matrix $P(CSD \parallel Reviews)$ y as the output feature. Cross-validate various classifiers using the training set and assess the F1 score and accuracy. The optimal model to investigate the relationship between numerous customer satisfaction dimensions and customer satisfaction, as well as to generate useful ideas for product improvement, is produced by comparing the prediction impacts of various models.

4. Empirical research

4.1. Data description

With a total of 11,450 samples, we collected the online review information for two Fitbit devices from the official Amazon website using the Instant Data Scraper Extension. After data preprocessing, 11,349 samples have been collected. Customers IDs, Product IDs, Review IDs, Ratings, Review Titles, Review Bodies and Review Dates are among the dataset fields. Figure 2 shows a J-shaped distribution for product ratings, where the majority of reviews have a rating of five stars. The product has generally positive customer satisfaction ratings, but there are still a lot of unfavorable reviews, showing that there is still scope for improvement.

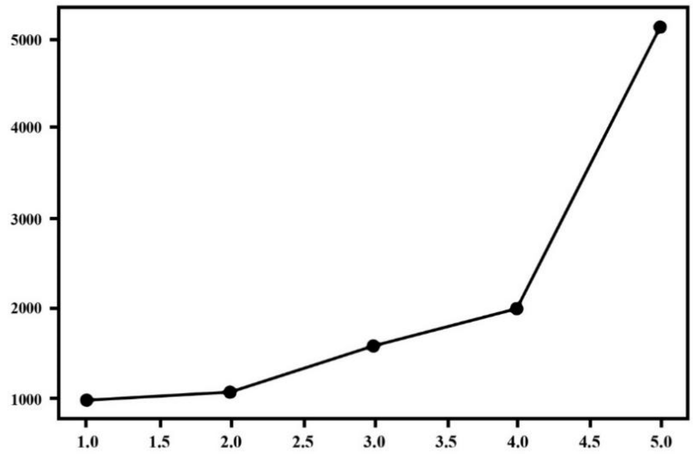

Figure 2: Distribution of customer ratings

4.2. Extract customer satisfaction dimensions

(1) Determining the optimal number of topics

Determining the number of topics k is crucial when using a topic model to extract dimensions from customer review texts. Absolutely, we must consider the topic model's readability and determine the best topic model in order to determine the ideal number of topics K*. Coherence of topics is a crucial metric for assessing the success of model-based topic extraction. Determine the ideal number of subjects K* by using the grid search method, spanning k across a wide range and combining the elbow rule and Occam's razor concept in accordance with the Coherence value. In this study, 200 LDA topic models are trained within a $k \in [1200]$ grid search and the candidate models coherence values are recorded (Figure 3). The elbow rule and Occam's razor state that the Coherence curve flattens at $k \in [98, 130]$ when the elbow rule is satisfied. The ideal number of subjects is 98 since, in theory, the model with the lowest level of complexity should be chosen when the model effects are the same.

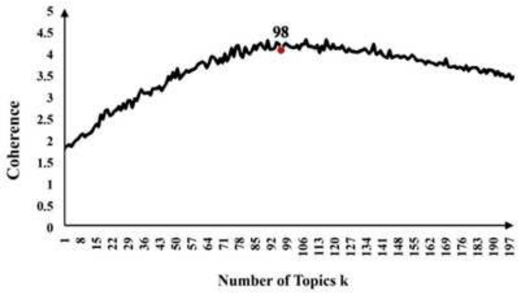

Figure 3: Coherence values for different topic models

(2) Extract customer satisfaction dimensions

We identified and defined the LDA extraction results using existing literature information and then summarized 98 subjects into 13 CSDs, including "step tracking", "logistics distribution", "ease of use", and "social attributes", "reminder function", "strap buckle", "price", "after-sales service", "endurance", "size", "sleep tracking", "heart rate tracking", and "utility". Table 2 presents each CSD, its top 10 most crucial keywords, and the pertinent details of the references that each CSD defines. Table 1 demonstrates that the CSD retrieved in this study is compatible with the findings of previous research on other brands and methodologies, demonstrating the applicability of the findings.

Table 2: Inductive CSD topic modeling

CSD	Key Words	References	Research Brand
Step Tracking	step, count, time, work, sleep, stair, walk, accurate, take, track	Wu Jiang, Zhou Lusha and others [8] (2017); Wu Jiang, Li Shanshan and others [9] (2017); Jeng M Y [14] (2022)	Huawei, Xiaomi, Fitbit
Delivery Service	delivery, family, complaint, rash, satisfied, push, fantastic, accountable, deliver	Wu Jiang, Zhou Lusha and others [8] (2017); Wu Jiang, Zhou Lusha and others [8] (2017); Wu Jiang, Li Shanshan and others [9] (2017);	Huawei, Xiaomi, Fitbit
Ease of Use	exactly, easy, expect, work, arrive, motivator, fast, good, phone, thank	Kim [12] (2021); Dong [10] (2018); Jeng M Y [14, 15] (2020, 2022)	Huawei, Xiaomi, Fitbit
Social Attributes	gift, daughter, birthday, purchase, present, instruction, receive, friend, happy, time	Wu Jiang, Li Shanshan and others [9] (2017); Kim [12] (2021)	Not Mentioned

Reminder Function	sleep, alarm, step, track, walk, night, wake, many, time, work	Wu Jiang, Zhou Lusha and others [8] (2017);	Huawei, Xiaomi, Fitbit
Strap Buckle	fall, band, clasp, lose, come, secure, apart, motivational, design, worth	Wu Jiang, Zhou Lusha and others [8] (2017); Kim [12] (2021)	Huawei, Xiaomi, Fitbit
Price	lose, money, pound, want, spend, waste, extra, since, shape, change	Wu Jiang, Zhou Lusha and others [8] (2017); Wu Jiang, Li Shanshan and others [9] (2017); Jeng M Y [14] (2022)	Huawei, Xiaomi, Fitbit, Honor
After Sales Service	band, month, fall, work, replacement, customer, replace, time, break, come	Wu Jiang, Zhou Lusha and others [8] (2017); Wu Jiang, Li Shanshan and others [9] (2017); Jeng M Y [14] (2022)	Huawei, Xiaomi, Fitbit, Honor
Battery Life	work, battery, month, stop, last, week, long, return, hold, life	Li Shuyun [11] (2019); Dong [10] (2018); Jeng M Y [15] (2020)	Huawei, Xiaomi, Fitbit
Size	small, large, wrist, size, band, wish, water, flex, waterproof, wear	Wu Jiang, Zhou Lusha and others [8] (2017);	Huawei, Xiaomi, Fitbit
Sleep Tracking	track, help, sleep, activity, calorie, step, exercise, weight, daily, food	Wu Jiang, Zhou Lusha and others [8] (2017); Kim [12] (2021)	Huawei, Xiaomi, Fitbit
Heart Rate Tracking	heart, rate, monitor, accurate, step, track, work, wear, seem	Wu Jiang, Zhou Lusha and others [8] (2017); Wu Jiang, Li Shanshan and others [9] (2017); Jeng M Y [14] (2022)	Huawei, Xiaomi, Fitbit
Utility	everyday, motivate, move, challenge, wear, goal, work, step, friend, enjoy	Wu Jiang, Zhou Lusha and others [8] (2017); Wu Jiang, Li Shanshan and others [9] (2017); Jeng M Y [14] (2022)	Huawei, Xiaomi, Fitbit, Honor

Let C be the set of all CSDs, R the set of all comments, $j \in C$, $i \in R$, $P_j^{(i)}$ be the probability of the i^{th} online comment about the j^{th} CSD obtained by the LDA topic j model. In order to measure the weight W_j of each CSD in all online reviews, we first calculate the normalized denominator W.

$$W = \sum_{j \in C} \sum_{i \in R} P_j^{(i)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. (01)$$

Thus, the calculation formula of W_j is obtained as:

$$W_j = \frac{\sum_{i \in R} P_j{}^{(i)}}{W} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \quad (02)$$

After calculation, the weight W_j of each CSD is presented in Table 3.

This study summarizes seven comprehensive features, including functional attributes, service attributes, quality attributes, and value attributes, ease of use attributes, social attributes, and utility attributes, in accordance with how CSD is defined. Product functions, which are a feature that users care about a lot, are what make products competitive and are the main factor influencing user utility. In order to meet user's needs for self-health management and be effective in helping them achieve their health goals and improve their lives, wearable health monitoring devices must have specific functional characteristics, such as "heart rate tracking" and "step tracking." The capacity of a product to help a consumer reach their health goals is known as a utility attribute. Effectivity basically relates to how well a product does its job. Whether the product can successfully help the user to fulfill the health goal or challenge that is specific to them and that they have established. Customers can immediately experience service qualities, which have an impact on their consumption behavior. The most talked-about ones among user groups are the product delivery service and the after-sales service. A product's suitability and longevity are indicated by its quality attributes. Customers pay more attention to the quality attributes that relate to the battery life, bracelet size, and buckle stability among these. The product's capacity to satisfy customers' social needs represents its social attribute. The value attribute, which is also known as cost performance and is a comparison of performance and price, is how the client evaluates how strongly a product's value and price match. How simple it is for clients to utilize the product is the ease-of-use attribute. Product design puts a strong emphasis on how users can quickly acquire the skills needed to use a product, which has a significant impact on customer satisfaction.

Table 3: Overview of combined characteristics

Comprehensive Attribute	**CSD**	$\boldsymbol{W_j}$
Functional Properties	Step Tracking	0.1084
	Sleep Tracking	0.0737
	Heart Rate Tracking	0.1808
	Reminder Function	0.0676
Service Attribute	Delivery Service	0.0359
	After Sales Service	0.1108
	Battery Life	0.0769
Quality Attribute	Size	0.0665
	Strap Buckle	0.0481
Social Attributes	Social Attributes	0.0426
Ease of Use	Ease of Use	0.0545
Value Attribute	Price	0.0374
Utility attribute	Utility	0.0966

(3) Classify customer concerns

The CSDs concerned by consumer groups are classified into three degrees of attention based on the weight W_j of each CSD (Figure 4). The first level includes "heart rate monitoring," "after sales service," "step tracking," and "utility"; the second level includes "life," "sleep tracking," "reminder function," and "size"; and the third level includes "ease of use," "strap Buckle," "social attribute," "price," and "delivery service".

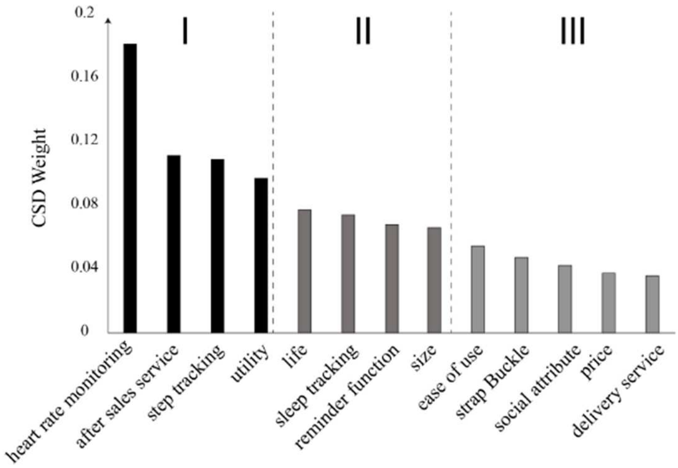

Figure 4: CSD weight distribution

Using Table 3 and Figure 4, we can obtain a ranking of the importance of various attributes (Table-04), which reads as follows: functional attribute > service attribute > utility attribute > quality attribute > ease of use attribute > social attribute > value attribute.

Table 4: Combined attributes in order of concern

Comprehensive Attribute	CSD Concern Hierarchy	Sort by Attention
Functional Properties	I, II	1
Service Attribute	I, III	2
Utility Attribute	I	3
Quality Attribute	II, III	4
Ease of Use	III	5
Social Attributes	III	6
Value Attribute	III	7

4) Customer satisfaction model based on machine learning

In this study, the 11349 sample CSD data set is divided into a training set (9079) and test set (2270) in an 8:2 ratio, and a customer satisfaction model is built using unordered multi-categorical dependent variable logistic regression (MNLogit), Bayesian Ridge regression, Support vector machine (SVM), gradient boosting tree (AdaBoost), and multi-layer perceptron (MLP). According to a comparative study (Table 5), MLP has the best influence on prediction; hence this model is chosen to explain the connection between input features and output features.

Table 5: Model prediction performance

Model	Training set	Test Set	
	Accuracy (Cross-Validation)	Accuracy	F1 Value
MNLogit	0.5148	0.5053	0.2276
Bayesian Ridge	0.2903	0.3216	0.2457
SVM	0.4987	0.5127	0.2225
DT	0.3862	0.3903	0.2756
AdaBoost	0.5050	0.5015	0.2901
MLP	0.7406	0.7386	0.6534

The influence weight of the model CSD in the multi-layer neural network known as MLP is defined as

$$W_j{}^y = \frac{\partial f_{mlp}}{\partial X}$$

Table 6 shows the weight of CSD_j about y_i $W_j{}^y$ for each element.

Table 6: Feature weights based on the MLP customer satisfaction model

Y	1	2	3	4	5
CSD	**Dissatisfied**	**Less Satisfied**	**Generally**	**Satisfied**	**Contentment**
Step Tracking	0.15380	1.4750	5.5943	17.0361	29.0240
Delivery Service	8.7646	3.2744	1.1306	2.3479	8.1153
Ease of Use	-31.9442	-7.9413	11.5810	39.3124	51.7736
Social Attributes	24.2895	7.9393	-1.3304	-7.1017	-0.6365
Reminder Function	-23.5167	-4.0587	15.5553	50.3719	74.5349
Strap Buckle	16.4689	4.4297	-4.651	-16.2446	-19.855
Price	-2.2343	1.3804	8.4228	25.9584	43.0629
After Sales Service	20.7896	5.5294	-6.1171	-21.2559	-26.3381
Endurance	7.2673	2.4435	-0.1307	-1.3099	1.1944
Size	-5.6066	-0.6482	4.9648	15.8392	24.2788
Sleep Tracking	-64.2790	-6.5043	21.2407	72.8164	93.4924
Heart Rate Tracking	-17.5446	-4.0646	7.5286	25.1522	34.4868
Utility	-14.5386	-3.3859	6.1721	20.6399	28.2333

When $y \in [1,3]$, $W_j{}^y$ represents the impact of CSD on negative evaluation, when $y \in [3,5]$ $W_j{}^y$ ability CSD Therefore, e is used to measure the overall effect of each CSD on customer satisfaction, where:

$$e = \sum\nolimits_{y\in[3,5]} W_j{}^y - \sum\nolimits_{y\in[1,3]} W_j{}^y \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(03)$$

When CSD satisfies requirement I, it implies that CSD has a positive impact on customer satisfaction; when CSD satisfies condition II, it means that CSD has a negative impact on customer satisfaction from the perspective of product enhancement and service improvement (Table 7). Utilize symbols to represent the relationship between CSD and satisfaction; for example, "+" represents an increase in customer satisfaction and "-" to represent a decrease in customer satisfaction.

Table 7: Conditions for analysis of factors influencing customer satisfaction

Condition	Description	Symbol
I	When e > 0, Indicating that CSD_j improves customer satisfaction	+
II	When e < 0, Indicating that CSD_j occupy customer satisfaction	-

Table 8 shows that social qualities, strap buckle, battery life, after-sales service, step tracking, and delivery are all important. Providing these six CSDs satisfies condition I. CSDs satisfying condition II have ease of use, reminder function, price, size, sleep tracking, heart rate tracking, and utility. Social attributes, strap buckle, battery life, after-sales service, step tracking, and delivery service are CSDs that have a negative impact on customer satisfaction. Ease of use, reminder function, price, size, sleep tracking, heart rate tracking, and performance use are CSDs that have a positive impact on customer satisfaction. According to comprehensive attributes, utility, ease of use, and value are the next three most important factors in increasing customer satisfaction after the functional feature. Customer satisfaction is most influenced by the service attribute, followed by the product quality and social attributes. This research suggests a comprehensive attribute attention based on CSD weights in comparison to the existing research. The relationship between CSD and satisfaction is also determined in this research by combining Table 7 with a neural network-based customer satisfaction model. The research conclusions of this paper are generally consistent with previous research conclusions based on questionnaire surveys for attributes with high attention (functional attributes, service attributes, utility attributes, and quality attributes), but there are differences for attributes with low attention (such as Ease of use attributes, social attributes, price, etc.).

Table 8: Analysis of factors influencing customer satisfaction based on comprehensive attribute perspective

Comprehensive Attribute	CSD	Comprehensive Attribute Attention	CSD and Satisfaction Relationship		
			This Research	Existing Research Outcome	Research Source
Functional Properties	Sleep Tracking	1	+	+	Wu Jiang, Zhou Lusha and others [8] (2017)
	Reminder Function	1	+	+	Wu Jiang, Zhou Lusha

					and others [8] (2017)
	Heart Rate Tracking	1	+	+	Wu Jiang, Zhou Lusha and others [8] (2017)
	Step Tracking	1	+	+	Wu Jiang, Zhou Lusha and others [8] (2017)
Service Attribute	Delivery Service	2	-	-	Li Shuyun [11] (2019)
	After Sales Service	2	-	-	Li Shuyun [11] (2019)
Utility Attribute	Utility	3	+	++	Wu Jiang, Zhou Lusha and others [8] (2017) Dong-SupYoum [10] (2018)
Quality Attribute	Size	4	+	-	Li Shuyun [11] (2019)
	Strap Buckle	4	-	-	Li Shuyun [11] (2019)
	Battery Life	4	-	-	Li Shuyun [11] (2019)
Ease of Use	Ease of Use	5	+	+--+	Dong-SupYoum [10] (2018) Wu Jiang, Li Shanshan and others [9] (2017) Kim [12] (2021) M Y [14] (2022)
Social Attributes	Social Attributes	6	-	+-	Wu Jiang, Zhou Lusha and others [8] (2017) Wu Jiang, Li Shanshan and

					others [9] (2017) Kim [12] (2021)
Value Attribute	Price	7	+	+-	Li Shuyun [11] (2019) M Y [14] (2022)

5. Conclusions

This research examined the customer group's attention dimension for electronic health monitoring products using the LDA topic model and many machine learning algorithms based on the text review data. It also develops a model of customer satisfaction. Customers prioritize battery life, after-sales service, heart rate tracking, step tracking, usability, delivery service, social qualities, pricing, size, strap clasp, and ease of use when buying electronic health monitoring goods, according to the research. The seven comprehensive attributes of functional attributes, service attributes, quality attributes, value attributes, ease of use attributes, social attributes, and utility attributes are used to summarize the 13 dimensions of customer satisfaction, including sleep tracking and reminder functions. Also, different customer groups have various priorities and concerns for the 13 dimensions. Also, different customer groups have various priorities and concerns for the 13 dimensions. In the ranking of attention weights, the work Performance attribute> service attribute> utility attribute> quality attribute> ease of use attribute> social attribute> value attribute. According to comprehensive attributes, utility, ease of use, and value are the next three most important factors in ensuring customer satisfaction after the functional attribute. Customers are more interested with features and functions when buying electronic health monitoring goods, and these features also make a product competitive. Because of this, as retailers update and iterate their products, they should prioritize the progressive upgrade of functionalities, particularly the heart-rate monitoring and step-counting functions. Function, wake-up function, and sleep monitoring function adaptive upgrades. The second comprehensive attribute that the customer group takes into consideration is the service attribute. In the pre-sales and after-sales operations, it specifically refers to the consulting service for customer service and the product delivery service. Furthermore, retailers may enhance customer satisfaction and improve purchase conversion rates by enhancing post-sale support and accelerating logistical delivery. The attribute that customers are satisfied with is value. The cost performance, or value attribute, evaluates how closely a product's value and price align in the eyes of the client. Customers believe the product to be cost-effective, proving that retailers do not need to focus too much on product optimization. Cost performance is not the most important factor as long as the functionalities can satisfy customer expectations, demonstrating that retailers can go above and beyond when it comes to their electronic health monitoring product research and development. Recognize and accept the product's added value.

This research extends on previous work on consumers' satisfaction with wearable healthcare technology. The majority of the previous research on the usage of health wearables relies on questionnaire surveys to gather data and draw conclusions, but this research finds results that are supported by review data mining, demonstrating the value of using review data to investigate consumer satisfaction. The viability of the variables and the relevance of the findings. In addition, this paper builds a customer satisfaction model based on neural networks to explore the relationship between CSD and satisfaction. These efforts aim to understand the product attributes that user groups focus on and how they affect satisfaction, as well as to provide enterprises with a primary and secondary order. Strategy for product improvement.

Finally, service attributes, quality attributes, and social attributes are the top areas where manufacturers should focus to optimize their products and services because they can have a negative impact on consumer satisfaction. This research may have certain limitations due to the diversity of the customer groups. The results based on LDA topic modelling, for example, may be impacted by false reviews or intentionally negative reviews created by customer groups due to brand loyalty. To increase the effectiveness of review data for business service development and product optimization, it can be considered to include customer demographic factors as a component of the research and classification of customer group review behaviour characteristics.

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