International Journal of Economics, Business and Accounting Research (IJEBAR)
Peer Reviewed – International Journal
Vol-8, Issue-2, 2024 (IJEBAR)
E-ISSN: 2614-1280 P-ISSN 2622-4771
https://jurnal.stie-aas.ac.id/index.php/IJEBAR

CONSUMER DECISION MODEL – ENGEL KOLLAT AND BLACKWEL: WEARABLE TECHNOLOGY -SMARTWATCH CONSUMER BEHAVIOR POST COVID-19 PANDEMIC IN SURABAYA

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Abstract: This research uses quantitative methods using an exploratory factor analysis approach. This research explores the factors that influence consumers' decisions in choosing a smartwatch as a wearable technology that helps monitor health. This research was conducted in Surabaya, East Java and involved 120 respondents to describe data regarding the reasons for choosing a smartwatch as wearable technology that helps monitor health. From the results of the analysis, it was found that seven factors shape the choice of the smartwatch as a health monitoring tool, including social factors, motivational factors, reference factors, cultural factors, service factors, individual factors, and psychological factors.

Keywords: *Smartwatch, Consumer Health, Exploratory Factor Analysis, Consumer Decision Model.*

Submitted: 2024-05-08; Revised: 2024-06-12; Accepted: 2024-06-16

1. Introduction

In the increasingly advanced digital era, wearable technology, including smartwatches, has become a significant trend in the technology industry (Xintarakou, Sousonis, Asvestas, Vardas, & Tzeis, 2022); wearable technology allows a person to carry out health monitoring and diagnosis via blood pressure (Konstantinidis et al., 2022).

In early December 2019, the world was faced with the Coronavirus Disease 2019 (COVID-19) pandemic (Choma, Hodson, Sumantry, Hanoch, & Gummerum, 2021), which hit almost all countries. The spread of COVID-19 also attacked Indonesia in early 2020 (Fadli, 2023). This pandemic has also changed the landscape of consumer behavior drastically and influenced consumer preferences and decisions regarding the use of smartwatches with the aim of obtaining information about health (Hunter et al., 2022) because awareness of the importance of monitoring health and living a good lifestyle is very supportive for surviving the situation. which is not good (Saah, Amu, Seidu, & Bain, 2021).

Indonesia, as a country with a large and growing population, provides an attractive market share for wearable technology, including smartwatches. Digital consumers in Indonesia are ranked number 1 in ASEAN, with 153 million people in 2021, then increasing by 9.09% in 2022 to 168 million people (Rizaty, 2022).

One of the phenomena that cause anxiety regarding choice in wearable technology-smartwatch consumer behavior is the existence of various choices, product variations, and functions available on the market (Basha, Aw, & Chuah, 2022; Chuah et al., 2016; Page, 2015).

This can cause confusion and failure in choosing the right product according to consumer needs and preferences.

Research (Indahingwati et al., 2019), which refers to consumer preference theory, found that screen display, battery life, and integration with smartphones are the main factors that influence consumer preferences when choosing a smartwatch. Battery life and compatibility with other devices are important considerations.

Research conducted by Dehghani, Kim, and Dangelico (2018) shows that brands have a significant role in consumer decision-making for smartwatches. Brands that are known and trusted tend to be more popular even at higher prices.

Through this research, it is hoped that in-depth insights will be obtained about consumer preferences, motivations, and factors that influence consumer decisions regarding smartwatches after the COVID-19 pandemic in Indonesia. The results of this research can provide an important contribution to practitioners and decision-makers in the wearable technology industry to develop marketing strategies that are more effective and in line with consumer needs.

This research is limited in analyzing consumer behavior regarding wearable technology, especially smartwatches, in Surabaya. Based on the background of the problem described, this research faces several main problems. What factors influence consumers' decisions in choosing a smartwatch as wearable technology that helps monitor health? The specific objective related to this research is to analyze the factors influencing consumer decisions in choosing a smartwatch as a wearable technology that helps monitor health.

2. Literature Review

Wearable Technology

Wearable technology, also known as wearable technology or "wearables," refers to a group of electronic devices designed to be worn on the human body or attached to clothing (J. Lee, Kim, Ryoo, & Shin, 2016). These wearable devices integrate advanced technologies such as sensors, microprocessors, and wireless connectivity and often have intuitive user interfaces. The main goal of wearable technology is to bring functionality closer to the user so that it becomes a comfortable and everyday part of their lifestyle.

One of the most significant potentials for wearable technology lies in the health sector. Wearable devices can monitor health parameters such as heart rate, blood pressure, blood oxygen levels, and physical activity (Luo, 2015). These data can be used for early diagnosis, chronic disease management, and patient monitoring.

Smartwatch

A smartwatch is a type of wearable technology device with a shape similar to a watch but is equipped with advanced technological capabilities and broader features. Smartwatches function as watches and devices connecting users with digital technology, providing notifications, information, and various other features.

Several factors determine consumer behavior regarding smartwatches. Firstly, personal needs and preferences are essential in smartwatch purchasing decisions. Factors such as lifestyle, daily activities, and the smartwatch's purpose will influence the type and features chosen. Also, perceptions about quality, brand, and price influence consumer behavior in choosing a smartwatch. Influences from friends, family, and fashion trends can also play a role in purchasing decisions.

Smartwatches have great potential in the development of the health sector. With integrated sensors, smartwatches can monitor various health parameters such as heart rate, blood pressure, blood oxygen levels, and body temperature. This data can provide users with important information about their health conditions and can be used in chronic disease monitoring or early detection of health problems.

Consumer Decision Model – Engel, Kollat, dan Blackwel

Consumer decision-making models have existed and developed in various forms; this cannot be separated from the development of consumer behavior, which experienced many changes after the Second World War in the 1950s.

Engel, Kollat, and Blackwell's consumer decision model has undergone several changes. Engel's Consumer Decision Making (CDM) was first discovered in 1968 by Engel, Kollat, and Blackwell; Engel updated it in 1995 during its development.

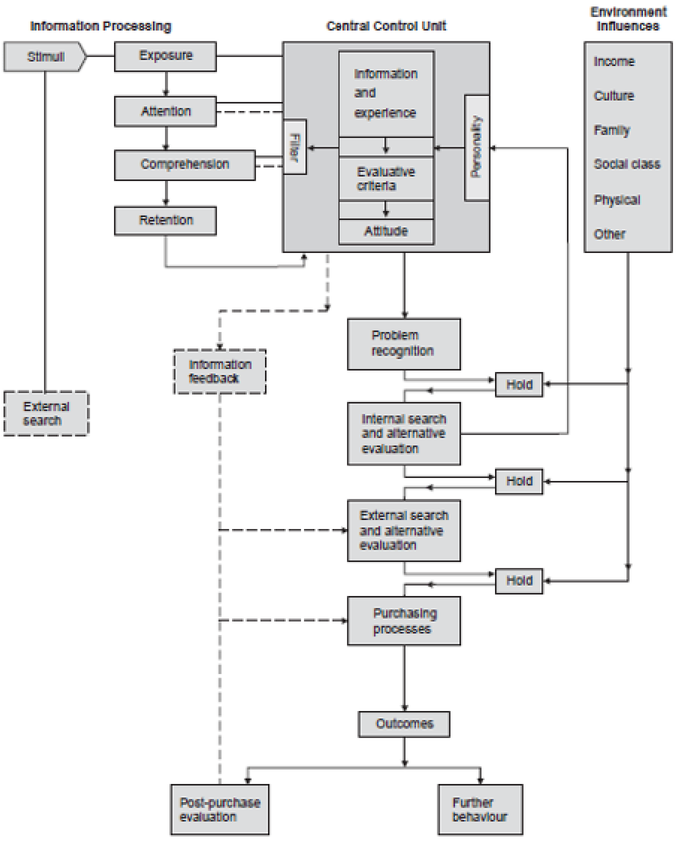

Figure 1. Concept of purchasing behavior, Engel, Kollat, and Blackwell (1962)

The latest model consists of five stages: information input, information processing, decision process stages, decision process variables, and external influences. Information input includes all types of stimuli that consumers are exposed to and develops into specific consumer behaviors that lead to decision-making. At this stage, consumers get information from marketing (advertising, promotions, personal sales, store displays, purchase stimulus points). Non-marketing sources (family, friends, co-workers), which also influence problem recognition stages of decision-making, are stimuli received at the first stage. This provides information that is then processed into meaningful information.

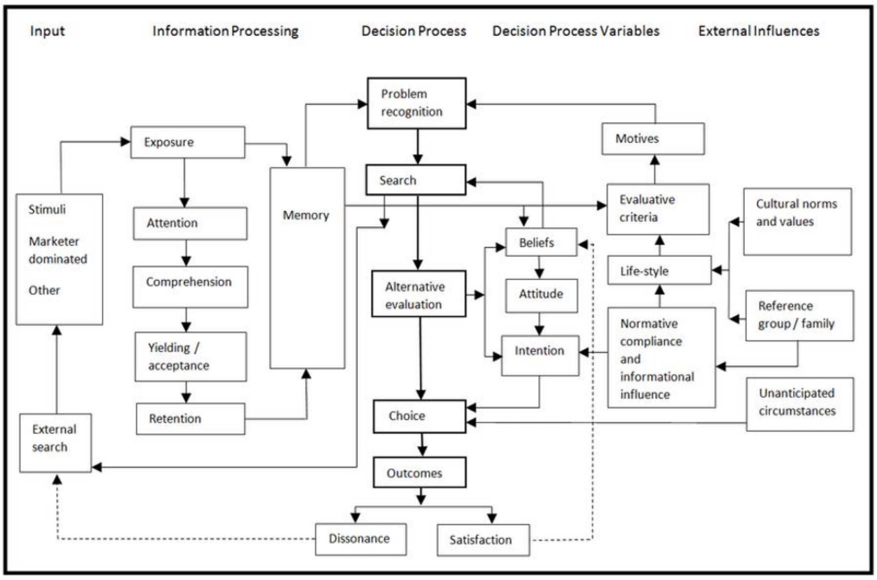

Figure 2. CDM-EKB Framework (1995)

In the 1995 CDM – EKB model, this model focuses on how individuals make decisions regarding a choice. At the input stage, consumers are given a stimulus provided by marketers or other people interested in entering a choice. After input, the stimulus will enter the information processing stage. The stimulus provided will be an exposure for the individual, either briefly or periodically; the exposure will generate attention so that a comprehensive picture is obtained, and if the information becomes more robust, it will enter memory. Memory can be long-term. If a consumer has a problem, the stored memory will appear as a search in long-term memory or other media.

On the other hand, consumers' ability to find problems arises due to external influences such as the culture and preferences of a group. External influences will create actions based on personal motives, lifestyle, norms, and information influence. External influences that become behavior will create beliefs, intentions, and behavior that will make it easier for someone to find the results of their search and determine a choice in their behavior.

3. Research Method

This research uses a quantitative approach with a factor analysis approach that utilizes primary and secondary data for analysis. This research analyzes consumer behavior factors in choosing wearable technology as a health monitoring tool after the COVID-19 pandemic in Surabaya. The data collection method used is non-probability sampling because the size of the population is unknown. The sampling method uses a convenience sampling method, namely selecting samples based on a population that is easily accessible to obtain information.

The population used in this research is wearable technology users in Surabaya; the sampling method in this research uses non-probability sampling, according to Malhotra (Ningsih, 2021), to obtain good results in a factor analysis of the number of respondents taken to fill out the questionnaire is five times the variables contained in the questionnaire. In this study, 24 variables were studied, so the total number of respondents used was 120; the number of respondents was obtained through a formula of five times the number of variables studied.

Primary data was collected through a questionnaire distributed directly to wearable technology-smartwatch users by applying five Likert scales as a measure of responses from respondents. Strongly agree has a weight of 5, agree has a weight of 4, undecided has a weight of 3, disagree weights 2, and strongly disagree weights 1. Meanwhile, secondary data was obtained through books, notes, journals, and literature, used as references in this research.

The validity used in this research is comparing the calculated r-value with the table for the degree of freedom (df)=n-2; in this case, n is the number of samples (Anshori & Iswati, 2019). Reliability Test is a number that shows the consistency of a measuring instrument in measuring the same symptoms (Gunawan, 2018). Three essential aspects of a measuring instrument can be said to have high reliability or can be trusted if the instrument is stable, dependable, and predictable.

Factor analysis is a multivariate statistical technique that reduces and summarizes all dependent and interdependent variables. Exploratory Factor Analysis (EFA) is the method of choice used in this research. Using EFA, the number of factors that will be formed has yet to be determined. Instead, it is sought until it can answer the need to explain the diversity of data from the original variables.

To construct a correlation matrix, several tests are required. Firstly, Bartlett's Test of Sphericity assesses whether the variables in the data are interrelated. Secondly, the Kaiser-Meyer-Olkin (KMO) test evaluates sample adequacy. A KMO value greater than 0.5 indicates that factor analysis is suitable for the data. Finally, the Sampling Adequacy (MSA) test measures the correlation between variables, with an MSA criterion of greater than 0.5 being desirable.

Determine the number of factors by selecting factors with an eigenvalue>1, then rotate the factors to facilitate interpretation in determining variables with a high correlation. Rotation can use orthogonal and oblique rotation.

4. Results and Discussion

4.1. Results

This research trial used a sample size (n) = 20, and the pdf size could be calculated as 20-2 = 18, with df = 18 and Alpha = 0.05, the r table = 0.4438. The question item is declared valid if the r calculated is greater than the r table. Data was obtained from the tryout results, which stated that of the 24 questions, two questions were invalid, namely for cultural indicators and product characteristics.

Table 1. Tryout Results for Validity Test

No	Indicator	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Information
1.	Culture	-.024	.958	Invalid
2.	Sub Culture	.837	.944	Valid
3.	Social class	.704	.945	Valid
4.	Reference Group	.573	.947	Valid
5.	Family	.724	.945	Valid
6.	Social Roles	.650	.946	Valid
7.	Social status	.503	.947	Valid
8.	Age	.717	.945	Valid
9.	Work	.726	.945	Valid
10.	Economic Situation	.481	.948	Valid
11.	Lifestyle	.668	.946	Valid
12.	Personality	.764	.945	Valid
13.	Self-concept	.840	.944	Valid

14.	Motivation	.745	.945	Valid
15.	Perception	.749	.944	Valid
16.	Learning	.848	.943	Valid
17.	Belief	.869	.943	Valid
18.	Attitude	.723	.945	Valid
19.	Brand Name	.830	.943	Valid
20.	Product Features	.806	.944	Valid
21.	Product Design	.841	.944	Valid
22.	Product quality	.828	.944	Valid
23.	Product Appearance	.840	.944	Valid
24.	Product Characteristics	.166	.954	Invalid

Source: Primary data is processed, 2024

The try-out reliability test uses the Cronbach Alpha (α) statistical test via SPSS calculations. According to Nunnally in Ghozali (2005:42), a construct is reliable if it provides a Cronbach Alpha value > 0.60. Table 1 shows that the Cronbach Alpha value is 0.948 > 0.60, which means that the questionnaire construct in this study can be reliable.

Table 2. Tryout Results for Reliability Testing

Cronbach's Alpha	Cronbach's Alpha Based on Standarized Items	N of Items
0.948	0.959	24

Source: Primary data is processed, 2024

After conducting a research tryout to test the validity and reliability of the questionnaire questions, the researcher decided to reuse the invalid question items for the subsequent distribution of the questionnaire to 120 respondents by correcting the question sentences first so that the number of questions remained 24.

The first thing that must be done in factor analysis is to assess which variables are suitable for inclusion in further analysis. Prior to conducting factor analysis, it is essential to assess the suitability of the data matrix. This is achieved by evaluating the level of correlation among variables. Bartlett's Test of Sphericity is employed to test the null hypothesis of no correlation. Additionally, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is utilized, with a value exceeding 0.5 generally indicating data suitability for factor analysis. Similarly, the Measure of Sampling Adequacy (MSA) test assesses the degree of correlation, with a criterion of >0.5 considered desirable. The results of these tests, conducted using SPSS 17 software, are presented in Table 3.

Table 3. KMO and Barlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.819
Barlett's Test of Sphericity	Approx. Chi-Square	1253.697
	Df	276
	Sig.	.000

Source: Primary data is processed, 2024

Table 3 above shows the value obtained from Barlett's test of Sphericity is 1253.697 with a significance of 0.000; this means there is a correlation between variables (significant < 0.05).

The Kaiser-Meyer-Olkin (KMO) test results obtained a value of 0.819, where this figure is already above 0.5. In this way, the variables in this research can be processed further.

The next step is testing the Measure of Sampling Adequacy (MSA), where each variable is analyzed to determine which variables can be processed further and which ones must be excluded. Each variable must have an MSA value > 0.5 to be processed further. The MSA value is found in the Anti-Image Matrice table in the Anti-Image Correlation section. Namely, the correlation number is marked "a" diagonally from the top left to the bottom right. (see attachment). The MSA test results for this research variable are shown in Table 4.

Table 4. MSA Value of Research Variables

No	Indicator	MSA Value	Information
1.	Culture	0.896	Valid
2.	Sub Culture (Religion, Race, Nationality)	0.843	Valid
3.	Social class	0.814	Valid
4.	Reference Group	0.760	Valid
5.	Family	0.857	Valid
6.	Social Roles	0.838	Valid
7.	Social status	0.793	Valid
8.	Age	0.780	Valid
9.	Work	0.750	Valid
10.	Economic Situation	0.755	Valid
11.	Lifestyle	0.875	Valid
12.	Personality	0.815	Valid
13.	Self-concept	0.585	Valid
14.	Motivation	0.794	Valid
15.	Perception	0.869	Valid
16.	Learning	0.749	Valid
17.	Belief	0.848	Valid
18.	Attitude	0.811	Valid
19.	Brand	0.669	Valid
20.	Features	0.756	Valid
21.	Design	0.711	Valid
22.	Quality	0.907	Valid
23.	Appearance	0.822	Valid
24.	Characteristics	0.773	Valid

Source: Primary data is processed, 2024

From table 4 above, it is known that the variables in this study have MSA values > 0.5 so that the variables can be analyzed as a whole further.

In this research, the author determines the number of factors using eigenvalues with the eigenvalue criterion> 1 (Anshori & Iswati, 2019). The eigenvalue arrangement is always ordered from largest to smallest. You can see the total variance explained in the table to determine the number of factors formed from the extraction results.

In table 5, it is known that of the 24 variables entered for factor analysis, there were only seven factors formed because from component 1 to component 7 showed eigen values > 1, the factoring process only reached seven factors, if continued until the next factor the eigenvalues were already less than 1, namely 0.910. So, it is known that seven factors is the most optimal number.

Table 5. Rotated Component Matrix[a]

		Component						
		1	**2**	**3**	**4**	**5**	**6**	**7**
1.	Culture	.134	.460	.131	**.504**	.407	-.096	.087
2.	Sub Culture (Religion, Race, Nationality)	-.025	.237	.442	**.479**	.171	.225	.213
3.	Social class	.275	.021	**.753**	.215	.128	-.026	-.059
4.	Reference Group	.111	.180	**.806**	.029	.078	.099	.105
5.	Family	.344	.387	-.175	**.547**	.123	-.019	.019
6.	Social Roles	**.723**	.178	-.087	.192	.110	.120	-.046
7.	Social status	.139	.067	.212	**.707**	.070	.097	.115
8.	Age	.139	-.157	.090	.365	.294	**.565**	.001
9.	Work	.411	.029	.185	**.501**	-.254	.305	-.332
10.	Economic Situation	**.583**	.056	.076	-.057	-.070	.363	.272
11.	Lifestyle	.162	**.751**	.144	.103	.002	.144	.307
12.	Personality	-.161	.243	.340	-.366	.173	**.440**	-.071
13.	Self-concept	.305	**.640**	.208	.007	.085	.058	-.255
14.	Motivation	.346	**.527**	.427	.043	-.032	.025	.162
15.	Perception	.104	.093	.092	.135	.124	.051	**.809**
16.	Learning	**.647**	.325	.104	.003	.031	.194	.293
17.	Belief	.235	**.750**	.004	.194	.231	.033	.056
18.	Attitude	.137	.051	-.026	.082	.080	**.735**	.133
19.	Brand	-.182	.438	.092	-.035	.218	**.578**	-.183
20.	Features	.251	.105	.143	.086	**.742**	.308	.149
21.	Design	**.694**	.136	.270	.235	.168	-.104	.052
22.	Quality	**.784**	.104	.169	.158	.320	-.150	-.022
23.	Appearance	**.757**	.221	.223	.138	.282	-.007	-.044
24.	Characteristics	.266	.176	.107	.079	**.789**	.176	.041

Extraction Methode: Principal Component Analysis
Rotation Methode: Varimax with Kaiser Normalization
a. Rotation converged in 9 iterations.
Source: Primary data is processed, 2024

The component matrix resulting from the rotation process (rotated component matrix) shown in Table 5 shows a more precise and realistic distribution of variables. The complete division of variables based on the factors formed can be seen in Table 6. variables are sorted based on the loading factor value from the largest.

Giving a name to each new factor that is formed is subjective; sometimes, the variable that has the highest factor loading value is used to name the factor (Jati & Juliannisa, 2022).

Table 6. Distribution of Formed Indicators

Indicator	Factors Formed	Eigen Value	Loading Factor	% Variance	% Cumulative
Social Roles (Q6)	Social Factors	7.415	0.723	30.897	30.897
Economic Situation (Q10)			0.583		
Learning (Q16)			0.647		
Design (Q21)			0.694		
Quality (Q22)			0.784		
Appearance (Q23)			0.757		

Indicator	Factors Formed	Eigen Value	Loading Factor	% Variance	% Cumulative
Lifestyle (Q11) Self-concept (Q13) Motivation (Q14) Belief (Q17)	Motivation Factors	2.115	0.751 0.64 0.527 0.75	8.814	39.711
Social class (Q3) Reference Group (Q4)	Reference Factors	1.546	0.753 0.806	6.443	46.153
Culture (Q1) Sub Culture (Religion, Race, Nationality) (Q2) Family (Q5) Social status (Q7) Work (Q9)	Cultural Factors	1.399	.208 .427 .092 .104 .004	5.831	51.984
Features (Q20) Characteristics (Q24)	Service	1.320	0.742 0.789	5.501	57.485
Age (Q8) Personality (Q12) Attitude (Q18) Brand (Q19)	Individual Factors	1.215	0.565 0.44 0.742 0.789	5.064	62.549
Perception (Q15)	Psychological Factors	1.119	0.801	4.661	67.211

Source: Primary data is processed, 2024

This research found seven factors influencing consumers to use post-covid-19 smartwatches as a health monitoring tool. These factors are (a) social factors, (b) motivation factors, (c) reference factors, (d) cultural factors, (e) service factors, (f) individual factors, and (g) psychological factors.

4.2. Discussion

Social Factors

Social factors, such as social roles, economic conditions, learning, design, quality, and appearance, play a significant role in shaping consumer behavior. For instance, a busy professional's social role might drive their preference for time-saving products, while economic conditions could affect their perception of value. Previous studies support these insights, demonstrating that social influence and peer recommendations significantly impact consumer choices in technology adoption (Venkatesh, Thong, & Xu, 2012). Furthermore, the design and quality of smartwatches can enhance user satisfaction and adoption rates, aligning with findings from the technology acceptance model (TAM) which highlights perceived usefulness and ease of use as critical determinants of technology adoption (Ogbanufe & Gerhart, 2018). The EKB model highlights the importance of social influences and external environment factors in the decision-making process, corroborating the impact of social factors on consumer behavior

Motivational Factors

Motivational factors encompass psychological aspects such as lifestyle, self-concept, motivation, beliefs, personality, attitudes, brands, and perceptions. For example, individuals with a strong focus on health and wellness are likely motivated by products that promote a healthy lifestyle, while those who value convenience may prioritize ease of use. Research by S. Lee and Pounders (2019) on self-determination theory emphasizes the importance of intrinsic and extrinsic motivations in consumer behavior, suggesting that products aligning with consumers' intrinsic goals (e.g., health and well-being) are more likely to be adopted and used consistently. The EKB model incorporates psychological influences, such as motivation and beliefs, in its comprehensive approach to understanding consumer decision-making.

Reference Factors

Reference factors include the influence of social class, reference groups, and cultural affiliations. These elements can guide consumer preferences and purchasing decisions. For example, individuals often look to their social groups for cues on acceptable and desirable products, a phenomenon extensively studied in social identity theory (Zeugner-Roth, Žabkar, & Diamantopoulos, 2015). Moreover, cultural norms and values can significantly influence consumer behavior, as evidenced by Hofstede's cultural dimensions theory, which explains how cultural differences impact consumer expectations and behaviors (Sağlam & Abdullah, 2021; Soares, Farhangmehr, & Shoham, 2007). The EKB model acknowledges the role of external influences, including reference groups and social class, in shaping consumer behavior.

Cultural Factors

Cultural factors involve general culture, subcultures (e.g., religion, race, nationality), family influences, social status, and work environment. These factors shape individual behaviors and perceptions. For instance, cultural norms may dictate specific preferences in product features, while religious beliefs could influence dietary choices linked to health monitoring features in smartwatches. Studies have shown that cultural congruence between a product and its target market can enhance product acceptance and satisfaction (Song, Moon, Chen, & Houston, 2018). The EKB model integrates cultural and social influences, highlighting their significance in the consumer decision process.

Service Factors

Service factors relate to the characteristics and quality of service associated with smartwatches, such as customer support, warranty, and after-sales service. High-quality service can significantly enhance customer satisfaction and loyalty, as indicated by the service-profit chain model (Heskett, Jones, Loveman, Sasser, & Schlesinger, 1994; Yee, Yeung, & Cheng, 2011), which links service quality to customer satisfaction and business profitability. Effective service features can differentiate a product in a competitive market, leading to higher consumer retention rates. The EKB model's emphasis on post-purchase behavior and satisfaction aligns with the importance of service factors in influencing consumer behavior.

Individual Factors

Individual factors include age, personality, and specific psychological characteristics. These factors provide a more granular understanding of consumer behavior. For example, younger consumers might be more tech-savvy and open to adopting new technologies, while older consumers might prioritize ease of use and reliability. Personality traits, as outlined in the Big Five personality traits model (Loehlin, McCrae, Costa Jr, & John, 1998), can also predict technology adoption behaviors, with traits like openness to experience being positively correlated with early adoption of new technologies. The EKB model accounts for individual differences in its analysis of consumer behavior, emphasizing the role of personal characteristics in the decision-making process

Psychological Factors

Psychological factors, such as perception, motivation, beliefs, and attitudes, play a crucial role in shaping consumer behavior. The health belief model (HBM) provides a framework for understanding how individual beliefs about health risks and benefits influence behavior (Champion & Skinner, 2008). Consumers who perceive a high risk of health issues and recognize the benefits of health monitoring are more likely to adopt smartwatches for health purposes. Attitudes towards technology, shaped by past experiences and knowledge, also significantly influence adoption decisions (W. K. Lee & Shin, 2023). The EKB model's inclusion of psychological influences aligns with the understanding that perceptions and attitudes are critical in consumer decision-making

5. Conclusion

Through factor analysis, seven factors can be obtained that have the most dominant influence on the decision to use a smartwatch after the COVID-19 pandemic to monitor health; these factors are social factors, including role, economic situation, learning, design, quality, and appearance. Motivational factors include lifestyle, self-concept, motivation, and beliefs. Reference factors consist of social class and reference groups. Cultural factors include culture, sub-culture (religion, race, nationality), family influence, social status, and work. Service factors consist of features and characteristics. Individual factors include age, personality, attitude, and brand. psychological factors consist of perception.

After this, the follow-up plan is to conduct qualitative research to gain deeper insight into user perceptions, experiences, and preferences regarding using smartwatches for post-pandemic health monitoring. In-depth interviews or focus group discussions can be helpful methods.

After the qualitative stage, the researcher will validate the instrument and conduct research using confirmatory factor analysis techniques. This research has great potential to be developed because the world of digital health is developing rapidly, so there are opportunities to continue exploring this topic.

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