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Identification of Herzberg's Motivators and Hygiene Factors for Mobile Shopping Service System based on Topic Modeling of User Reviews

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Abstract. Many previous studies focusing on quality factors affecting the user satisfaction of mobile shopping apps were based on Davis's Technology Acceptance Model, and recently, there have been more studies using user reviews of mobile shopping apps to efficiently collect various opinions. However, there is an increasing question whether the Technology Acceptance Model should include quality factors specialized in mobile shopping apps, and studies using user reviews also requiring user surveys or sentiment dictionaries for sentiment analysis. This study presents a framework for identifying satisfaction and dissatisfaction factors for customers using mobile apps for online shopping through a topic analysis of user review and a discrimination analysis of the rating distribution of user review, apart from solely relying on surveys or separate sentiment dictionaries. This study fundamentally differs from previous studies in that it takes a more efficient approach through semi-automating the quality factor identification process using a topic analysis algorithm, and utilizing only the rating distribution to determine Herzberg's motivators and hygiene factors without relying on user surveys or sentiment dictionaries. It is expected that the framework discussed in this study can be applied to efficiently derive user satisfaction and dissatisfaction factors in various fields including mobile shopping apps.

Keywords: Mobile shopping app, user reviews, text mining, topic modeling, herzberg's two-factor theory, motivator, hygiene factor

1. Introduction

The online shopping market space is experiencing significant growth, powered by the wide availability of mobile devices and the mobile ecosystem. Ongoing research and development efforts are taking place, as a result, around mobile shopping and e-commerce apps. The majority of existing studies on mobile shopping apps analyze the effects of related quality factors on customer satisfaction and customer loyalty based on the Technology Acceptance Model (TAM) and the Expanded Technology Acceptance Model (ETAM) (Natarajan, Thamaraiselvan, Senthil A. B. and Dharun L. K., 2017), (Sohn, S., 2017). In recent periods, studies leveraging user reviews of mobile shopping apps have been taking place, as the use of big data has expanded.

User review is an opportunity for users who purchase a specific service or product to post their end-to-end experience typically on an online forum in the form of comments. This serves as an important source of information for potential purchasers as well as the providers of products and services. Recent studies in the e-commerce, healthcare, and tourism sectors have utilized user review data to address inadequacies including restrictions on data collection, subjective responses, and costs in the existing expert group interviews or survey methods, and to collect various opinions more efficiently (Xu Gang, 2020) (Park, H. J., Lee, D. H. and Kim, K. O., 2021).

Previous studies using user reviews in mobile shopping apps have identified keywords corresponding to quality factors through content analysis (Kim, Y. H., Kim, J. H., Park, J. H. and Lee, S. J., 2016), and conducted regression analysis on customer satisfaction and topics corresponding to quality factors through topic modeling (Lee, B. G. and Son, C. H., 2020), (Kim, K. K., Kim. Y. H. and Kim, J. H., 2018), and discriminate users' positive or negative opinions through sentiment analysis (Chae, S. H., Lim, J. I. and Kang, J. Y., 2015).

This study proposes a methodology for extracting key quality factors of mobile shopping apps from their user reviews through topic modeling and identifying Herzberg’s motivators and hygiene factors by analyzing the distribution of review ratings.

This study distinguishes itself from previous studies in that it takes a more efficient approach through semi-automating the quality factor identification process specialized for mobile shopping apps using a topic analysis algorithm, and utilizing only the rating distribution to determine Herzberg’s motivators and hygiene factors without relying on surveys or sentiment dictionaries.

The structure of this paper is as follows. Section 2 analyzes previous studies on quality factors of mobile shopping apps, and explains topic modeling techniques and Herzberg's Two-Factor Theory. Section 3 presents research procedures and research methods through the research framework, and section 4 elucidates the research contents and analyzes the results. Finally, section 5 interprets the results of this study and presents the significance and limitations of the study.

2. Related research

2.1. Quality factors of mobile shopping apps

Mobile shopping refers to an experience in which purchases are made through mobile devices using an online platform or a mobile app. According to the "Online Shopping Trends" of the National Statistical Office of the Republic of Korea, online shopping transactions in December 2020 alone amounted to KRW 16.0 trillion, an increase of 26.1% from the year-ago period. Moreover, mobile shopping transactions amounted to KRW 11.1 trillion, a 33.8% increase from the year-ago period. The proportion of mobile shopping among online shopping increased to 70% from 66% in the year-ago period, signifying a growing importance of mobile as a transacting platform (http://kostat.go.kr/, 2021).

The mobile shopping app serves as a key platform that encompasses a series of processes from product search to purchase and payment. Various research and developments efforts are being conducted by providers to evolve the efficacy of the app and provide a better experience to the users.

Many previous studies that focused on quality factors affecting user satisfaction of mobile shopping apps were based on Davis's (Davis, F. D., 1989) Technology Acceptance Model (TAM), widely used as a tool to explain and predict technology acceptance behavior, or used various quality factors suitable for mobile shopping characteristics by referring to surveys or previous studies.

Natarajan et al. (Natarajan, Thamaraiselvan, Senthil A. B. and Dharun L. K., 2017) analyzed factors affecting customer satisfaction and customer loyalty by adding "perceived risk", "personal innovativeness", and "perceived enjoyment" as independent variables in addition to the "perceived usefulness" and "perceived ease of use" of TAM.

Sohn (Sohn, S., 2017) used "technical quality", "information quality", "aesthetic quality", and "security quality" as independent variables to study the perceived sources of usefulness of mobile shopping app users using ETAM. Target et al. (Tarute, Asta, Shahrokh, N. and Rimantas, G., 2017) used functionality, design solution, interaction, and information quality as independent variables by referring to previous studies to study which quality factors induce mobile app users' participation and affect customer loyalty.

However, these studies also show limitations in identifying the specific needs of mobile shopping app users. To overcome this limitation, one can argue it is necessary to extend TAM to include quality factors specialized in mobile shopping apps (Sohn, S., 2017), (Zhang, Liyi, Jing Z. and Qihua L., 2012). Therefore, recent studies have taken place that leverage more user reviews that include users' satisfaction, complaints, and requirements, in hopes of addressing and identifying direct and specific needs of users (Kim, Y. H., Kim, J. H., Park, J. H. and Lee, S. J., 2016), (Chae, S. H., Lim, J. I. and Kang, J. Y., 2015).

2.2. Text mining of user reviews in mobile shopping apps

This study used a text mining technique to analyze user reviews of mobile shopping apps. Text mining is a technology that refines and structures text using morphological analysis technology from unstructured data composed of characters or texts, rather than numerical structured data, and derives information through methods such as statistical analysis and machine learning. Text mining is widely used as a method to supplement the limitations of qualitative research by quantifying various objective data (Shah, A. M., Yan, X., Tariq, S. and Ali, M., 2021).

In particular, we used the topic modeling algorithm among the text mining techniques which grasp the abstract topic of a document set by identifying the patterns of words that appear simultaneously using context-related clues found in a large number of documents. The widely used topic modeling algorithms are latent semantic analysis (LSA), probabilistic latent semantic analysis (pLSA), and latent dirichlet allocation (LDA) (Lee, B. G. and Son, C. H., 2020), (Gurcan, F. and Nergiz E. C., 2019).

The LDA topic modeling used in this study is an algorithm designed by Blei (Blei, D. M., 2012), (Blei, D., Ng, A. and Jordan, M., 2003). It is a probabilistic model developed based on the Dirichlet distribution to compensate for the failure of the pLSA to secure a document-level probabilistic model. The graphical model of LDA is shown in Fig. 1. Here, K is the number of topics, D is the total number of documents forming the corpus, N is the number of words in the d-th document, and $\mathrm{W}_{d,n}$ is the n-th word appearing in the d-th document. LDA infers latent topics through them. α is a hyper parameter that affects θ, θ determines topic proportions for each document, and $Z_{d,n}$ refers to a potential probability variable that allocates the n-th word appearing in the d-th document to the topic. β_k means the probability distribution of words for the k-th topic and means the topic, the latent structure to be inferred. η is a hyper parameter that affects the β_k value. In LDA, it is assumed that $Z_{d,n}$ is determined according to θ_d, which is the distribution value of topics for each document, and $W_{d,n}$ are determined according to $Z_{d,n}$ and β_k values during the document creation process. Under this assumption, LDA topic modeling can predict that the corresponding document covers the topic of which words are composed. LDA is widely used in academic research, and it is known to be effective in processing documents that are relatively shorter than methodologies such as LSA and pLSA (Lee, B. G. and Son, C. H., 2020), (Shah, A. M., Yan, X., Tariq, S. and Ali, M., 2021).

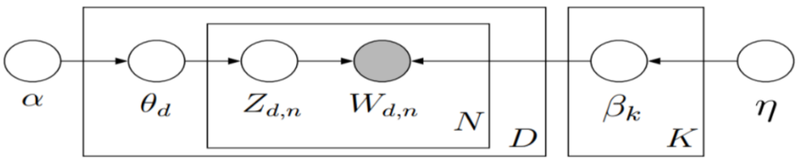

Fig. 1: Graphical model of LDA (Blei, 2012)

2.3. Herzberg's two-factor theory

Two-Factor Theory developed by Frederick Herzberg (Herzberg, F., Mausner, B. and Snyderman, B. B., 1993) states that the factors that stimulate individual motivation can be classified into motivators and hygiene factors, and motivators mainly contribute to satisfaction, and hygiene factors mainly contribute to dissatisfaction. Herzberg defined satisfaction and dissatisfaction as two distinct elements on the same continuum, that is, the opposite concept of a satisfaction is no satisfaction, and the opposite concept of dissatisfaction is no dissatisfaction. Therefore, if the hygiene factor is insufficient, dissatisfaction occurs, but even if the hygiene factor is satisfied, it does not necessarily cause satisfaction, and only dissatisfaction is removed. On the contrary, if the satisfaction factor is insufficient, satisfaction does not occur, and dissatisfaction does not necessarily occur (Herzberg, F., 2008), (Kim, B., Kim, S. and Heo, C. Y., 2016).

Previous studies based on Herzberg's Two-Factor Theory have been conducted in various fields of job satisfaction (Warrier, A. G. and Prasad, R., 2018), (Moon, Y. J., 2013). In the field of information systems, studies were initially conducted to derive motivators and hygiene factors through surveys (Tuch, A. N. and Hornbæk, K., 2015), and recent studies show an analysis of motivators and hygiene factors through user review analysis.

Kim et al. (Kim, B., Kim, S. and Heo, C. Y., 2016) studied motivators and hygiene factors using user reviews and satisfaction ratings, but it is susceptible to subjectivity as the researchers participated in extracting factors based on previous studies without using automated algorithms such as topic analysis. Adnan et al. (Shah, A. M., Yan, X., Tariq, S. and Ali, M., 2021) identified patients' online reviews of doctors as Herzberg's motivators and hygiene factors using topic analysis and sentiment analysis rather than the rating distribution analysis.

However, in the sentiment dictionary required for sentiment analysis, the same vocabulary can be used with different meanings depending on the domain, so in order to increase the accuracy, it is required to construct a sentiment dictionary suitable for a specific domain rather than a general sentiment dictionary (Park, H. J., Lee, D. H. and Kim, K. O., 2021), (Cho, S. H., Kim, B. S., Park, M. S., Lee, G. C. and Kang, P. S., 2017).

In this study, quality factors were extracted using topic analysis algorithms, not user surveys, and Herzberg’s motivators and hygiene factors were identified only by analyzing the rating distribution without relying on a sentiment dictionary. To help the study participants understand Herzberg’s Two- Factor Theory, it was discussed as follows. The motivator is a quality factor that leads to satisfaction if it is met, although it does not mean dissatisfaction even if not met. The hygiene factor is a quality factor that is no satisfaction if it is not met, although it does not mean satisfaction even if it is met.

3. Research methods

This study proceeded in five steps as shown in Fig. 2 to identify the quality factors of the mobile shopping app and to extract Herzberg's motivators and hygiene factors of mobile shopping apps.

In the first step, user reviews of mobile shopping apps were collected from the app market and data refining was performed.

In the next step, the topic was analyzed using the LDA algorithm, and the topic was confirmed by the nominal group technique in which experts with extensive experience in using mobile shopping apps and IT expertise participate.

In the third step, Herzberg's motivators and hygiene factors were discriminated by the analysis of the rating distribution by topic. In the fourth step, a survey was designed for empirical analysis and a survey was conducted on mobile shopping app users. In the final stage, the level of consistency was tested by analyzing the correlation between the discrimination results and the survey results.

The following hypothesis is established to test that the Herzberg's motivators and hygiene factors discriminated by the analysis of the rating distribution are not mutually independent of users' survey results.

H0: p = 0, There is no correlation between the discrimination results of ratings distribution and the users' survey results.

3.1. Collecting user reviews

User reviews were collected from Google Play. The target mobile shopping apps were including Coupang, 11th Street, and Timon as apps with cumulative installations ranked in the top 10 as of June 2019, in OpenAds, which provides app usage rankings. For the 10 mobile shopping apps selected, user reviews were collected by sorting them by the usefulness criteria provided by Google using a Python program. Considering the capacity problem of collection and topic analysis, the target period for collection data was limited from January 1, 2017, to May 31, 2019, and a total of 66,270 reviews were collected. The collected data consists of user name, review time, content, and rating, and the rating is on a five-point scale from one to five.

The collected reviews were morphologically analyzed using Okt, a Twitter morpheme analyzer among Korean morpheme analyzers. In morpheme analysis, due to the characteristics of the Korean language, words corresponding to quality factors exist in the form of nouns in most sentences, and it is often difficult to grasp the meaning of a word when the length of the word is one syllable. Therefore, only nouns with two or more syllables were extracted from all user reviews and analyzed. Also, nouns with an appearance frequency of less than 10 times were additionally removed to obtain meaningful analysis results.

3.2. Topic analysis

Topic analysis was performed using the LDA algorithm. The LDA was applied by constructing a Document-Term-Matrix (DTM) using the nouns extracted from the review. It is one of the unsupervised learning methods. Unlike supervised machine learning methods, there are no absolute evaluation indicators to help select an optimal model, and the model is evaluated mainly through indicators called perplexity or topic coherence. However, these indicators have a drawback that they do not accurately evaluate the intrinsic meanings of topics in interpreting topics.

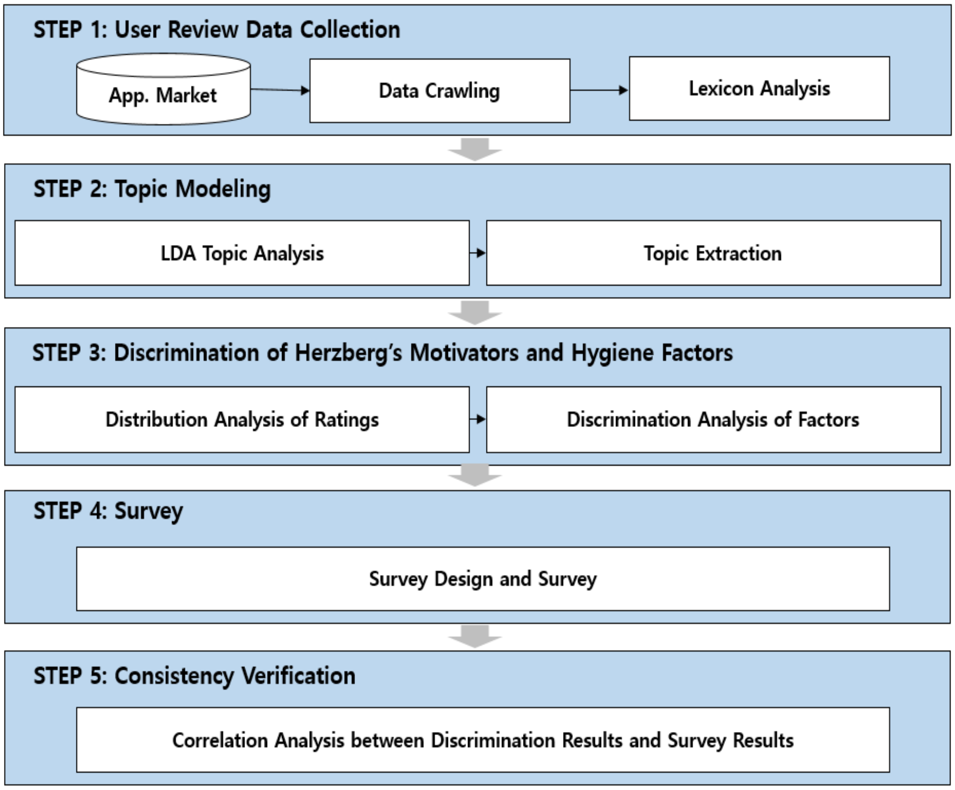

Fig. 2 Research framework

To overcome this, Porter (Porter, K., 2018), Gurcan et al. (Gurcan, F. and Nergiz E. C., 2019), and Cho et al. (Cho, S. H., Kim, B. S., Park, M. S., Lee, G. C. and Kang, P. S., 2017) did not use these indicators in LDA topic modeling, but decided the hyperparameter that was judged to be the easiest to analyze topic and proceeded with the analysis. This study also used hyperparameters to select the optimal model.

Since the top words constituting each topic derived from LDA topic analysis are words derived based on probability, a decision-making process in which experts participate was required to determine the topic corresponding to the service quality factor. A decision-making activity called the nominal group technique was conducted for rational decision-making excluding the individual judgment of the researcher. The nominal group technique is a decision-making technique in which a large number of people who participated in decision-making activities analyze key words of topics to derive candidates for topics and finally define topics through majority vote and agreement. In the nominal group technique, a total of five people, one in their 20s, three in their 30s and 40s, and one in their 50s, who had extensive experience in using mobile shopping apps and had IT expertise, participated.

3.3. Identification of herzberg’s motivators and hygiene factors

In order to identify the quality factors extracted from topic analysis as Herzberg's motivators and hygiene factors, the classification standard for rating was required and previous studies were referenced. Chae et al. (Chae, S. H., Lim, J. I. and Kang, J. Y., 2015) in a study comparing and analyzing the experience in using of social commerce and open markets, Kim et al. (Kim, B., Kim, S. and Heo, C. Y., 2016) in a study to derive satisfaction and dissatisfaction factors of hotel users using the ratings of online reviews, classified one point and two points as dissatisfied reviews, three points as neutral reviews, four points and five points as satisfaction reviews.

In this study, in reference to previous studies, user reviews were classified into three categories: one point and two points for dissatisfied reviews, three points for neutral, and four points and five points for dissatisfied reviews. In addition, it was defined that the overall rating of user reviews has a one-dimensional property with a high rating when the quality factor is satisfied and a low rating when the quality factor is not satisfied.

Based on this, the identification criteria were established as follows. If the rating distribution of a specific quality factor has a higher proportion of one point and two points compared to the overall rating distribution, it is a hygiene factor, which is a quality factor that is not very satisfied even if it is met and is dissatisfied if it is not met. If the rating distribution of a specific quality factor has a higher proportion of four points and five points compared to the overall rating distribution, it is a motivation factor, which is a quality factor that gives satisfaction if it is met, although there is no significant dissatisfaction even if it is not met. Whether or not the distribution of ratings of specific quality factors is the same as the distribution of overall ratings was confirmed by performing a chi-square test.

3.4. Survey

A survey was conducted for mobile shopping app users to verify the consistency of motivators and hygiene factors discriminated by the distribution of user review ratings. The survey was conducted for those who had experience of using mobile shopping apps for a total of five days from September 21 to 25, 2020. As shown in Table I, a total of 320 people were surveyed: 80 people in their 20s, 80 people in their

30s, 80 people in their 40s, and 80 people over 50 years old. The gender ratio of men and women was the same.

Table 1: Characteristics of respondents (N=320)

Age	Sex	Frequency	Percentage
20 years - under 29 years	Male	40	12.5
	Female	40	12.5
30 years - under 39 years	Male	40	12.5
	Female	40	12.5
40 years - under 49 years	Male	40	12.5
	Female	40	12.5
over 50 years	Male	40	12.5
	Female	40	12.5
total		320	100.0

3.5. Consistency test

In order to test the consistency between the discrimination results of ratings distribution and the survey results of mobile shopping app users, cross-analysis between two nominal variables, the results and the survey results, was performed, and the correlation coefficient was confirmed with Phi value.

4. Study results

4.1. Topic analysis

In the LDA topic analysis of user reviews, the number of topics was determined to be 18 because it was judged that topic interpretation is the easiest when α and β were 0.01 and 0.1, using hyperparameters.

As a result of decision-making activities on 18 topics derived from LDA topic analysis, Topic 3 and Topic 12, which confirmed the similarity of topics, were integrated into "premium delivery service", Topic 7 and Topic 9 into "app functionality", and Topic 8 and Topic 10 into "product information". Meanwhile, Topic 2, which consists of keywords "mobile, benefits, time, where, member, existing, computer, when, now, very", is a key element of mobile services, but while it may signify a general characteristic of mobile devices, it may not represent a characteristic of mobile shopping apps. Therefore, it was excluded from the topic of the mobile shopping app. In addition, Topic 4, which consists of keywords "use, purchase, person, first, friend, thanks to, gift, letter, one, mood" was excluded from the topic of the mobile shopping app as most reviews contain user reviews about purchased products.

Finally, as shown in Table II, 13 topics were summarized for the quality factors of mobile shopping apps. In previous studies, quality factors that can be classified as "perceived ease of use" were derived as "premium delivery service" and "order cancellation and return", in previous studies, quality factors that can be classified as "perceived usefulness" were derived as "discount benefits" and "benefit management", in previous studies, quality factors that can be classified as "technology quality" were derived as "app functionality", "pop-up advertisement control", and "app update". It can be discerned that the quality factors were derived as quality factors specialized for mobile shopping apps. Also, it is possible to conjecture the primary users' interest among user reviews corresponding to 13 topics, "price" and "app functionality" accounted for a large proportion at 19.3% and 15.9%, while "payment process" and "benefit management" account for 2.3% and 2.0% which are relatively small.

Table 2: Topic lists

ID	Topic Labels	Topic Num.	Key Words	Review Weights
T1	price	0	price, delivery, product, best, product, always, stuff, very, comparison, home shopping	19.3%
T2	app functionality	7	error, fix, connect, continue, button, internet, continuation, loading, check, data	15.9%
		9	app, run, problem, again, access, continue, install, keep, quit, suddenly	
T3	premium delivery service	3	shipping, inquiry, payment, service, goods, order, delivery, product, every time, sale	12.1%
		12	use, often, shipping, favorite, different, free, price, not much, site, most	

T4	product information	8	choice, category, buy, thing, consumer, best, part, case, company, degree	9.0%
		10	product, search, screen, view, detail, photo, page, click, fail, again	
T5	order cancellation and return	5	order, inquiry, cancellation, sale, refund, customer, return, stuff, consultation, today	8.3%
T6	customer service	1	event, customer, center, worst, authority, information, person, one, design, request	7.0%
T7	membership registration and login	11	login, authentication, subscription, membership, continuity, input, again, number, ID, password	6.6%
T8	discount benefit	6	coupon, discount, application, benefit, reserve, use, bankbook, amount, gradually, deposit	5.4%
T9	pop-up Ad control	14	application, deletion, advertisement, installation, notification, down, setting, continuing, restarting, alarm	5.1%
T10	specialized ordering function	16	purchase, item, shopping basket, product, report, first, lowest, review, start	3.7%
T11	app update	15	update, update, after, confirm, this time, my, continue, message, decide, hara	3.3%
T12	payment process	17	payment, card, pay, smile, registration, process, method, culture, cash, delivery address	2.3%
T13	benefit management	13	points, daily, old, earn, version, check, attendance, slide, fun, inconvenience	2.0%

4.2. Identification of motivators and hygiene factors

For the 13 quality factors, observation values were calculated by classifying the review ratings of each quality factor into three categories: one point & two points, three points, four points & five points, and whether the distribution of observation value was the same as the distribution of expected value of the entire review ratings was verified through chi-square test. The chi-square test value for all 13 quality factors satisfies the significance level ($p < 0.05$), and it was confirmed that there was a significant difference between the distribution of observation values and the distribution of expected values.

If the distributions were not the same and the observation value at one point and two points were higher than the expected value, then it was discriminated as a hygiene factor, and if the distributions are not the same and the observation value at four points and five points was higher than the expected value, it was discriminated as a motivator. As a result, four quality factors "price", "premium delivery service", "discount benefit", and "specialized ordering function" were discriminated as motivators, and nine quality factors, including "app functionality" and "product information", were discriminated as hygiene factors.

Table III shows the results of the chi-square test and the discrimination results of Herzberg's motivators and hygiene factors. Fig. 3 is a graph that shows the distribution of review ratings constituting 13 topics and the discrimination results of motivators and hygiene factors.

Table 3. The discrimination results of motivators and hygiene factors

ID	Factor Labels	Topic Num.	1point & 2points		3points		4points & 5points		Chi2stat	P_value	Results
			Observation Value	Expected Value	Observation Value	Expected Value	Observation Value	Expected Value			
F1	price	0	499 (9.0%)	2,417	84 (1.5%)	431	4,954 (89.5%)	2,669	6780.67017	0.00E+00	M
F2	app functionality	7, 9	3,224 (70.5%)	1,997	646 (14.1%)	356	704 (15.4%)	2,205	3567.730119	0.00E+00	H
F3	premium delivery service	3, 12	625 (18.0%)	1,517	136 (3.9%)	270	2,714 (78.1%)	1,675	2247.216047	0.00E+00	M
F4	product information	8, 10	1,489 (57.9%)	1,122	338 (13.1%)	200	744 (28.9%)	1,239	698.020446	5.64E-151	H
F5	order cancellation and return	5	1,393 (58.5%)	1,040	159 (6.7%)	185	831 (34.9%)	1,149	385.969807	2.42E-83	H
F6	customer service	1	1,130 (56.4%)	875	134 (6.7%)	156	740 (36.9%)	966	237.517467	3.28E-51	H

F7	membership registration and login	11	1,449 (76.7%)	825	210 (11.1%)	147	230 (12.2%)	911	1850.410 55	0.00E+0 0	H
F8	discount benefit	6	558 (36.3%)	672	130 (8.4%)	120	851 (55.3%)	742	66.18757	2.79E-14	M
F9	pop-up Ad control	14	1,112 (75.7%)	641	148 (10.1%)	114	209 (14.2%)	708	1303.222 506	2.94E-282	H
F10	specialized ordering function	16	220 (20.6%)	466	45 (4.2%)	83	802 (75.2%)	514	559.6704 91	5.57E-121	M
F11	app update	15	690 (72.0%)	418	144 (15.0%)	75	124 (12.9%)	462	860.7625 76	2.87E-186	H
F12	payment process	17	391 (58.0%)	294	81 (12.0%)	52	202 (30.0%)	325	163.1121 61	3.90E-35	H
F13	benefit management	13	254 (45.0%)	247	61 (10.8%)	44	250 (44.2%)	272	11.09941 7	1.12E-02	H

Note: M = Motivator, H = Hygiene Factor

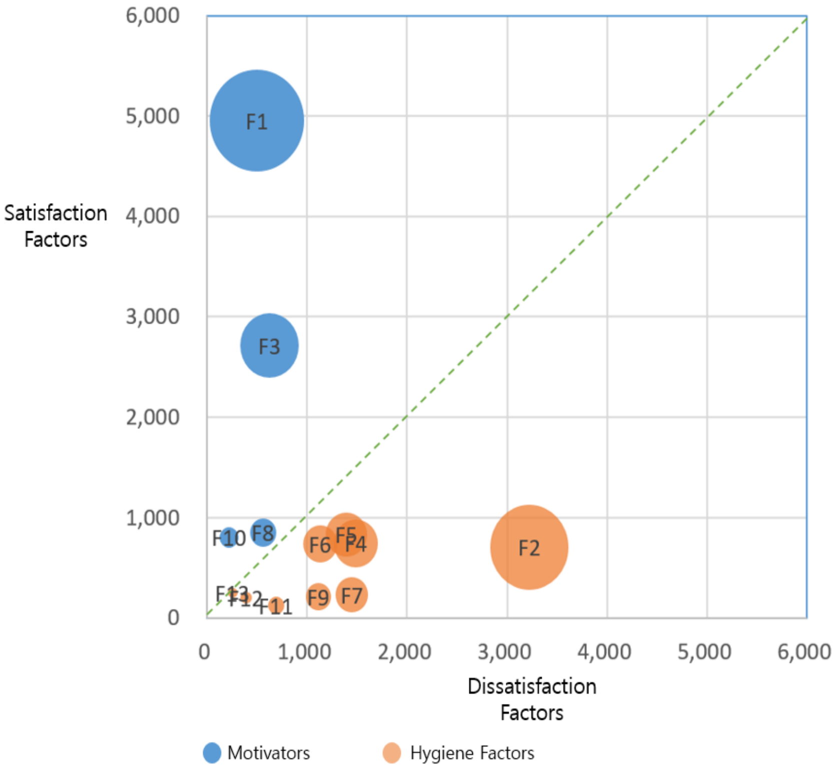

Fig. 3: Ratings distribution and Herzberg’s motivators and hygiene factors

4.3. User survey

Table IV shows the results of a survey on the 13 quality factors in which 320 mobile shopping app users participated to verify the consistency of the motivators and hygiene factors discriminated by the distribution of user review ratings.

"price", "premium delivery service", "discount benefit", "benefit management", and "specialized ordering function" were investigated as motivators, while eight other factors such as "customer service", "order cancellation and return" were investigated as hygiene factors. When comparing the discrimination results using the ratings distribution and the users' survey results, 12 of the 13 quality factors excluding "benefit management" were investigated equally.

Table 4: Survey results of motivators and hygiene factors (N=320)

ID	Factor Labels	Motivators (%)	Hygiene Factors(%)	Survey Results	Distribution Discrimination Results
F1	price	244(76.3%)	76(23.8%)	M	M
F2	app functionality	95(29.7%)	225(70.3%)	H	H
F3	premium delivery service	244(76.3%)	76(23.8%)	M	M
F4	product information	71(22.2%)	249(77.8%)	H	H
F5	order cancellation and return	72(22.5%)	248(77.5%)	H	H
F6	customer service	116(36.3%)	204(63.8%)	H	H
F7	membership registration and login	66(20.6%)	254(79.4%)	H	H
F8	discount benefit	273(85.3%)	47(14.7%)	M	M
F9	pop-up Ad control	136(42.5%)	184(57.5%)	H	H
F10	specialized ordering function	203(63.4%)	117(36.6%)	M	M
F11	app update	80(25.0%)	240(75.0%)	H	H
F12	payment process	105(32.8%)	215(67.2%)	H	H
F13	benefit management	192(60.0%)	128(40.0%)	M	H

Note: M = Motivator, H = Hygiene Factor

Cross-analysis was conducted to analyze whether there was a significant difference in the survey results of the motivators and hygiene factors by user's gender and age.

As a result of cross-analysis by gender, it was tested at the five percent significance level that there were significant differences by gender in six quality factors such as "app functionality", "product information", "customer service", "member registration and login", "app update", and "payment process" as shown in Table V. It can be discerned that all six quality factors were perceived by females as hygiene factors to a greater extent than male.

Table 5: Cross-analysis by gender

ID	Factor Labels	M/H	Male		Female		Chi2stat	P_value	Difference
			Observation Value	Expected Value	Observation Value	Expected Value			
F1	price	M	129 (40.3%)	122	115 (35.9%)	122	3.382	.066	
		H	31 (9.7%)	38	45 (14.1%)	38			
F2	app functionality	M	57 (17.8%)	47.5	38 (11.9%)	47.5	5.404	.020	existence
		H	103 (32.2%)	112.5	122 (38.1%)	112.5			
F3	premium delivery service	M	119 (37.2%)	122	125 (39.1%)	122	.621	.431	
		H	41 (12.8%)	38	35 (10.9%)	38			
F4	product information	M	43 (13.4%)	35.5	28 (8.8%)	35.5	4.073	.044	existence
		H	117 (36.6%)	124.5	132 (41.3%)	124.5			
F5	order cancellation and return	M	42 (13.1%)	36	30 (9.4%)	36	2.581	.108	
		H	118 (36.9%)	124	130 (40.6%)	124			
F6	customer service	M	67 (20.9%)	58	49 (15.3%)	58	4.381	.036	existence
		H	93 (29.1%)	102	111 (34.7%)	102			
F7	membership registration and login	M	47 (14.7%)	33	19 (5.9%)	33	14.965	.000	existence
		H	113 (35.3%)	127	141 (44.1%)	127			
F8	discount benefit	M	134 (41.9%)	136.5	139 (43.4%)	136.5	.623	.430	
		H	26 (8.1%)	23.5	21 (6.6%)	23.5			
F9	pop-up Ad control	M	71 (22.2%)	68	65 (20.3%)	68	.460	.497	
		H	89 (27.8%)	92	95 (29.7%)	92			
F10	specialized ordering function	M	103 (32.2%)	101.5	100 (31.3%)	101.5	.121	.728	
		H	57 (17.8%)	58.5	60 (18.8%)	58.5			

F11	app update	M	53 (16.6%)	40	27 (8.4%)	40	11.267	.001	existence
		H	107 (33.4%)	120	133 (41.6%)	120			
F12	payment process	M	66 (20.6%)	52.5	39 (12.2%)	52.5	10.334	.001	existence
		H	94 (29.4%)	107.5	121 (37.8%)	107.5			
F13	benefit management	M	99 (30.9%)	96	93 (29.1%)	96	.469	.494	
		H	61 (19.1%)	64	67 (20.9%)	64			

Note: M = Motivator, H = Hygiene Factor

In addition, as a result of cross-analysis by age, it was tested at the five percent significance level that there were significant differences by age group in the two quality factors of "product information" and "order cancellation and return" as shown in Table 6. It can be discerned that both quality factors are perceived as hygiene factors more significantly by young people in their 20s and 30s.

Table 6: Cross-Analysis by Age

ID	Factor Labels	M/H	20s		30s		40s		over 50 years		Chi2stat	P_value	Difference
			Observation Value	Expected Value	Observation Value	Expected Value	Observation Value	Expected Value	Observation Value	Expected Value			
F1	price	M	55 (17.2%)	61	60 (18.8%)	61	62 (19.4%)	61	67 (20.9%)	61	5.108	.164	
		H	25 (7.8%)	19	20 (6.3%)	19	18 (5.6%)	19	13 (4.1%)	19			
F2	app functionality	M	21 (6.6%)	23.8	22 (6.9%)	23.8	19 (5.9%)	23.8	33 (10.3%)	23.8	7.111	.068	
		H	59 (18.4%)	56.3	58 (18.1%)	56.3	61 (19.1%)	56.3	47 (14.7%)	56.3			
F3	premium delivery service	M	64 (20.0%)	61	64 (20.0%)	61	60 (18.8%)	61	56 (17.5%)	61	3.037	.386	
		H	16 (5.0%)	19	16 (5.0%)	19	20 (6.3%)	19	24 (7.5%)	19			
F4	product information	M	10 (3.1%)	17.8	15 (4.7%)	17.8	24 (7.5%)	17.8	22 (6.9%)	17.8	9.032	.029	existence
		H	70 (21.9%)	62.3	65 (20.3%)	62.3	56 (17.5%)	62.3	58 (18.1%)	62.3			
F5	order cancellation and return	M	11 (3.4%)	18	12 (3.8%)	18	19 (5.9%)	18	30 (9.4%)	18	16.487	.001	existence
		H	69 (21.6%)	62	68 (21.3%)	62	61 (19.1%)	62	50 (15.6%)	62			
F6	customer service	M	30 (9.4%)	29	31 (9.7%)	29	32 (10.0%)	29	23 (7.2%)	29	2.705	.439	
		H	50 (15.6%)	51	49 (15.3%)	51	48 (15.0%)	51	57 (17.8%)	51			
F7	membership	M	11 (3.4%)	16.5	14 (4.4%)	16.5	18 (5.6%)	16.5	23 (7.2%)	16.5	6.185	.103	

	registration and login	H	69 (21.6%)	63.5	66 (20.6%)	63.5	62 (19.4%)	63.5	57 (17.8%)	63.5			
F8	discount benefit	M	71 (22.2%)	68.3	68 (21.3%)	68.3	64 (20.2%)	68.3	70 (21.9%)	68.3	2.868	.412	
		H	9 (2.8%)	11.8	12 (3.8%)	11.8	16 (5.0%)	11.8	10 (3.1%)	11.8			
F9	pop-up Ad control	M	27 (8.4%)	34	38 (11.9%)	34	33 (10.3%)	34	38 (11.9%)	34	4.194	.241	
		H	53 (16.6%)	46	42 (13.1%)	46	47 (14.7%)	46	42 (13.1%)	46			
F10	specialized ordering function	M	51 (15.9%)	50.8	54 (16.9%)	50.8	46 (14.4%)	50.8	52 (16.3%)	50.8	1.873	.599	
		H	29 (9.1%)	29.3	26 (8.1%)	29.3	34 (10.6%)	29.3	28 (8.8%)	29.3			
F11	app update	M	22 (6.9%)	20	19 (5.9%)	20	16 (5.0%)	20	23 (7.2%)	20	2.000	.572	
		H	58 (18.1%)	60	61 (19.1%)	60	64 (20.0%)	60	57 (17.8%)	60			
F12	payment process	M	24 (7.5%)	26.3	27 (8.4%)	26.3	27 (8.4%)	26.3	27 (8.4%)	26.3	.383	.944	
		H	56 (17.5%)	53.8	53 (16.6%)	53.8	53 (16.6%)	53.8	53 (16.6%)	53.8			
F13	benefit management	M	46 (14.4%)	48	54 (16.9%)	48	45 (14.1%)	48	47 (14.7%)	48	2.604	.457	
		H	34 (10.6%)	32	26 (8.1%)	32	35 (10.9%)	32	33 (10.3%)	32			

Note: M = Motivator, H = Hygiene Factor

4.4. hypothesis test

To test the research hypothesis, cross-analysis was performed to analyze the correlation between the discrimination results of ratings distribution and the users' survey results, and the correlation coefficient was confirmed with the Phi value.

As for the measurement data, the discrimination results of ratings distribution and the users' survey results on the 13 quality factors were set as samples and analyzed without missing cases. As shown in Table VII, all four quality factors discriminated as a motivator in the distribution discrimination were also investigated as a motivator in the survey. However, in the nine quality factors discriminated as a hygiene factor, eight quality factors were investigated as a hygiene factor in the survey, but one quality factor was investigated as a motivator.

As a result of cross-analysis, the p value of 0.002 rejected the null hypothesis that "There is no correlation between the discrimination results of ratings distribution and the users' survey results." at the five percent significance level, and the correlation coefficient, Phi of 0.843 proves that the discrimination results of ratings distribution and the users' survey results have a very high positive correlation. However, the quality factor of "benefit management" was analyzed as a hygiene factor in distribution identification, but it was investigated as a motivator in the user survey. This different result is assumed that it can be attributed to that the number of reviews corresponding to "benefit management" is significantly less at 2.0% of all reviews, and the proportion of reviews in the one point & two points category at 44.96% and the four points & five points category at 44.25% are not significantly different.

Table 7: Cross-analysis between the distribution discrimination results and the survey results

Frequency					Phi Value	P_value
Valid Data (N=13, 100%)		Survey		Total	.843	.002
		Motivator	Hygiene Factor			
Discrimination	Motivator	4	0	4		
	Hygiene Factor	1	8	9		
Total		5	8	13		

5. Conclusion

This study presents a framework for identifying satisfaction and dissatisfaction factors of mobile shopping app users more efficiently by distinguishing the Herzburg's motivators and hygiene factors using only the users' review and rating of mobile shopping apps.

We collected user reviews of mobile shopping apps and extracted 13 distinct topics that represent quality factors of mobile shopping apps using LDA topic modeling, and each quality factor was identified as a motivator or a hygiene factor through the distribution discrimination. The quality factors of "price", "premium delivery service", "discount benefits", and "specialized ordering function" were identified as motivators, which are quality factors that give satisfaction if they are satisfied, although there is dissatisfaction even if they are not met. In addition, "customer service", "order cancellation and return", "app functionality", "product information", "member registration and login", "pop-up ad control", "app update", "payment process" were identified as hygiene factors, which are quality factors that are not very satisfied even if they are satisfied and cause dissatisfaction if they are not met. Through a survey involving 320 mobile shopping app users, we verified that the discrimination results of rating distribution and the users' survey results had a very high positive correlation. As per survey result, 12 factors, excluding the "benefit management" factor, among 13 quality factors were investigated in the same way as the discrimination result.

The result of this study shows that the quality factors of mobile shopping apps can be derived in detail through user review analysis of mobile shopping apps, and quality factors can be discerned as Herzberg's motivators and hygiene factors only by analyzing the ratings distribution.

Many existing studies that focus on service quality factors rely on surveys, and studies that analyze user reviews have also conducted sentiment analysis that require a sentiment dictionary. This study shows that user reviews with ratings do not depend on the sentiment dictionary and can find satisfaction and dissatisfaction factors only by discriminating the rating distribution.

If companies or institutions use the topic modeling of user review and the discrimination method of ratings distribution as in this study, they cannot only reduce the costs of surveys and sentiment dictionary construction, but also be able to more quickly derive service quality factors to reflect users' requirements. Despite many contributions, this study has potential for expansion. There is a need for a method that can more accurately discriminate quality factors that do not differ significantly in the distribution of ratings, such as the quality factor "benefit management".

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