Factors Analysis for Customer Behavior on The E-Commerce Platform in Thailand

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Abstract

To investigate customer behavior on an e-commerce platform in Thailand that was expanding in response to the increasing value of a market in which more people purchase online. Furthermore, e-commerce is an advertising medium since it instantly connects information or user needs to target customers while also responding to market demands by reducing the time it takes to bring products to market, allowing for rapid market expansion. The study aims to study consumer behavior in online shopping through an application or platform and analyze the critical aspects of online shopping of customer behavior in e-commerce. Data were collected and processed using exploratory factor analysis (EFA) techniques, and a sample of 400 general people was chosen for survey research using questionnaires. The study's findings were as follows: Reliability testing; KMO and Bartlett's tests; total variance explained; Scree plot; rotated component matrix. The result of the EFA analysis came down to two components from 21 variables. As a result, they have been extremely positive and have garnered the most attention.

Keywords
Customer Behavior, E-Commerce, Exploratory Factor Analysis and E-Commerce Platform

1. Introduction
E-commerce in Thailand is growing at an unprecedented pace with the increasing value of a market where more consumers shop online than in-store. Especially the emergence of new technologies that change the presentation as well. E-commerce is running a business using electronic, text, audio, image, or video clips. E-commerce operators must pay the same tax as other operators. Same as with other online services, income tax and value-added tax (VAT) are payable over the internet. Financial transactions and capital are considered e-commerce. These business transactions can be done in four different ways: business-to-business (B2B), business-to-consumer (B2C), consumer-to-consumer (C2C), consumer-to-business (C2B), and e-commerce standards. It is a commercial transaction made via the Internet. Online stores like Amazon, Flipkart, and Shopify.

Electronic commerce, commonly known as ‘E-Commerce’, refers to the model that allows both businesses and consumers to acquire or trade either goods or services through an electronic network or the internet. As well as the transmission of funds or data. E-commerce can be conducted through various devices such as computers or smartphones. These transactions can either be business-to-business (B2B), business-to-consumer (B2C), consumer-to-consumer (C2C), or consumer-to-business (C2B). These terms are usually used interchangeably. E-tailing or electronic retailing can sometimes be referenced to any transaction process that constructs online retail shopping.

In Thailand, there are 3 main platforms of E-commerce, which are Shopee, Lazada and J&D central. All platforms use a hybrid of C2C and B2C as their e-commerce transactions and model. C2C business is a business model that proceeds with e-commerce technology and the sharing economy. The C2C model capacitates customers to trade with each other, usually in an online environment. B2C is where a company that sells products or services directly to the consumer. B2C generally involves a higher level of customers but lower revenue per customer with shorter sales cycles.

Today, the growing consumer behavior of online shopping this year does not match the lockdown period. As more and more people want to shop online during these times. There are many advantages, such as reduced decision-making time for consumers. and increase the likelihood of purchasing a product or service online shopping. Consumers can shop 24 hours a day as consumers can buy anywhere, anytime. Therefore, online shopping is more responsive to the needs of consumers.

In summary, the research will be a study of consumer behavior in online purchases on applications or platforms in Thailand. To understand the behaviors that occur and analyze the factors that are important to online purchases or services on e-commerce.

1.1 Objectives

The objectives of this research are to study and analyze the important factors in shopping online of customer behavior on e-commerce and study the consumers' behavior in shopping online through an application or platform.

2. Literature Review

Customer behavior merges ideas from diverse sciences including psychology, biology, chemistry, and economics. It is the study of consumers and the procedures they use to select, use (consume), and defeat the products and services, including consumers' emotional, mental, and behavioral responses. The method by which customers make purchasing decisions in e-commerce is known as online consumer behavior (Wenzl 2021). Five major e-commerce trends influence online consumer behavior. In which all of these tendencies are founded on one central concept, namely, convenience, easy access across devices, omnichannel shopping, hassle-free payment, and quick and reliable delivery are all available features.

2.2 Sample Size

Although the sample size is an important problem in factor analysis, there are various alternative views and guiding rules of thumb in the literature (Gorsuch R. L. 1983; Tabachnick and Fidell 2001; Hogarty et al. 2005). According to Hogarty et al. (2005), these "discordant guidelines have not served researchers well." General guidelines include Tabachnick and Fidell's rule of thumb, which states that factor analysis requires at least 300 examples. Hairet al. (1995) recommended sample sizes of 100 or more. In his guide to sample sizes, Comrey (1973) defined 100 as poor, 200 is acceptable, 300 as good, 500 as very good, and 1000 or more as superb. When communalities are high (more than 0.60) and each component is described by numerous items, sample sizes might be reasonably small (MacCallum et al. 1999; Henson and Roberts 2006). Other researchers, such as Guadagnoli and Velicer (1988), claimed that solutions with correlation coefficients of more than 0.80 necessitate smaller sample sizes, whereas Sapnas and Zeller (2002) argued that even 50 examples may be sufficient for factor analysis. Previous research has shown that the nature of the data will decide the appropriate sample size (Fabrigar et al. 1999; MacCallum et al. 1999). Commonly, the stronger the data, the smaller the sample can be for an accurate analysis. "Strong data" in factor analysis means uniformly high communalities without cross-loadings, plus several variables loading strongly on each factor (Costello and Osborne 2005).

2.3 Factor analysis

Factors that influence e-commerce marketing (Child 1990). The essential element, factor analysis is a statistical approach for converting data from a large number of variables into a smaller number of unrelated factors. Because it increases the amount of variance described by a factor while minimizing the correlation across factors, an orthogonal varimax rotation was used. In data reduction, factor analysis is frequently used to identify a small number of factors that explain the majority of the variance observed in a large number of manifest variables. Hypotheses can also be generated via factor analysis. By factors that have web store quality, product display, and pricing promotion. As a result of the EFA findings, the components are clustered into three different variables to evaluate the strongest marketing stimulation elements to better understand customer perceptions of online buying behavior (Pavan and Nirmaladevi 2017).

2.4 Factor Extraction

Principal components analysis (PCA), principal axis factoring (PAF), picture factoring, maximum likelihood, alpha factoring, unweighted least squares, generalized least squares, and canonical least squares are all methods for extracting factors (Tabachnick and Fidell 2001; Thompson 2004; Costello and Osborne 2005). However, in most investigations, principal components analysis and primary axis factoring are used (Tabachnick and Fidell 2001; Thompson 2004; Henson and Roberts 2006). The choice between PCA and PAF is hotly debated among analysts (Henson and Roberts 2006), although the practical differences between the two are often insignificant Thompson, and Gorsuch states that there are no significant differences when factors have high reliability or when there are thirty or more factors. According to Thompson (2004), PCA is widely utilized because it is the default method in many statistical software packages. When there is no prior theoretical underpinning or model, PCA is recommended (Gorsuch R. L. 1983). Furthermore, Pett et al. (2003) suggested that PCA be used to establish preliminary solutions in EFA. Factor analysis is better than principal components analysis, which is just a data reduction strategy, according to Costello and Osborne (2005). The PCA is beneficial if researchers have constructed an instrument with a large number of items and want to reduce the number of items (Netemeyer et al. 2003). It's calculated without taking into account any underlying structure generated by latent variables; components are derived using all of the manifest variables' variations, and all of that variance shows up in the solution (Ford et al. 1986). When the factors are uncorrelated and commonalities are moderate, the variation accounted for by the components can be exaggerated (McArdle 1990; Gorsuch R. L. 1997). Principle axis factoring, on the other hand, is useful when researchers are trying to figure out what the underlying factors are for a group of objects (Burton and Mazerolle, 2011). Maximum likelihood (ML) is the best choice if data are relatively normally distributed, according to Fabrigar, Wegener et al. (1999), because "it allows for the computation of a wide range of indexes of the model's goodness of fit and permits statistical significance testing of factor loadings and correlations among factors, as well as the computation of confidence intervals." Depending on whether data are generally normally distributed or notably non-normal, maximum likelihood or principal axis factoring will provide researchers with the best findings, according to Costello and Osborne (2005).

The researcher must pick how many constructs to keep for rotation after the extraction step. The retention of factors is more significant than in the previous steps. Three reasons are cited by Hayton et al. (2004) for the importance of this decision. For starters, there is evidence of resilience for these other judgments across options (Zwick and Velicer 1986). Second, exploratory factor analysis must strike a balance between parsimony and accurately capturing underlying relationships; hence, its effectiveness is contingent on the ability to distinguish large from small components (Fabrigar et al. 1999). There is both conceptual and empirical evidence that both under and over-extraction are significant mistakes that influence outcomes, however, specifying too few is typically thought to be more severe. Both sorts of misspecifications have been shown to cause poor factor-loading pattern reproduction and interpretation, as well as have an impact on EFA efficiency and meaning (Velicer et al. 2000).

When researchers pick how many constructs to evaluate the data using, they must consider if a variable may be related to more than one component (Williams et al. 2010). Rotation will aid in the production of a more understandable and simplified solution by boosting high item loadings and decreasing low item loadings. Rotation techniques include oblique and orthogonal rotations. When evidence does not match prior assumptions, oblique rotation is more accurate (Costello and Osborne 2005). This strategy assigns components to correlate, or in other words, creates correlated construct structures. Oblique rotation can be done in a variety of ways, including quarti-min, straight noblemen, and Promax. Orthogonal rotation, on the other hand, results in uncorrelated components. Varimax rotation is the most frequent kind of rotational approach for exploratory factor analysis. There is no universally recognized oblique rotation approach, and all procedures provide identical results.

Construct labeling is a theoretical, subjective, and inductive process (Pett et al. 2003). Construct labels must reflect theoretical and conceptual intent. For example, a construct may comprise four variables that are all relevant to user happiness, hence the label "user satisfaction" will be allocated to that construct. According to Henson and Roberts (2006), at least two or three variables must load on a factor to offer a meaningful interpretation.

3. Methodology

To examine the data that has been collected, we decided to use the Exploratory Factor Analysis (EFA), we would have to first do the reliability test. The degree to which a test measures without error is referred to as test reliability. It has a lot to do with testing validity. Precision can be conceived of as test reliability; the degree to which measurements are error-free (Franzen 2011). By doing the reliability test, we would be able to find Cronbach's Alpha and such. We would have to do this test to see whether or not our questionnaire is reliable or not. After finding the reliability, we would move on to find the EFA results as shown in figure 1.

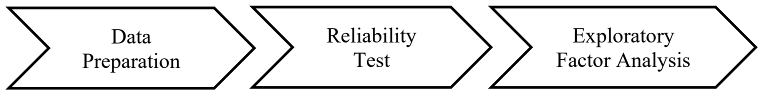

Figure 1. Analysis Approach

Exploratory factor analysis is a multivariate and complicated statistical technique used in information systems, social science, education, and psychology. To make it easier for academics and practitioners to do exploratory factor analysis (EFA) and make conclusions about best practices by providing a simpler collection of information. And, to provide practical and theoretical knowledge on sample size decisions, extraction, the number of components to keep, and rotating approaches.

3.1 Sample and data collection

The study's population and sample group are normal people who bought goods and services online through the Shopee app, using the principle of picking a specified random sample of 400 people. The study tools were divided into 4 parts: General information of the participants as gender/age, Shopee Information, Attitude of Online shopping in the Shopee application which is about the factors the user has in using the application, and suggestions.

Collecting the information is divided into 2 data sources:

1. Primary data is data collection from questionnaires that students fill out the questionnaires themselves to provide true data by answering 400 questionnaires that have been checked for quality.
2. Secondary data is the study of information from the Internet, databases from Shopee, and related documents.

3.2. Models, factors and data analysis

The process of taking a questionnaire and encoding a number depending on the instrument's data requirements is known as data analysis. After that, statistics are created for the study's processing in an analytical table format. The findings are presented, debated, and recommendations are given. The statistics used were descriptive statistics and descriptive statistics to test the results of the study on behavior, frequency and cost of purchasing products through the Shopee application. The attitude towards online shopping consists of seven factors, 1) product, 2) price, 3) location, 4) marketing communication, 5) technology adoption, 6) safety and reliability and 7) personal service.

Exploratory factor analysis (EFA) is a type of factor analysis that is unique. It is used to determine the number of factors and variable loadings. The original 29 attributes were subjected to a principal components exploratory factor analysis with varimax rotation. Analysis of study results is a commonly used method to refer to the effectiveness of questionnaires in two categories: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA has described the simplification measures and has been used to explore the possible structure of variables by performing a number of constructs and identifying So, this approach is applied to identify and impact components of equity in influencing consumers' purchase intentions. For example, there will be a small number of common factors that influence the potential of the attribute for a variation on common factors due to unique factors, alternative factors, or specific reasons for the explanation of covariation. In part, CFA is used to test hypotheses and the relationship between variables and theoretical and empirical constructs. Thus, although CFA is not the central analysis in SEM, an acceptable measurement model is required before estimating and interpreting the structural relationship between variables. And the process of selecting variables that are traceable to a construct and providing a name to that construct is known as interpretation.

4. Results and Discussion

4.1. Sample size

The KMO test is used to determine the strength of the partial correlation (how the variables' components explain one another) between the variables. From the study, the sample size is 400 and the factor to appropriate this sample is 21. According to figure 1, the result of the examination KMO result indicated that the material was suitable for analysis (KMO = 0.967). Bartlett's test of sphericity the result was Chi-square = 7022.302, df = 210 with the found significant statistical test that is at .000 indicates that the correlation matrix isn't an identity matrix at all. Therefore, reject the null hypothesis and accept the alternative hypothesis, as statistically significant interrelationships exist between variables. It also indicates that the correlation coefficients between all variables are appropriate for EFA (table 1).

Table 1. KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.967
Bartlett's Test of Sphericity	Chi-Square	7022.302
	df	210
	Sig.	.000

4.2 Exploratory Factor Analysis (EFA)

Out of the 21 variables, there are only two underlying factors. When using SPSS to find the factor analysis, the "Total Variance Explained" table in the result is to be looked at. The "Total" column in the "Extraction Sums of Squared Loadings" column shows the Eigenvalues for each component that is extracted, which should be greater than. Table 2 shows exactly that. The second column "Percent of Variance", illustrates how much variance each factor/ component explains. The percentages of total variation explained by the factors which should be more than 60are shown in the "Cumulative Percent" column. Where the found cumulative percent of component one is at 60.358 percent and component two at 65.705 percent, as shown in the table 2.

Table 2. Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.675	60.358	60.358	12.675	60.358	60.358	7.552	35.961	35.961
2	1.123	5.347	65.705	1.123	5.347	65.705	6.246	29.744	65.705
3	.889	4.234	69.939						
4	.727	3.462	73.401						
5	.627	2.987	76.388						
6	.518	2.467	78.855						
7	.470	2.238	81.093						
8	.424	2.019	83.112						
9	.380	1.809	84.921						
10	.374	1.782	86.703						
11	.338	1.609	88.312						
12	.325	1.550	89.862						
13	.317	1.507	91.369						
14	.271	1.290	92.659						
15	.257	1.223	93.882						
16	.242	1.154	95.036						
17	.235	1.117	96.153						
18	.224	1.068	97.221						
19	.203	.969	98.189						
20	.201	.956	99.145						
21	.179	.855	100.000						

Extraction Method: Principal Component Analysis.

The values in the Extraction Sums of Squared Loadings table are based on the covariance which is always less than the total variance. And as you can see in the table, the two rows that appear correspond to the component to be maintained. The Rotated Component Matrix includes correlation estimates for each of the variables as well as the estimated components. The Pearson correlations between items and components/ factors are included. Table 3., can be interpreted the same way as Total Variance Explained (Table 2.) and the Scree Plot (Figure 1).

According to Table 3, the most important factor that customers are concerned to choose a product is the price of the product. Customers in Thailand are concerned about the price that is worth it when buying through this application. The second rank factor that customers are concerned about is the application has clear policies or regulations for collecting the personal information of customers. And the third rank that customer concern is there is a clearly stated product price in the application.

Table 3. Results of Exploratory Factor Analysis

Factors	Variables included	Factor loading
Product	Products purchased through the application are diverse.	0.696
	Products purchased through the application meet the needs.	0.729
	The application that chooses to buy products has products ready for immediate delivery.	0.733
Price	The price is worth it when buying through this application.	0.812
	In the application, there is a clearly stated product price.	0.778
	Receive discounts or special privileges by purchasing through this application, you can buy products at a cheaper price than other stores.	0.718
Location	The application is ready to use. You can order products anywhere, anytime.	0.742
	The application has a delivery service that covers all areas.	0.668
	The application has a variety of payment methods.	0.635
Marketing	Advertising of the application is widely publicized on social media.	0.658
	The application has regular promotional activities such as giving discounts on various festivals.	0.668
	The application provides profits to consumers who continue to use the service regularly, such as reduced prices or free shipping. Reduced price when there is a balance minimum order required by the application.	0.623
Communication	The application is easy to use.	0.542
	The application has an attractive design.	0.546
	Applications can help consumers to be more convenient.	0.634
Safety and reliability	The application has a verifiable identity.	0.706
	The application has clear policies or regulations for collecting the personal information of customers.	0.796
	Able to track payment and delivery results from the application conveniently and safely.	0.723
Personal service	The application provides convenient and fast communication channels with individual customers, such as online chats, emails, or messaging systems (inbox).	0.776
	The application has a channel to help solve problems for customers immediately. In the event if an error such as sending the wrong product.	0.683
	The application has regular after-sales follow-up, for example, to provide feedback level after use of the service.	0.774

4.3 Reliability Testing

According to the calculated Cronbach's Alpha that is shown in Table 4., it is at 0.928 which is over 0.7, or over the acceptable rate, this implies that the test's reliability is relevant information.

Table 4. Statistics

Cronbach's Alpha	Number of Items	Sum of item of the variance	Variance of total score
.928	21	13.18	113.11

4.4 A Scree Plot

A Scree Plot has a downhill curvature at all times. The number of factors created by the analysis is indicated by the point where the slope of the curve levels off (the "elbow"). An excellent curve will start steep, then bends at an "elbow"; the cutting-off point, before it flattens out. As seen in Figure 2. below, can see the curve flattens fast. The 21 variables can be reduced to two components; where the curve starts to flatten.

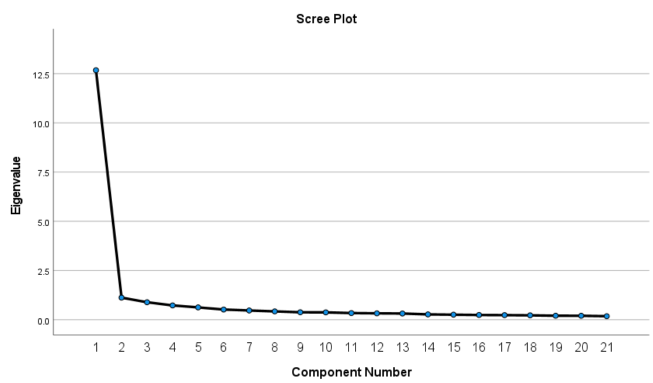

Figure 2. Scree Plot

4.5 The analysis of E-commerce platforms in Thailand

Thailand has three main online shopping platforms that Thai people know and regularly use. These are Shopee, Lazada and J&D. These three platforms are open to the general public to open the stores by themselves; including stores that have a storefront and official stores of various brands. From The Rotated Component Matrix, we've taken the results obtained to find the average of the three most important factors for customers on the online shopping platform. The result: the most important factor is the Price factor with an average of 0.7693, followed by Personal Service factors at 0.7443, and thirdly the Safety and Reliability factor at 0.7417.

Shopee has the lowest product price when compared to Lazada and J&D. Shopee has a lot of the same products, causing competition in terms of price. Lazada has not much price difference compared to Shopee but J&D has. The price of J&D is somewhat higher than both applications. Shopee, Lazada, and J&D also have promotions, discounts, or special privileges by purchasing through applications such as flash sales or bringing various products to create promotions, and discounted prices according to different periods. Shopee differs from the two by having flash sales four times a day, giving the flexibility to order multiple products a day compared to Lazada and J&D, which are twice a day. All three platforms have a way for customers to rate/ review products which is also beneficial to other customers in decision making as well; Shopee has the most customer reviews on a product compared to others with the same product sold. All three platforms are known for their reliability. Customers can do various types of payments as well as track and trace their orders on all three platforms. Customers are also able to chat with the customer service sector. In Shopee and Lazada, customers are also able to chat directly with the shops although on J&D it's only possible to chat through them and not the shops. There are important policies or regulations that everyone may need to know clearly for everyone to be able to see by yourselves for the correctness before your order and after order or if there is any problem, you can see the conditions yourself, for example. How to request a refund, return the product if the product is damaged. for the speed of using the services of customers.

6. Conclusion

For this study, most consumers choose to shop online because it is more convenient and they can buy goods and services anywhere, anytime. Most of them choose to use Shopee because of the diversity of the products, which was counted as 53.7 percent from 400 responses and the major thing that most of them consider purchasing is the price which is 66.6 percent. We chose to study consumers in Thailand that use the Shopee application through a questionnaire form and using exploratory factor analysis (EFA) tools to analyze the data and results using the SPSS program. The results analysis showed from 21 questions that Cronbach's Alpha is an excellent level of reliability. To determine sampling adequacy, the KMO test is employed. With said results, we can see that consumers use online shopping because of the convenience and the diversity of goods or services on the application by concentrating on the price.

Most customers in Thailand are concerned about the price of the product, they will choose the product from an application that has the lowest price. When they had experience with that application, they will have a perception about that application is the cheapest. The customer has the perception that the Shopee application sells the product lower than another application, the customer will re-purchase the product from the Shopee application again. The seller of the application owner should concern with the price of the product. If the seller can sell the product at a lower price, then customers will come back and re-purchase. The application also has a chance to sell another product.

References

Bartlett, M. S., Tests of significance in factor analysis. *British Journal of Psychology*, 77–85, 1950.

Berg, R. G., *SPSS Factor Analysis – Intermediate Tutorial*. Retrieved from SPSS TUTORIALS: https://www.spss-tutorials.com/spss-factor-analysis-intermediate-tutorial/#:~:text=Matrix%20shown%20below.-,SPSS%20FACTOR%20Output%20II%20%2D%20Rotated%20Component%20Matrix,traits%20our%20components%20may%20reflect.

Burton, L. J., & Mazerolle, S. M., Survey Instrument Validity Part I: Principles of Survey Instrument Development and Validation in Athletic Training Education Research. *Athletic Training Education Journal*, 27–35, 2011.

Cattell, R. B., The Scree Plot Test for the Number of Factors. *Multivariate Behavioral Research*, 1, 140-161, 1966.

Child, D. , *The essential of factor analysis.* London: Cassel Education Limited, 1990.

Comrey, A. L., *A first course in factor analysis.* New York, NY: Academic Press, 1973.

Comrey, A. L., & Lee, H. B., *A First Course in Factor Analysis.* Hillsdale, NJ: Lawrence Erlbaum, 1992.

Costello, A. B., & Osborne , J., Best Practices in Exploratory Factor Analysis: Four Recommendations for Getting the Most From Your Analysis. *Practical Assessment, Research, and Evaluation*, 10(7):1-9, 2005.

Displayr., *Principal Components Analysis*. Retrieved from Displayr: https://docs.displayr.com/wiki/Category:Principal_Components_Analysis, 2021.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J., Evaluating the Use of Exploratory Factor Analysis inPsychological Research. *Psychological Methods* , 4(3):272-299, 1999.

Ford, J. K., MacCallum, R. C., & Tait, M., The application of exploratory factor analysis in applied psychology: A critical review and analysis. *Personnel Psychology*, 291-314, 1996.

Franzen, M. D., *Test Reliability*. Retrieved from SpringerLink: https://link.springer.com/referenceworkentry/10.1007/978-0-387-79948-3_2241, 2011.

George, D., & Mallery, P., *SPSS for Windows Step-by-Step: A Simple Guide and Reference, 14.0 update (7th Edition)*. https://www.researchgate.net/publication/234827666_SPSS_for_Windows_Step-by-Step_A_Simple_Guide_and_Reference_140_update_7th_Edition, 2003.

Gliem, J. A., & Gliem, R. R., *Calculating, Interpreting, and Reporting.* Retrieved from ScholarWorks: https://scholarworks.iupui.edu/bitstream/handle/1805/344/gliem+&+gliem.pdf?sequence=1#:~:text=Cronbach's%20alpha%20reliability%20coefficient%20normally,the%20items%20in%20the%20scale, 2003.

Gorsuch, R. L., *Factor analysis.* Hillsdale, NJ: Lawrence Erlbaum Associates, 1983.

Gorsuch, R. L., Exploratory factor analysis: Its role in item analysis. *Journal of Personality Assessment*, 532–560, 1997.

Guadagnoli, E., & Velicer, W. F., Relation of Sample Size to the Stability of Component Patterns. *Psychological Bulletin*, 103(2); 265-275, 1988.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C., *Multivariate data analysis.* Englewood Cliffs, NJ: Prentice-Hall, 1995.

Hayton, J. C., Allen, D. G., & Scarpello, V., Factor Retention Decisions in Exploratory Factor Analysis: a Tutorial on Parallel Analysis. *Organizational Research Methods*, 191-205, 2004.

Henson, R. K., & Roberts, J. K., Use of Exploratory Factor Analysis in Published Research: Common Errors and Some Comment on Improved Practice. *Educational and Psychological Measurement*, 66(3), 393–416, 2006.

Hogarty, K. Y., Hines, C. V., Kromrey, J. D., Ferron, J. M., & Mumford, K. R., The Quality of Factor Solutions in Exploratory Factor Analysis: The Influence of Sample Size, Communality, and Overdetermination. *Educational and Psychological Measurement*, 65(2): 202-226, 2005.

INN, A., *KMO and Bartlett's test of sphericity*. Retrieved from Analysis INN: https://www.analysisinn.com/post/kmo-and-bartlett-s-test-of-sphericity, 2020.

Kaiser, H. F., The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, 141-151, 1960.

Kaiser, H. F., A second generation little jiffy. *Psychometrika*, 35, 401–415, 1970.

Ledesma, R. D., & Valero-Mora, P., Determining the Number of Factors to Retain in EFA: An easy-to-use computer program for carrying out Parallel Analysis. *Practical Assessment, Research, and Evaluation*, 12(2): 1-11, 2007.

MacCallum, R. C., Widaman, K. F., Zhang, S., & Hong, S., Sample Size in Factor Analysis. *Psychological Methods*, 4: 84-89, 1999.

McArdle, J. J., Principles versus principals of structural factor analyses. *Multivariate Behavioral Research*, 81-87, 1990.

Mercado, J., Urrutia, J. D., & Bautista, L. A., *Reading Attitudes of the Students of Polytechnic University of the Philippines: A Principal Component Factor Analysis*. 2015. Retrieved from ResearchGate: https://www.researchgate.net/figure/Kaiser-Meyer-Olkin-Criterion_tbl1_280098112

Netemeyer, R. G., Bearden, W. O., & Sharma, S., *Scaling Procedures: Issues and Applications.* Thousand Oaks, CA: Sage Publications, 2013.

Pavan, K. A., & Nirmaladevi, N., *EXPLORATORY FACTOR ANALYSIS FOR E-COMMERCE MARKETING STIMULI FACTORS*. Retrieved from Academia: https://www.academia.edu/33299896/EXPLORATORY_FACTOR_ANALYSIS_FOR_E_COMMERCE_MARKETING_STIMULI_FACTORS, 2017.

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making Sense of Factor Analysis: The Use of Factor Analysis for Instrument Development in Health Care Research.* Thousand Oaks: SAGE Publications.

Rahn, M. , *Factor Analysis: A Short Introduction, Part 4–How many factors should I find?* Retrieved from The Factor Analysis: https://www.theanalysisfactor.com/factor-analysis-how-many-factors/#:~:text=A%20scree%20plot%20shows%20the,be%20generated%20by%20the%20analysis

Sapnas, K. G., & Zeller, R. A., Minimizing Sample Size When Using Exploratory Factor Analysis for Measurement. *Journal of Nursing Measurement*, 10(2): 135-153, 2002.

Shojaei, A. S., *How to find out how much variance is explained by each factor (or component) in EFA?* Retrieved from ResearchGate: https://www.researchgate.net/post/How-to-find-out-how-much-variance-is-explained-by-each-factor-or-component-in-EFA, 2019.

Tabachnick, B. G., & Fidell, L. S., *Using Multivariate Statistics.* Needham Heights, MA: Allyn & Bacon., 2001.

Team, B., *How to read PCA biplots and scree plots*. Retrieved from BioTuring: https://bioturing.medium.com/how-to-read-pca-biplots-and-scree-plots-186246aae063, 2018.

Thompson, B., *Exploratory and confirmatory factor analysis: Understanding concepts and applications.* Washington, DC: American Psychological Association, 2004.

Velicer, W. F., & Fava, J. L., Affects of variable and subject sampling on factor pattern recovery. *Psychological Methods*, 3: 231-251, 1998.

Velicer, W. F., & Jackson, D. N., Component analysis versus common factor analysis: Some further observations. *Multivariate Behavioral Research*, 97–114, 1990.

Velicer, W., Eaton, C., & Fava, J., *Construct explication through factor or component analysis: A review and evaluation of alternative procedures for determining the number of factors or components. Problems and solutions in uman assessment: Honoring Douglas N. Jackson at seventy.* Norwell, MA: Kluwer Academic, 2000.

Wenzl, M., *Understanding Online Consumer Behaviors for a Better Customer Journey*. Retrieved from ShipBob: https://www.shipbob.com/blog/online-consumer-behavior, 2021.

Williams, B., Onsman, A., & Brown, T., Exploratory factor analysis: A five-step guide for novices. *Australasian Journal of Paramedicine*, 8(3), 2010.

Zwick, W. R., & Velicer, W. F., Comparison of five rules for determining the number of components to retain. *Psychological Bulletin*, 99(3), 432–442, 1996.

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