Journal of Management and Business Review
Volume 21, Number 1 (2024) Page: 51-59
ISSN: 2503-0736 **(Online)**; ISSN: 1829-8176 **(Print)**
doi: https://doi.org/10.34149/jmbr.v20i2.473

Investigating the Influence of Indecision on Customer's Decision Satisfaction

Hui-Hsin Huang

Department of Advertising & Public Relations, Fu Jen Catholic University
No.510, Zhongzheng Rd., Xinzhuang Dist., New Taipei City 242062, Taiwan (R.O.C.)
hoyasophia2020@gmail.com

(*) Corresponding Author

Received: 28-12-2022 | Accepted: 03-03-2023 | Published: 30-01-2024

How to cite: Huang, H. (2024). Investigating the influence of indecision on customer's decision satisfaction. *Journal of Management and Business Review*, 21(1), 51–59. https://doi.org/10.34149/jmbr.v21i1.473

ABSTRAK
Perilaku ketidakpastian sering terjadi saat berbelanja. Sifat ini dalam proses pengambilan keputusan akan mempengaruhi kepuasan pelanggan terhadap keputusan yang diambilnya. Penelitian ini mengusulkan model Bayesian untuk menggambarkan fenomena ketidakpastian dan kepuasan dari keputusan pelanggan. Kepuasan akibat dari keputusan pelanggan diperlakukan sebagai variabel acak, yang distribusinya dipengaruhi oleh ketidakpastian. Data empiris dari Google Analytics digunakan untuk mengukur perilaku ketidakpastian dan untuk kalibrasi model. Kesimpulan ditunjukkan untuk aplikasi dalam penelitian perilaku konsumen aktual. Penelitian ini dapat membantu manajer mengendalikan ketidakpastian untuk meningkatkan kepuasan akibat keputusan pelanggan. Selanjutnya, faktor-faktor yang mempengaruhi ketidakpastian dapat diteliti untuk merancang platform yang lebih menarik dan memberikan insentif untuk mempercepat proses pembayaran

Kata Kunci:
Ketidakpastian; keputusan kepuasan; bayesian model; keraguan; perilaku konsumen

ABSTRACT
Indecision behavior usually appears in daily life, especially on purchase occasions. This trait in the decision process will influence customers' decision satisfaction. This research proposes a Bayesian model to portray the phenomena of indecision and decision satisfaction. The decision satisfaction is a random variable with the prior density in which the parameter given in the density function is demonstrated as indecision. The empirical data of Google Analytics is used to measure indecision behavior and model calibration. Finally, the conclusion is shown to make an application in actual consumer behavior research. This research can help managers control the tendency of indecision to achieve higher decision satisfaction. In advance, the impact factors of indecision can be investigated to design more incentive and attractive platforms to accelerate the payment process.

Keywords:
Indecision; decision satisfaction; bayesian model; hesitation; consumer behavior

INTRODUCTION

In daily life, to face situations that require choosing among several alternatives in the marketplace. The traditional focus in the decision-making literature has been understanding how people choose among a given set of alternatives (Dişli Bayraktar, 2023; Dhar, 1997; Lee et al., 2021). In reality, many decisions involving choice among several desirable alternatives can be difficult and give way to a more fundamental preference- whether or not to choose. A recent analysis of a sample of consumers finds that the difficulty of selecting a single alternative was one of the essential causes of delaying several purchase decisions (Sabioni et al., 2021; Dhar, 1997; Yunus et al., 2022). Thus, the level of indecision or deferring decision can cause different satisfaction estimations in the decision process.

In the previous research, the definitions of indecision are not all at the same level of specificity (König, et al., 2022; Potworowski, 2010). Some though indecision is a decision impasse while experiencing negative affect and experience of negative decision-related emotions before, during, and after deciding (Manisera et al., 2020; Potworowski, 2010). The extant definition of indecisiveness is that some conflict with one another. Ferrari & Dovidio (2001) define indecisiveness as chronic decisional procrastination. Their definition is in direct contrast to many other conceptions of indecisiveness. Since Bacanli (2006) thought indecisiveness is prolonged decision latency and multidimensional definitions—another example of conflicting conceptions of indecisiveness centers on the role of the negative decision effect. On the one hand, several scholars hold negative effects as integral to indecisiveness (Alcantud et al., 2022; Camilleri, 2022; Elaydi, 2006; Potworowski, 2010). On the other hand, others make no mention of the effect (Camilleri, 2022; Dişli Bayraktar, 2023; Milgram &Tenne,2000; Potworowski, 2010). These problems caused when trying to integrate the conceptual definitions of indecision are that they are often not completely congruent with their operationalizations, thus calling into question the validity of the measures. For example, some researchers define indecisiveness as inability in the weak sense, which is continuous, whereas indecisiveness denotes a lower degree of ability. How to validly measure the degree of decision ability (i.e., the ability to come to a decision, regardless of the quality of that decision) would be contingent on how the degree of ability to decide would manifest so that it can be observed and measured (Sanyal et al., 2021; Potworowski, 2010). However, it is hard to measure by observing the behavior.

Thus, considering the problem of the measuring method, this research focuses on online shop indecision behavior. In recent years, worldwide patterns have demonstrated a move towards web-based business. The explosive growth of e-commerce and rapidly increasing numbers of consumers shop online (Alcantud et al., 2022; Khalid & Farooq, 2019). This causes the ubiquity of web-based business. Another reason to choose online shopping behavior as the indecision case study is due to the big data that can be easily collected from electronic businesses; it is easy to calculate the time of staying in the payment stage or from the shopping cart to the final payment. Thus, it can measure the customers' indecision more accurately and concretely by obtaining the duration of stay on a specific webpage.

Regarding the hesitation or indecision in customers' online shopping, Camilleri (2022) explores the factors influencing consumer hesitation or delay in online product purchases. They designed four input variables, including consumer characteristics, contextual factors, perceived uncertainty factors, and medium/channel innovation factors, to predict three types of online shopping hesitation. These output factors are hesitation, shopping cart abandonment, and hesitation at the final payment stage.

To discuss the relationships between indecision and decision satisfaction, according to previous research (König, et al., 2022; Manisera et al., 2020; Huang et al., 2018; Fitzsimons, 2000; Zhang & Fitzsimons, 1999), decision satisfaction is the degree of satisfaction with the choice process, such as decision quality which includes the ability that the customer feels he can make a good choice. Thus, the indecision behavior can influence choice-process satisfaction. When consumers feel they can effectively make good choices, decision satisfaction increases. However, when consumers have lower confidence in their decision-making and show indecision characteristics, their satisfaction with decision-making will decrease. Thus, indecision can influence the evaluation of decision satisfaction.

Based on the above discussion, this research uses Google's online shop as a case study to explore the influence of indecision on decision satisfaction. The article can be divided into three parts. First, the introduction and literature research has been demonstrated. Then, the proposed model will be introduced, including the probability density function and cumulative distribution function calculation. Thirdly, the case study of customers' indecision in Google's online shop is used as data analysis from Google Analytics. Finally, the conclusion is made.

RESEARCH METHODS

The Proposed Model

Based on the literature review, decision satisfaction is influenced by indecision. We consider a Bayesian model to portray this relationship between these two variables. The Bayesian model is suitable for considering the relation of variables' affection in different levels of consumers' data, such as heterogeneous transaction-sales time series (Berry et al., 2020). The proposed model of decision satisfaction is prior density, in which its parameter is considered a random variable as indecision behavior. Moreover, it can calculate the marginal density. As follows, the decision satisfaction and indecision model are demonstrated. Bayesian models are often used to predict consumer behavior and probability calculations. It is also widely implicated in marketing(Khattak & Khattak, 2023; Gandhmal & Kumar, 2019).

Decision Satisfaction

We consider the dissatisfaction of decision as a random variable α follows a log-normal distribution with its probability density function (p.d.f.).

$$h(\alpha|\mu,\sigma) = \frac{1}{\alpha\sigma\sqrt{2\pi}}\exp\left[-\frac{(\log\alpha-\mu)^2}{2\sigma^2}\right], \quad \alpha > 0 . \tag{1}$$

And its cumulative distribution function (c.d.f.) as

$$H(\alpha|\mu,\sigma) = \Phi\left[\frac{\log\alpha-\mu}{\sigma}\right]. \tag{2}$$

Indecision Behavior

The duration time of decision-making is used to measure indecision behavior. Based on the literature review, the decision satisfaction of customer is influenced by their indecision behavior. Taking this into consideration, it is reasonable to consider a Bayesian model. Thus, we consider indecision behavior μ a conjugate prior to log-normal distribution. μ follows normal distribution as

$$f(\mu) = \frac{1}{\varepsilon\sqrt{2\pi}} \exp\left[-\frac{(\mu-\theta)^2}{2\varepsilon^2}\right] \tag{3}$$

Then we can calculate the marginal density of α the as

$$h(\alpha|\theta,\varepsilon,\sigma) = \int_0^\infty h(\alpha|\mu,\sigma)\cdot f(\mu)d\mu$$

$$= \frac{1}{\alpha\sigma\varepsilon 2\pi}\int_0^\infty \exp\left[-\frac{(\log\alpha-\mu)^2}{2\sigma^2} - \frac{(\mu-\theta)^2}{2\varepsilon^2}\right] d\mu \tag{4}$$

Through this density, decision satisfaction can be predicted by indecision behavior.

Case Study

We use the customers' online shopping as a case to investigate the relationships between indecision and decision satisfaction. Also, we use the data from the case to estimate the parameters of the proposed model and model calibration.

1. **Empirical Data**

Google Analytics (GA) is used to apply empirical data on customers' shopping behavior from Google's online shop. To adopt the GA data, we define that the event includes the money-paying (settle accounts) stage should be done. Moreover, this duration of the session is the indecision time. Higher duration means a higher indecision tendency. The Bounce rate is denoted as the decision satisfaction. If the Bounce rate is low, it means more decision satisfaction.

The date of analysis is from 1 April to 31 April 2020. There are 44,542 users, of which 83.2% are new users, the total number of sessions is 58,015 (the average number of sessions is 1.30), the total number of page views is 232,634 (the average number of pageviews is 4.01), the average duration of sessions is 2mins 48seconds, the bounce rate is 49.21%. About the event profile, most events are Enhanced E-commerce 62,991 (99.11%).

Tables 1 and **2** show the customer's portfolio and payment behavior. In **Table 1**, 55-64-year-old customers have the most significant average duration of sessions (202.07) and the highest E-commerce conversion rate (0.15%). However, 25- 34-year-olds contribute higher revenue(307.35) and make the most transactions (3 times). The 18-24 age group has the highest Bounce rate (50.88%) of all segments. In **Table 2**, we find that returning users have a higher give-up rate (88.04%) than new users

(73.71%) in the payment stage. Suppose we denote the give-up rate as g. Then, we can obtain the no-give-up rate by 1-g.

Table 1. Consumer profile in the database

Age	Numbers of users	Numbers of new users	Session	Bounce rate	The average number of signal sessions	The average duration of sessions	Numbers of transactions	Revenues	E-commerce conversion rate
18-24	5449	5139	7156	50.88%	3.67	164.42	2	100.00	0.03%
25-34	8262	7704	10872	47.88%	4.11	181.37	3	307.35	0.03%
35-44	3328	3105	4434	47.65%	4.27	177.83	2	156.60	0.05%
45-54	1805	1664	2387	43.78%	4.45	182.84	1	19.60	0.04%
55-64	1039	953	1306	47.17%	4.68	202.07	2	113.55	0.15%
65+	771	726	996	47.39%	4.32	187.82	0	0.00	0.00%
Sum	20654	19291	27151	48.22%	4.09	177.69	10	697.10	0.04%

Source: Author's data processing results (2022)

Table 2. The analysis of payment behavior

	Billing and Shipping		Payment		Session of transactions	Review	
	sessions	give up rate	sessions	give up rate	Sessions	sessions	give up rate
Returning Visitor	408	297 (72.79%)	209 (51.23%)	184 (88.04%)	16 (4.90%)	20 (3.92%)	19 (95.0%)
New Visitor	377	248 (65.78%)	175 (46.42%)	129 (73.71%)	40 (4.24%)	16 (10.61%)	16 (100%)
Sum	785	545	384	313	56	36	35

Source: Author's data processing results (2022)

RESULT AND DISCUSSION

It uses MLE (maximum likelihood estimate) to estimate the parameters of the proposed model—20654 data conducted to estimate θ, ε, and σ, according to equation (4). Let L denote the likelihood.

$$L(\theta,\varepsilon,\sigma) = \prod_{i=1}^{20654} h_i\,(\alpha|\theta,\varepsilon,\sigma)$$

$$= \left[\frac{1}{\alpha\sigma\varepsilon 2\pi}\right]^{20654} \int_0^{\infty} \exp - 20654\left[\frac{(\log\alpha-\mu)^2}{2\sigma^2}+\frac{(\mu-\theta)^2}{2\varepsilon^2}\right] d\mu \qquad (5)$$

We differentiate L(θ,ε,σ) respectively concerning θ, ε,σ and set them to zero. The results are shown in **Table 3**.

We use the survey data to compare the difference of prediction data, which Google Analytics uses to estimate. 315 sample size is collected from1 April to 31 April in2020. The questionnaire items on indecision are based on Potworowski (2010), and the items on decision satisfaction are based on Huang et al. (2018). The reliability of indecision, Cronbach α, is 0.897, and decision satisfaction, Cronbach α, is 0.921.

Table 3. The analysis of payment behavior

θ	ε	Σ
3.24	20.53	15.32

Source: Author's data processing results (2022)

The root-mean-square deviation (RMSD) (Busch et al., 2014) is calculated to compare survey and prediction data. If the value of RMSD is low, they are close to each other and show more goodness fit of the proposed model. The result of RMSD is 0.553. It shows the middle level of goodness fit in the proposed model. Thus, the proposed model can portray consumer purchase behavior and describe the relationship between customer indecision reflection and decision satisfaction.

CONCLUSION AND RECCOMENDATION

This paper uses online shopping behavior as a case study to explore the impact of customers' indecision on their decision satisfaction when they purchase in Google online shop. The results find that people of higher ages (55-64) have more indecision than younger ones. They also have a higher E-commerce conversion rate. However, younger users (25-34) contribute higher revenue and make the highest transactions. When comparing new and returning users, new visitors have lower give-up rates when they process the payment. It means the new visitors have a higher probability of making a purchase. To sum up, the more indecision tendency is less decision satisfaction. When people defer the decision, it can mean that they may think of some problem and need more information to help them make a decision; then, their decision satisfaction may decrease.

This paper provides a probability model to make the relationships between indecision and decision satisfaction become computable, specific quantification, and measurable. It helps managers control the tendency of indecision to achieve higher decision satisfaction. In advance, the impact factors of indecision can be investigated to design more incentive and attractive platforms to accelerate the payment process.

The limitations of this research are that only one probability model distribution is used as the assumption of the indecision and satisfaction variables. In the future, other probability density functions of the model can be considered, such as exponential distribution, when using the duration time of decision-making to measure indecision behavior. Other variables can be included in exploring the relationships between indecision and decision satisfaction. For example, to find the predictor variables of indecision or the outcome variables of decision satisfaction. Besides the Bayesian model, another form of the model can be discussed. The causes study only uses Google Analytics data, another limitation of this paper. Some other industry applications, such as other retail e-commerce data, can be used to extend the proposed model and test its prediction accuracy.

REFERENCES

Alcantud, J. C. R., Cantone, D., Giarlotta, A., & Watson, S. (2022).Rationalization of indecisive choice behavior by majoritarian ballots. arXiv:2210.16885, 1-33. https://dx.doi.org/10.2139/ssrn.4499212

Bacanli, F. (2006). Personality characteristics as predictors of personal indecisiveness. *Journal of Career Development*, Volume 32 Issue 4, pp. 320-332. https://doi.org/10.1177/0894845305282941

Berry, L. R., Helman, P., & West. M. (2020).Probabilistic forecasting of heterogeneous consumer transaction–sales time series. *International Journal of Forecasting,* Volume 36 Issue 2, pp. 552-569. https://doi.org/10.1016/j.ijforecast.2019.07.007

Busch, P., Lahti, P., & Werner,R. F.(2014). Colloquium: Quantum root-mean-square error and measurement uncertainty relations. *Reviews of Modern Physics,* Volume 86 Issue 4, pp. 1261 -1283. https://doi.org/10.1103/RevModPhys.86.1261

Camilleri, M.A. (2022). E-commerce websites, consumer order fulfillment, and after-sales service satisfaction: The customer is always right, even after the shopping cart check-out. *Journal of Strategy and Management*, Volume 15 Issue 3, pp. 377-396. https://dx.doi.org/10.2139/ssrn.3853156

Chernev, A., Böckenholt, U., & Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. *Journal of Consumer Psychology*, Volume 25 Issue 2, pp. 333–358. https://doi.org/10.1016/j.jcps.2014.08.002

Cho, C.-H., Kang, J., & Cheon, H. J. (2006). Online Shopping Hesitation. *CyberPsychology & Behavior*, Volume 9 Nomor 3, pp. 261-74. https://psycnet.apa.org/doi/10.1089/cpb.2006.9.261

Dhar, R. (1997). Consumer Preference for a No-Choice Option. *Journal of Consumer Research,* Volume 24 Issue 2, September 1997, pp. 215–231, https://doi.org/10.1086/209506

Dişli Bayraktar, E. (2023). Examining the relationship between relationship marketing, cognitive dissonance, customer satisfaction, and repurchase behavior: A study on online purchasing behavior. *Fiscaoeconomia*, Volume 7 Issue 1, pp. 508-524. https://doi.org/10.25295/fsecon.1186447

Elaydi, R. (2006). Construct development and measurement of indecisiveness. *Management Decision*, Vol. 44 No. 10, pp. 1363-1376. https://doi.org/10.1108/00251740610715696

Ferrari, J. R., & Dovidio, J. F. (2001). Behavioral information search by indecisive. *Personality and Individual Differences*, Volume 30 Issue 7, pp. 1113-1123. https://doi.org/10.1016/S0191-8869(00)00094-5

Fitzsimons, G. J. (2000). Consumer response to stockouts. *Journal of Consumer Research*, Volume 27, Issue 2, September 2000, pp. 249–266, https://doi.org/10.1086/314323

Gandhmal, D. P., & Kumar, K. (2019). Systematic analysis and review of stock market prediction techniques. *Computer Science Review*, Volume 34, pp. 215-232. https://doi.org/10.1016/j.cosrev.2019.08.001

Huang, Guei-Hua, Korfiatis, Nikolaos & Chang, Chun-Tuan (2018). Mobile shopping cart abandonment: The roles of conflicts, ambivalence, and hesitation. *Journal of Business Research*, Volume 85, pp.165-174. https://doi.org/10.1016/j.jbusres.2017.12.008

Inesi, M. E., Botti, S., Dubois, D., Rucker, D. D., & Galinsky, A. D. (2011). Power and choice: Their dynamic interplay in quenching the thirst for personal control. *Psychological Science*, 22(8), 1042-1048.

Khalid, R. & Farooq, M. (2019). Online Shopping Hesitation in Pakistan. *Global Journal of Emerging Sciences*, 1(1), pp.53-65.

Khattak, Z. H., &. Khattak, A. J. (2023) Using behavioral data to understand shared mobility choices of electric and hybrid vehicles. *International Journal of Sustainable Transportation*, Volume 17 Issue 1, pp. 1-18, https://doi.org/10.1080/15568318.2021.2004627

König, P. D., Wurster, S., & Siewert, M.B. (2022). Consumers are willing to pay a price for explainable, but not for green A.I. Evidence from a choice-based conjoint analysis. *Big Data & Society*, pp1-13. https://dx.doi.org/10.2139/ssrn.3890774

Lee, I., P., Jilke, S. & James, O. (2020). Do more options always benefit the users of public services? An experimental study of school choice, performance, and satisfaction. *Public Administration Review, Forthcoming*, http://dx.doi.org/10.2139/ssrn.3677465

Manisera, M., Zuccolotto, P., & Brentari, E. (2020). How perceived variety impacts on choice satisfaction: a two-step approach using the C.U.B. class of models and best-subset variable selection. *Electronic Journal of Applied Statistical Analysis*, 13(2), pp.519-535.

Manyaga, F., & Hacioglu, U. (2021). Investigating the impact of mobile telecom service characteristics on consumer satisfaction in urban Uganda. *International Journal of Research in Business and Social Science* (2147- 4478), Volume 10 Nomor 6, pp. 19-33. https://doi.org/10.20525/ijrbs.v10i6.1382

Milgram, N., & Tenne, R. (2000). Personality correlates of decisional task avoidant procrastination. *European Journal of Personality*, Volume 14 Issue 2, pp. 141–156. https://doi.org/10.1002/(SICI)1099-0984(200003/04)14:2<141::AID-PER369>3.0.CO;2-V

Potworowski, G. A. (2010). Varieties of Indecisive Experience: Explaining the Tendency to Not Make Timely and Stable Decisions. *Dissertation Abstracts International: Section B: The Sciences and Engineering*, Issue 71(5-B), 3340. https://psycnet.apa.org/record/2010-99220-325

Sabioni, R, Wartelle, L., Daaboul, J., Le Duigou, J. (2021).Attribute-based integrated product process configurator for mass customization. *Procedia CIRP*, Volume 103, pp. 104-145. https://doi.org/10.1016/j.procir.2021.10.022

Sanyal, N. H., Mazumder, R., Singh, R., & Sharma, Y. (2021).Uncertainty and affluent teenagers' luxury buying-decision: The role of avoidance-related indecisiveness. *Journal of Retailing and Consumer Services*, Volume 58, pp. 1-21. https://doi.org/10.1016/j.jretconser.2020.102305

Yunus, M., Fauzi, A., & Rini, E. S. (2022). The effect of e-service quality and customer satisfaction on repurchase intention through online consumer review as intervening variables in the marketplace Shopee. *Journal Research of Social, Science, Economics, and Management,* Volume 1 Nomor 6, pp. 669–679. https://doi.org/10.59141/jrssem.v1i6.75

Ryals, L. (2005). Making customer relationship management work: the measurement and profitable management of customer relationships. *Journal of Marketing*, Volume 69 Issue 4, pp. 252-261. https://doi.org/10.1509/jmkg.2005.69.4.252

James, A., Bradshaw, M., Coe, N. M., & Faulconbridge, J. (2018). Sustaining economic geography? Business and management schools and the U.K.'s great economic geography diaspora. *Environment and Planning A: Economy and Spaces*, Volume 50 Issue 6, pp. 1355-1366, https://doi.org/10.1177/0308518X18764120