Journal of Innovation in Business and Economics
Vol. 08 No. 02 December 2024 Page 1-10
P-ISSN: 2580-9431 E-ISSN: 2581-2025 http://ejournal.umm.ac.id/index.php/jibe

Received: 23-05-2024 | Revised in Revision: 13-10-2024 | Accepted: 14-10-2024| Published: 24-10-2024

Dynamic pricing and consumer inertia: An empirical analysis

Ronnie Togar Mulia Sirait[1], Maretta Ginting[2], Wan Suryani[3]

Department Master of Management, Faculty of Economics and Business, Univesitas Sari Mutiara, Indonesia[1,2]
Department Master of Management., Faculty Post Graduate Program, Univesitas Medan Area, Indonesia[3]

DOI: https://doi.org/10.22219/jibe.v8i02.36013

Abstract
This study aims to examine the impact of dynamic pricing on Gen Z consumer inertia. This study defines consumer inertia as the tendency to continue using the same product or service. In addition to focusing on dynamic pricing, this study also involves several control variables: consumer reviews, loyalty, brand image, and influencer marketing. They use 103 respondents who frequently purchase personal care products from online marketplaces. Through regression analysis using Ordinary Least Squares (O.L.S.), Generalized Least Squares (G.L.S.), and Robust Least Squares (R.L.S.), we found that dynamic pricing and consumer reviews have a significant effect on consumer inertia. Specifically, price reductions on competing products and positive reviews for these items encourage Gen Z to switch brands. In contrast, loyalty, brand image, and influencer marketing do not significantly affect consumer inertia. The findings of this study suggest that brands seeking to capture Gen Z's market share should focus on price competition and product quality transparency instead of building loyalty, brand image, and promoting influencer marketing.

Keywords: Dynamic pricing; consumer inertia; Gen Z

Introduction

E-commerce significantly changes the interaction between sellers and buyers (Chen, Mislove, & Wilson, 2016). One of the main aspects of this change is the possibility for sellers to implement dynamic pricing, which was previously very difficult to do in traditional transaction models. Sellers can easily change prices in real time depending on certain factors, such as customer traffic or moments (Ferreira, Lee, & Simchi-Levi, 2015). Unlike static pricing models, dynamic pricing allows for rapid price adjustments; for example, when stock is running low and demand is high, sellers can quickly increase their prices periodically, or vice versa to increase sales amidst declining demand, prices can gradually be lower (Chen et al., 2016). This adaptive approach aims to optimize revenue for merchants, improve market efficiency, and personalize individual shopping experiences (Ferreira et al., 2015).

However, as dynamic pricing becomes more common in digital markets, concerns have been raised about transparency, fairness, and the potential for consumer exploitation, prompting a re-evaluation of the ethical implications of this pricing strategy (Ferreira et al., 2015). Dynamic pricing can encourage changes in consumer behaviour, including reducing consumer inertia resistance, where customers are reluctant to change their purchasing decisions towards competitors' products (Anderson & Simester, 2019). Dynamic pricing marks a fundamental change in the pricing strategy used by online merchants.

The question is, can the implementation of dynamic pricing affect consumer inertia, which generally already has preferences and is also loyal to specific brands? To answer this, this study examines

[1] E-mail: ronnie.sirait@gmail.com
[2] E-mail: gintingmaretta11@gmail.com
[3] E-mail: wansuryani@staff.uma.ac.id

whether dynamic pricing can affect consumer inertia. In detail, dynamic pricing can shake the inertia of consumers who tend to buy the same product repeatedly. In a rapidly changing digital market, understanding the relationship between these two factors is essential for academic investigation and practical application for industry stakeholders. This study is critical both academically and practically. For academics, we provide the latest evidence on how price changes affect consumer decisions. For the industry, this study provides an understanding of whether dynamic pricing strategies can be relied on to gain market share.

Literature Review

Dynamic Pricing

Dynamic pricing, also known as surge pricing, demand-based pricing is a new strategy that can be used in digital marketing. Dynamic pricing allows sellers to optimize by responding to indicators such as unique visits or sales trends. Dynamic pricing can also be associated with supply chain dynamics. The practice has its roots in revenue management techniques pioneered in industries such as airlines and hospitality. Still, its application has expanded rapidly with e-commerce, machine learning, and advanced algorithms (Elmaghraby & Keskinocak, 2003). This dynamic pricing method differs from traditional fixed pricing mechanisms. Through dynamic pricing, businesses can leverage algorithms to improve their pricing strategies. Machine learning models allow companies to predict demand, monitor competitor actions, and respond to inventory levels more precisely. These technological advancements benefit sectors such as e-commerce, ride-sharing, and hospitality, where demand fluctuations can significantly impact pricing strategies essential to maximizing short-term revenue and long-term Profitability (Grewal et al., 2011).

From an economic perspective, dynamic pricing offers significant advantages. This is because companies can capitalize on periods of high demand by raising prices while appealing to price-sensitive consumers by lowering prices during periods of low demand. As Elmaghraby and Keskinocak (2003) found, industries with high demand elasticity stand to benefit the most from this strategy. For example, during peak shopping seasons or periods of high demand for travel and accommodation, dynamic pricing helps businesses align prices with demand, thereby maximizing revenue. Research shows that companies that use dynamic pricing can experience increased profit margins and better inventory management, minimizing instances of unsold stock or unused service slots.

While dynamic pricing has promising financial benefits, it does pose challenges to price fairness. The psychological impact of dynamic pricing can be significant, especially when consumers perceive that prices fluctuate due to factors beyond their control. Grewal et al. (2011) highlight that consumers tend to respond negatively to dynamic pricing if they perceive it as unfair or exploitative, which can damage brand loyalty and trust. Therefore, companies must effectively communicate the reasons for price fluctuations and ensure consumers feel they receive value for money. Research shows that when consumers understand the reasons behind dynamic pricing, such as variations in demand or supply, they are more likely to perceive it as fair and accept it. Furthermore, implementing price guarantees or price adjustment policies can help alleviate concerns, reducing consumers' likelihood of switching to competitors that offer more stable or predictable prices (Grewal et al., 2011).

Consumer Inertia and Its Implications

Consumer inertia has been extensively examined across various fields, including psychology, economics, and marketing. Beyond factors such as loyalty, satisfaction, and perceived switching costs, inertia can also stem from cognitive biases like the status quo bias (Kahneman, Knetsch, & Thaler, 1991), wherein individuals prefer their current situation due to a fear of potential loss associated with change. This bias is often amplified by the default effect (Thaler & Sunstein, 2008), which leads consumers to stick with their initially chosen option, even when better alternatives are available.

Additionally, the concept of bounded rationality (Simon, 1955) significantly contributes to consumer inertia, as individuals may lack the time, energy, or information necessary to thoroughly evaluate all alternatives, prompting them to make decisions that are satisfactory rather than optimal. The phenomenon of information overload in online marketplaces (Eppler & Mengis, 2004) further exacerbates this issue, as consumers may feel overwhelmed by excessive choices, thereby increasing their reliance on established brands or familiar sellers.

In the context of online marketplaces, consumer inertia is shaped by factors unique to the digital environment. Research on choice paralysis (Schwartz, 2004) indicates that the abundance of options characteristic of e-commerce platforms can diminish the likelihood of consumers switching to alternatives. Moreover, studies on algorithmic curation reveal that personalized recommendations and filtering mechanisms can reinforce consumer behavior by providing suggestions based on past interactions, thereby creating a “filter bubble” effect (Pariser, 2011). This effect limits exposure to new alternatives, further entrenching consumer inertia.

While dynamic pricing is designed to optimize consumer behavior theoretically, it can have unintended consequences when inertia is present. Frequent or unpredictable price fluctuations may lead consumers to perceive pricing practices as unfair or manipulative, resulting in decision fatigue (Baumeister, 2002). As a consequence, consumers may continue to engage with a familiar seller or brand, even when better prices are available elsewhere. This outcome illustrates a paradox of dynamic pricing: rather than promoting switching behavior, it can reinforce loyalty and resistance to change (Tversky & Shafir, 1992).

The Intersection of Dynamic Pricing and Consumer Inertia

For online marketplaces, the interplay between dynamic pricing and user inertia presents serious difficulties. Although the goal of dynamic pricing is to optimise prices based on real-time data, its efficacy may be hampered by consumer reluctance. Numerous research have examined this link, determining if inertia restricts the effectiveness of pricing schemes or whether dynamic pricing may effectively overcome it. Customers with high degrees of inertia, for instance, have been shown to be less responsive to price adjustments, which leads to dynamic pricing producing lower-than-anticipated revenue growth. On the other hand, other study indicates that certain strategies, including tailored pricing or promotions, might lessen the impact of inertia by emphasising the advantages of moving to customers.

The relationship between inertia and dynamic pricing can also be complicated by temporal considerations. Customers who have spent a lot of time or money on a brand or seller are less inclined to switch, even if they are offered a better deal, according to research on the sunk cost effect by Gourville and Soman (2002). As a result, dynamic pricing tactics that disregard this psychological barrier can find it difficult to draw in brand-loyal customers.

This problem can be further explained from the standpoint of behavioural economics by the idea of reference pricing theory (Winer, 1986). According to this hypothesis, customers use previous transactions to determine internal reference pricing. Customers may get confused and dissatisfied if dynamic pricing throws off these reference points, which could lead them to return to their old buying habits and reinforce inertia (Mazumdar, Raj, & Sinha, 2005).

Research Method

Research Design

Generation Z is the sample in this study, considering the characteristics of this generation that grew up in the digital era, so they are sensitive to changes in information (Priporas et al., 2017; Smith, 2019). This study is a quantitative study using a survey method. The survey method is used with the hope that the sample used in this study can represent the characteristics of the Gen Z population well (Biyalogorsky & Gerstner, 2004; Grewal et al., 2011). In order to focus the research, this study focuses on Gen Z, who use active bike care products, and the majority buy them through online services. This study uses 103 Gen Z respondents. The questionnaire has several dimensions; the first is the dynamic pricing dimension. In general, this dimension measures whether consumers relatively pay attention to and consider dynamic price changes to be something to consider in purchasing decisions.

Furthermore, the second dimension is the customer review dimension; the rubric in this dimension focuses on measuring whether customer comments can influence purchasing decisions. In addition, this study also designs a question rubric for the loyalty and brand image dimensions. The loyalty rubric is designed to evaluate the strength of consumer attachment to a particular brand, while the brand image is used to measure their perception of a brand. In addition to the four independent variables, this study also measures the consumer inertia dimension, which indicates consumer resistance to switching to competitor products.

All responses were measured using a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." The Likert scale is a well-established tool in behavioural research, known for its ability to quantitatively capture subtle variations in attitudes and perceptions (Allen & Seaman, 2007). This scale provides a nuanced understanding of consumer behaviour across multiple dimensions. To maximize outreach and ensure accessibility, the questionnaire was distributed electronically via social media platforms favoured by Generation Z. This targeted approach effectively engaged a highly active demographic in the digital space, ensuring a broader and more relevant sample for analysis. For technical accuracy, we used negatively worded questions to measure consumer inertia, where a higher score indicates a greater tendency to switch to other products, and a lower score reflects a stronger resistance to switching from a product that has been previously used.

Data Analysis Procedure

This study uses three regression approaches: ordinary least squares (O.L.S.), Generalized Least Squares (G.L.S.), and Robust Least Squares (R.L.S.). OLS-based regression is used as the basic model to estimate the linear relationship between independent variables, explaining how the influence of dynamic pricing and several control variables, such as consumer reviews, loyalty, brand image, and influencers, affect consumer inertia.

G.L.S. is used to overcome the potential for heteroscedasticity, a condition where the error variance is not constant across observations. In consumer behaviour research, heteroscedasticity can come from differences in respondent income levels or consumer preferences. G.L.S. improves the efficiency of parameter estimation when the error variance is not the same (Greene, 2018). Because this study does not involve income and consumer preferences, G.L.S. is appropriate for a comparative test of the O.L.S. results. Furthermore, this study also uses the Robust Least Squares (R.L.S.) test. R.L.S. is applied to account for potential outliers or non-normality in the data set. Given that Generation Z consumers can provide extreme or highly variable responses that may be influenced by personal preferences, social media, or trends, this can distort the results. R.L.S. increases the robustness of the regression analysis by reducing the impact of such outliers, thus providing more reliable estimates even when the assumption of normality is violated (Huber & Ronchetti, 2009). After conducting tests using various regression methods, this study also tested several assumptions, including 1) Normality Test, the aim is to verify whether the data follows a normal distribution; specifically, this test checks whether the residuals (errors) of the model are typically distributed; 2) Multicollinearity Test, multicollinearity occurs when the independent variables are highly correlated, thus violating the assumption of independence of the independent variables (Wooldridge, 2016).

Result and Discussion

The descriptive analysis results in Table 1 indicate that the standard deviations for each variable are relatively low, suggesting a high degree of homogeneity within the sample. Table 2 confirms the absence of multicollinearity, as the correlation values between the independent variables are all below 0.8. Furthermore, Tables 3, 4, and 5 demonstrate that the estimates from the OLS, GLM, and robust least squares models are consistent in both direction and magnitude of coefficients, indicating the stability of the model. The results across all three models show that dynamic pricing and consumer reviews significantly increase the intention to switch to a competitor, or in other words, they tend to reduce consumer inertia. In contrast, loyalty, brand image, and influencer marketing are found to be statistically insignificant.

Table 1. Descriptive statistic

	Consumer Inertia	Dynamic Pricing	Loyalty	Brand Image	Review	Influencer
Mean	3.565534	2.398058	4.000000	3.582524	3.941748	3.145631
Median	3.500000	2.333333	4.000000	4.000000	4.000000	3.000000
Maximum	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000
Minimum	2.500000	1.000000	1.000000	1.000000	1.800000	1.000000
Std. Dev.	0.486284	0.583092	0.863191	0.760860	0.559153	1.003990
Skewness	0.125368	0.617371	-0.827165	-0.482044	-0.885807	-0.235949
Kurtosis	2.682748	5.680646	3.709141	4.257802	5.078214	2.552721
Jarque-Bera	0.701763	37.38235	13.90366	10.77865	32.00549	1.814290
Probability	0.704067	0.000000	0.000957	0.004565	0.000000	0.403675
Sum	367.2500	247.0000	412.0000	369.0000	406.0000	324.0000
Sum Sq. Dev.	24.12015	34.67961	76.00000	59.04854	31.89049	102.8155
Observations	103	103	103	103	103	103

Price Awareness Among Generation Z

Born in an era where everything is digital, it is unsurprising that Generation Z is very well-informed and sometimes sensitive to information exposure. The results of this study also indicate that it supports the findings (Smith, 2019). Gen considers price reductions, discounts, or vouchers as "limited opportunities" that must be taken advantage of immediately when there are similar products with perceived quality that are almost the same. This makes them finally change their previous purchasing decisions and make new decisions based on better offers (Grewal et al., 2011). In addition, dynamic pricing also often creates a sense of urgency, for example, with the warning "price will increase in 10 minutes" or "only 3 items left." This approach takes advantage of the Fear of Missing Out (F.O.M.O.) phenomenon, which Generation Z often feels because they don't want to miss out on getting the best deals (Przybylski et al., 2013).

Table 2. Correlation matrix

	Consumer Inertia	**Dynamic Pricing**	**Loyality**	**Brand Image**	**Review**	**Influencer**
Consumer Inertia	1	0.385	-0.0291	0.187	0.44	0.2463
Dynamic Pricing	0.385	1	-0.038	-0.034	0.46	0.162
Loyalty	-0.029	-0.038	1	0.134	0.09	-0.214
Brand Image	0.187	-0.034	0.1348	1	0.158	0.1573
Review	0.446	0.460	0.093	0.158	1	0.364
Influencer	0.246	0.162	-0.214	0.157	0.364	1

Dynamic pricing is not only aimed at optimizing prices but also works to overcome consumers' psychological resistance to change their purchasing decisions. Generation Z may initially be reluctant to switch from their preferred brands or products. However, with rational price adjustments this reluctance is reduced (Heitz-Spahn, 2013). This rationality is needed because it is very possible that if the price is too cheap relative to competitors, it is very possible that this can reduce credibility. In addition, of course, it is not only the price; other factors, such as positive reviews from customers, are also essential (Malthouse et al., 2013). However, it should be remembered that dynamic pricing tends to be only for short-term sales strategies and in the long term, it may be very different

Table 3. OLS

Variable		**t-Statistic**	**Prob.**
Dynamic Pricing	0.202478 (0.082436)	2.456176	0.0158
Loyalty	-0.029566 (0.051789)	-0.570886	0.5694
Brand Image	0.093159 (0.057567)	1.618264	0.1089
Review	0.254537 (0.092885)	2.740362	0.0073
Influencer	0.031966 (0.047385)	0.674590	0.5015
C	1.760626 (0.380715)	4.624520	0.0000
R-Squared	0.269441	Mean dependent var	3.565534
Adjusted R-Squared	0.231784	S.D. dependent var	0.486284

Note: Standard errors are in parentheses.

Positive Reviews from Other Customers as a Catalyst for Change

Research shows that online reviews serve to validate product quality. That is, Gen Z relies on the experiences and opinions of others to guide their own decisions (Cheung & Thadani, 2012). In the digital marketplace, where direct product inspection is impossible, positive reviews help reduce uncertainty and build trust in a product or service (Ba & Pavlou, 2002). In addition to reducing risk, positive reviews provide psychological reinforcement that strengthens consumer intentions and final purchasing decisions. The "bandwagon effect" explains how reviews greatly influence consumer inertia (Leibenstein, 1950). In other words, Gen Z also strongly believes in collective truth, therefore brands need to maintain product and service quality to gain positive sentiment from the market (Jin & Phua, 2014).

Furthermore, Cheung and Thadani (2012) emphasized that reviews reflect customer satisfaction and serve as a powerful marketing tool that influences purchasing decisions. In another study, Smith and Anderson (2018) explained that the tendency to pay attention to reviews is because this demographic is accustomed to consulting various sources of information, including peers. These peer reviews are the basis for determining purchases (Filieri et al., 2018). Thus, reviews strengthen consumer preferences and can change minds, eliminate doubts, and turn considerations into purchasing decisions (Park & Lee, 2009). Based on these findings and several studies, managing and promoting positive reviews in marketing strategies targeting Generation Z can be essential to marketing success.

Table 4. GLS

Variable	Coefficient	z-Statistic	Prob.
Dynamic Pricing	0.202478 (0.082436)	2.456176	0.0140
Loyalty	-0.029566 (0.051789)	-0.570886	0.5681
Brand Image	0.093159 (0.057567)	1.618264	0.1056
Review	0.254537 (0.092885)	2.740362	0.0061
Influencer	0.031966 (0.047385)	0.674590	0.4999
C	1.760626 (0.380715)	4.624520	0.0000
Mean Dependent Var	3.565534	S.D. dependent var	0.486284
Sum Squared Resid	17.62118	Root MSE	0.413618

Note: Standard errors are in parentheses.

Table 5. Robust least square

Variable	Coefficient	z-Statistic	Prob.
Dynamic Pricing	0.213173 (0.084442)	2.524489	0.0116
Loyalty	-0.061256 (0.053049)	-1.154688	0.2482
Brand Image	0.114997 (0.058968)	1.950160	0.0512
Review	0.276875 (0.095145)	2.910042	0.0036
Influencer	0.032210 (0.048539)	0.663592	0.5070
C	1.700310 (0.389980)	4.359998	0.0000
Robust Statistics			
R-Squared	0.249316	Adjusted R-squared	0.210621
Rw-Squared	0.345869	Adjust Rw-squared	0.345869
Akaike Info Criterion	98.26618	Schwarz criterion	116.7900
Deviance	15.39169	Scale	0.415904
Rn-Squared Statistic	40.95147	Prob. (Rn-squared stat.)	0.000000

Note: Standard errors are in parentheses.

The role of loyalty, brand image, Insignificant role of influencer

There are indications of higher levels of consumer loyalty, especially among Generation Z, making it more difficult to change their purchasing decisions, even when faced with dynamic pricing strategies (based on the negative but insignificant coefficient). While Generation Z is known for its receptiveness to new information and willingness to experiment with products, it also develops strong attachments to brands. This loyalty is shaped by positive experiences, alignment with brand values, and loyalty programs that enhance the overall customer experience (Keller, 2009).

However, we argue that dynamic pricing may be less effective with highly loyal consumers. However, it also provides valuable insights, especially in building long-term relationships between products and customers (Schiffman & Kanuk, 2007). However, since loyalty has an insignificant impact while customer reviews are significant, we argue that consumer loyalty is not only based on individual preferences but is also influenced by collective social perceptions and group dynamics (Escalas & Bettman, 2005). Consequently, we recommend that loyalty enhancement strategies consider collective loyalty, such as maintaining positive customer reviews.

While brand image is often seen as a critical driver of purchasing decisions, this study suggests that this is less the case for Generation Z (Smith & Johnson, 2023). Therefore, brands with a long-standing brand image reputation may not always win the market. This finding indicates that the Gen Z market is relatively dynamic and not necessarily dominated by big brands. Products that can provide competitive prices. Therefore, a strong brand image may not always be enough to convince them; instead, direct evidence of a product's quality or benefits is essential. This suggests that brands looking to appeal to Generation Z should provide tangible evidence for their claims and ensure that consumer reviews consistently reflect positive experiences (Nguyen, 2021).

This study also shows that influencers do not significantly impact purchasing decisions. The results of this study clearly show that Generation Z tends to trust consumer reviews more than influencers, who are often considered only to do work without emotional ties (Peterson et al., 2023). Another indication is that Gen Z sees influencers' work as inauthentic and tends to be just a business, thus reducing the product's value (Chen, 2023). Therefore, the effectiveness of influencer marketing may be more limited than expected data proven by several studies. However, this does not mean that influencers are ineffective, as long as the influencer is authentic and by their field; for example, a skin health influencer recommending body care products is undoubtedly likely to have a different impact than just relying on a famous figure.

Conclusions, suggestions and limitations

Based on the findings and discussions in this study, dynamic pricing and positive customer reviews are critical factors in capturing Generation Z's market share. Additionally, some indications are that building long-term loyalty is essential for retaining these customers. The findings also suggest that Generation Z prioritizes direct benefits and authentic reviews from other users over brand perceptions shaped by traditional marketing approaches. They place more excellent value on aspects that can be directly verified through testimonials or real-life experiences shared by other consumers.

Moreover, Generation Z tends to be sceptical of influencer content that appears overly commercial or lacks authenticity. They emphasise genuine engagement and integrity from influencers rather than transactional promotions. To attract and foster loyalty among Generation Z, brands must emphasize transparency, provide verifiable proof of product claims, and offer authentic consumer experiences. Marketing strategies that rely solely on a brand image or influencer endorsements may need to be reconsidered to align more effectively with Generation Z's values and their preference for authenticity and personal connection.

Competing Interests

The author(s) declare that there are no competing interests relevant to the content of this article.

References

Allen, I. E., & Seaman, C. A. (2007). Likert scales and data analyses. *Quality Progress, 40*(7), 64-65.

Anderson, E. T., & Simester, D. I. (2011). Price stickiness and customer antagonism. Quarterly Journal of Economics, 126(2), 729-765. https://doi.org/10.1093/qje/qjr015

Anderson, E. T., & Simester, D. I. (2019). Reviews without a purchase: Low ratings, loyal customers, and bias. Marketing Science, 38(5), 849-869. https://doi.org/10.1287/mksc.2019.1160

Ba, S., & Pavlou, P. A. (2002). Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior. *MIS Quarterly, 26*(3), 243–268. https://doi.org/10.2307/4132332

Baumeister, R. F. (2002). *Yielding to temptation: Self-control failure, impulsive purchasing, and consumer behavior*. Journal of Consumer Research, 28(4), 670–676.https://doi.org/10.1086/338209

Berman, B. (2016). Referral marketing: Harnessing the power of your customers. Business Horizons, 59(1), 19-28. https://doi.org/10.1016/j.bushor.2015.08.001

Biyalogorsky, E., & Gerstner, E. (2004). Contingent pricing to reduce price risks. Marketing Science, 23(1), 146-155. https://doi.org/10.1287/mksc.1030.0037

Chen, L. (2023). The Impact of Digital Marketing on Consumer Trust. International Journal of Consumer Studies, 47(1), 45-58.

Chen, L., Mislove, A., & Wilson, C. (2016). An empirical analysis of algorithmic pricing on Amazon Marketplace. Proceedings of the 25th International Conference on World Wide Web, 1339-1349. https://doi.org/10.1145/2872427.2883089

Cheung, C. M. K., & Lee, M. K. O. (2012). What drives consumers to spread electronic word of mouth in online consumer-opinion platforms. *Decision Support Systems, 53*(1), 218–225. https://doi.org/10.1016/j.dss.2012.01.015

Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems, 54*(1), 461–470. https://doi.org/10.1016/j.dss.2012.06.008

Elmaghraby, W., & Keskinocak, P. (2003). Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. Management Science, 49(10), 1287-1309. https://doi.org/10.1287/mnsc.49.10.1287.17315

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society*, 20(5), 325-344. https://doi.org/10.1080/01972240490507974

Escalas, J. E., & Bettman, J. R. (2005). Self-construal, reference groups, and brand meaning. *Journal of Consumer Research, 32*(3), 378–389. https://doi.org/10.1086/497549

Ferreira, K. J., Lee, B. H. A., & Simchi-Levi, D. (2015). Analytics for an online retailer: Demand forecasting and price optimization. Manufacturing & Service Operations Management, 18(1), 69-88. https://doi.org/10.1287/msom.2015.0561

Filieri, R., Alguezaui, S., & McLeay, F. (2018). Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. *Tourism Management, 51*, 174–185. https://doi.org/10.1016/j.tourman.2015.05.007

Grewal, D., Ailawadi, K. L., Gauri, D., Hall, K., Kopalle, P., & Robertson, J. R. (2011). Innovations in retail pricing and promotions. Journal of Retailing, 87(S1), S43-S52. https://doi.org/10.1016/j.jretai.2011.04.008

Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-commerce and the importance of social presence: Experiments in e-products and e-services. *Omega*, 32(6), 407-424. https://doi.org/10.1016/j.omega.2004.01.006

Gourville, J. T., & Soman, D. (2002). Pricing and the psychology of consumption. *Harvard Business Review*, 80(9), 90-96.

Greene, W. H. (2018). Econometric analysis (8th ed.). Pearson.

Heitz-Spahn, S. (2013). Cross-channel free-riding consumer behavior in a multichannel environment: An investigation of shopping motives, sociodemographics, and product categories. Journal of Retailing and Consumer Services, 20(6), 570-578. https://doi.org/10.1016/j.jretconser.2013.07.006

Homburg, C., Stierl, M., & Bornemann, T. (2013). Corporate social responsibility in business-to-business markets: How organizational customers account for supplier corporate social responsibility engagement. *Journal of Marketing, 77*(6), 54–72. https://doi.org/10.1509/jm.12.0089

Huber, P. J., & Ronchetti, E. M. (2009). Robust statistics (2nd ed.). Wiley.

Jin, S. V., & Phua, J. (2014). Following celebrities' tweets about brands: The impact of Twitter-based electronic word-of-mouth on consumers' source credibility perception, buying intention, and social identification with celebrities. *Journal of Advertising, 43*(2), 181–195. https://doi.org/10.1080/00913367.2013.827606

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives*, 5(1), 193-206. https://doi.org/ 0.1257/jep.5.1.193

Keller, K. L. (2009). Building strong brands in a modern marketing communications environment. *Journal of Marketing Communications, 15*(2-3), 139–155. https://doi.org/10.1080/13527260902757530

Kimery, K. M., & McCord, M. (2002). Third-party assurances: The road to trust in online retailing. *Proceedings of the 35th Annual Hawaii International Conference on System Sciences*. IEEE. https://doi.org/10.1109/HICSS.2002.994158

Kumar, V., & Shah, D. (2004). Building and sustaining profitable customer loyalty for the 21st century. *Journal of Retailing, 80*(4), 317–330. https://doi.org/10.1016/j.jretai.2004.10.007

Leibenstein, H. (1950). Bandwagon, snob, and Veblen effects in the theory of consumers' demand. *The Quarterly Journal of Economics, 64*(2), 183–207. https://doi.org/10.2307/1882692

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing, 80*(6), 69–96. https://doi.org/10.1509/jm.15.0420

Malthouse, E. C., Haenlein, M., Skiera, B., Wege, E., & Zhang, M. (2013). Managing customer relationships in the social media era: Introducing the social CRM house. Journal of Interactive Marketing, 27(4), 270-280. https://doi.org/10.1016/j.intmar.2013.09.008

Mazumdar, T., Raj, S. P., & Sinha, I. (2005). Reference price research: Review and propositions. *Journal of Marketing*, 69(4), 84-102. https://doi.org/10.1509/jmkg.2005.69.4.84

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly, 34*(1), 185–200. 7

Nguyen, T. (2021). Risk Aversion in Online Shopping Among Younger Consumers. Journal of Consumer Research, 48(5), 900-916.

Oliver, R. L. (1999). Whence consumer loyalty? *Journal of Marketing, 63*(4_suppl1), 33–44. https://doi.org/10.1177/00222429990634s105

Pariser, E. (2011). *The filter bubble: What the Internet is hiding from you*. Penguin Press.

Park, C., & Lee, T. M. (2009). Information direction, website reputation and eWOM effect: A moderating role of product type. *Journal of Business Research, 62*(1), 61–67. https://doi.org/10.1016/j.jbusres.2007.11.017

Peterson, R., Smith, A., & Johnson, B. (2023). The Effectiveness of Influencer Marketing in the Digital Age. Journal of Advertising Research, 63(2), 233-245.

Priporas, C. V., Stylos, N., & Fotiadis, A. K. (2017). Generation Z consumers' expectations of interactions in smart retailing: A future agenda. Computers in Human Behavior, 77, 374-381. https://doi.org/10.1016/j.chb.2017.01.058

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. Computers in Human Behavior, 29(4), 1841-1848. https://doi.org/10.1016/j.chb.2013.02.014

Rook, D. W. (1987). The buying impulse. Journal of Consumer Research, 14(2), 189-199. https://doi.org/10.1086/209105

Schiffman, L. G., & Kanuk, L. L. (2007). *Consumer behavior* (9th ed.). Pearson Education.

Schwartz, B. (2004). *The paradox of choice: Why more is less*. Ecco.

Shankar, V., Kleijnen, M., Ramanathan, S., Rizley, R., Holland, S., & Morrissey, S. (2021). How technology is changing retail. *Journal of Retailing*, 97(1), 13-27. https://doi.org/10.1016/j.jretai.2020.10.006

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99-118. https://doi.org/10.2307/1884852

Smith, A., & Anderson, M. (2018). Social media use in 2018. *Pew Research Center*. https://www.pewresearch.org/internet/2018/03/01/social-media-use-in-2018/

Smith, A., & Johnson, B. (2023). Brand Image and Consumer Loyalty in the Digital Market. Journal of Brand Management, 30(1), 45-60.

Smith, K. T. (2019). Marketing to Generation Z: The challenge of digital natives. Marketing Management Journal, 29(2), 90-103.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.

Tversky, A., & Shafir, E. (1992). Choice under conflict: The dynamics of deferred decision. *Psychological Science*, 3(6), 358-361.https://doi.org/10.1111/j.1467-9280.1992.tb00047.x

Winer, R. S. (1986). A reference price model of brand choice for frequently purchased products. *Journal of Consumer Research*, 13(2), 250-256. https://doi.org/10.1086/209064

Wooldridge, J. M. (2016). Introductory econometrics: A modern approach (6th ed.). Cengage Learning.