Efficacy of Digital Pricing Strategies on Customer Buying Decisions in the E-Commerce Industry: A PLS-SEM Approach

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Abstract

E-commerce is a vital component of global retail sustainability, expanding at a rate of 14% annually, fuelled by increased internet adoption (55%), with over five billion users worldwide. In Africa, e-commerce revenues have surged to $31.18 million, with Nigeria's Business to Consumer (B2C) index hitting 53.2 points and boasting a 55% internet penetration rate in 2023, ranking fourth highest on the continent. The globalisation of markets has exposed e-commerce companies to economic downturns, compelling them to adopt strategic pricing approaches to ensure sustained

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profitability and competitiveness. Consumers have become more price-sensitive, emphasising the need for firms to accurately gauge pricing sensitivity to influence purchasing decisions effectively. This research explores how e-commerce stores utilise digital pricing strategies to impact the purchasing behaviour of Gen Z consumers in Nigeria. By employing an exploratory research design, the study utilised an online survey distributed through Google Form, targeting tech-savvy Gen Z consumers, who represent over 85% of the 384-sample size derived using the Borden sampling model. By being guided by the theory of planned behaviour, the PLS-SEM model indicates that special event pricing (0.433, 91.8% effect), sample product pricing (0.236, 85.0% effect), and loss leader pricing (0.236, 93% effect) significantly impact Gen Z's consumer patronage (62.4%). Furthermore, product lining pricing (0.457, 93.7% high effect), captive pricing (0.161, 96.21% high effect), and optional pricing strategy (0.252, 96.0% medium effect) influence Gen Z's online purchase satisfaction (67.2%). This underscores the importance of digital pricing strategies in shaping Gen Z's online purchase behaviour. The research recommends the need for online stores to incorporate promotional and product mix strategies in business tactics; governments should monitor fair pricing practices, and online retailers should educate consumers about pricing strategies to foster informed purchasing decisions. The research acknowledges potential biases in data collection, stemming from unequal online access among Gen Z consumers, resulting in a partial representation of the diverse range of Gen Z behaviours across the continent, as various cultural, economic, and social factors can influence purchasing behaviours.

Keywords: E-commerce industry, Digital pricing strategies, Gen Z consumers, Nigeria, Online purchase behaviour

Introduction

E-commerce has become integral to global retail sustainability, growing at 14% annually in the past decade due to the fourth industrial revolution (4IR) and increased internet adoption (55%), with over five billion users globally (Gelder, 2024). Online consumer transactions surpassed \$6.3 trillion in sales worldwide, of which Asia emerged as the top e-commerce market, with \$1.7 trillion revenue in 2023, surpassing the Americas by \$800 million, driven primarily by China's revenue of over \$935 billion. Europe (\$533 million), Australia and Oceania (\$36.79 million), and Africa (\$31.18 million) had lower e-commerce revenues, each below \$40 billion in 2023 (Sugiharto, 2024). Nigeria's Business to Consumer (B2C) index reached 53.2 points with a 55% internet penetration rate in 2023; thus, emerging as the fourth highest in Africa, with smartphones accounting for nearly 80% of all retail website visits globally (Sasu, 2023). Digitalisation has become a home for business survival by transforming significantly industrial and consumer marketing, pushing marketers towards innovative strategies to engage diverse customer bases. This was facilitated by technological advancements that enhanced customer access to alternative forgone, information and interaction across social media and communication platforms, effectively shrinking the global marketplace (Li & He, 2024; Shang & Zong, 2024; Groenewald & Kilag, 2024).

Pricing is the bread baker element of the traditional marketing mix, alongside product, place, and promotion (Han *et. al.*, 2024; Cao *et. al.*, 2024) by providing revenue that resulted in profit maximisation, while others demand cost. Globalisation has exposed e-commerce companies to economic crises that necessitate strategic pricing approaches for sustained profitability and competitiveness. Revenue management techniques, like loss leader pricing, are widely used by e-commerce giants including Amazon and Walmart to align product pricing with market demand (Ramdani & Azzahra, 2024). Consumers then sensitise and prioritise pricing in purchasing decisions, making it essential for firms to gauge pricing sensitivity accurately. Technological advancements have transformed sales methods, requiring firms to adapt pricing strategies across product life cycles to cover costs and reflect product value. This is true as generic factors significantly influence not only the pricing strategies, but also impacting consumer willingness to pay based on perception and preferences, particularly in the digital goods market (Thota *et. al.*, 2024; Zhu, 2024). In response, firms must adjust pricing strategies to evolving consumer behaviours to achieve marketing goals and survival in competitive environments.

However, global businesses were challenged in adapting strategically to local and international markets to gain a competitive edge, particularly through effective pricing strategies. Pricing is a key aspect often underestimated by businesses, yet it profoundly influences consumer behaviour, preference for brand, brand recognition, customer image, and decision-making regarding new products (Zhang, Garimella, & Fan, 2024; Sharma, Sharma, & Mehta, 2024; Chen *et. al.*, 2024). Consequently, setting a price too high may push consumers towards competitors, while excessively low pricing can attract the wrong customer segment, while passing knowledge of undervalued product quality. By understanding these evolved dynamics, e-commerce companies can develop differentiated strategies that reflect digitalisation which will enhance their market competitiveness.

The emergence of big data analytics has transformed pricing strategies, facilitating personalised digital pricing based on consumer characteristics including preferences, income, and brand perception (Odeyemi *et. al.*, 2024; Chen *et. al.*, 2024). This approach is designed to enhance seller profitability by tailoring pricing strategies to reduce consumer surplus using robust data, including consumer purchasing power. However, the widespread adoption of digital pricing remains limited due to increased consumer awareness of firms' pricing tactics driven by advances in information and communication technology (Can Zhong & Yi Na, 2024; Zhang, Chen, & Liu, 2024). This fostered the concept of "Strategic Consumer" advocated for individuals making informed purchasing decisions to maximise personal utility over time. Strategic consumers leverage available information to postpone purchases until optimal price conditions, presenting revenue optimisation challenges for businesses (Berlilana *et. al.*, 2024). Although dynamic pricing was expected to counteract strategic consumer behaviour, consumers adeptly utilise price history and online product details, influencing seller profitability (Ahmed & Joshi, 2024). Consequently, understanding the drivers behind strategic consumer behaviour amidst digital pricing is crucial for businesses to implement effective strategies and gain a competitive edge while maintaining customer loyalty. Several prior studies (Ali & Anwar, 2021; Al-Salamin & Al-Hassan, 2016; Victor *et. al.*, 2019; Azad & Shankar-Singh, 2019) have examined changes in consumer behaviour within traditional pricing contexts across various economies and industrial domains. Empirical evidence suggests that around one-third of consumers are tech-savvy and willingly purchase goods reflecting current market trends (Shah & Zhongjun, 2021; Anand & Mantrala, 2019) despite the benefits of physical shopping in price management. This supply side presumption is seen as a key driver behind the growth of digital pricing. However, there remains a notable gap in research on the demand side, specifically why consumers choose e-commerce products (Khrais, 2020; Li, & Karahanna, 2015; Nogueira *et. al.*, 2021). Across economies and industry dimensions, prior researches have explored market factors influencing pricing strategy including revenue management (Xiang *et. al.*, 2021), cost considerations (Saharan, Bawa, & Kumar, 2020), product information and quality (Zhao *et. al.*, 2021; Neger & Uddin, 2020), brand attributes (Chai et al., 2021), marketing mix (Zhou *et. al.*, 2022) and demographic characteristics (Zhou *et. al.*, 2022; Yao & Bao, 2024). Despite their efficacy, traditional pricing approaches centred on cost, premium, penetration, and skimming pricing have been insufficient in explaining personalised digital pricing and Gen Z consumer behaviour (Wu, Zhang, & Zhou, 2022), often neglecting vital tech-related aspects. Therefore, survey research is needed to delve into the symbolic dimensions of digital pricing strategy to advance theoretical and empirical understanding within the Gen Z's purchase behaviour context. This research explores how e-commerce giants and their counterparts employ digital pricing strategies to influence the purchasing behaviour of Gen Z consumers in Nigeria. The specific objectives include to:

i. Analysing the key dimension of digital pricing strategies used in Nigeria's e-commerce industry and identifying the drivers behind their adoption amidst consumer price sensitivity;
ii. Examining the influence of digital pricing strategies on the online buying decisions of Gen Z consumers in Nigeria;
iii. Proposing actionable recommendations that can enhance the efficacy of digital pricing practices within the e-commerce industry,

specifically targeting improved purchase responses among Gen Z consumers in Nigeria.

The research is highly significant as it builds upon existing empirical and theoretical knowledge of pricing by examining consumer behaviour within Nigeria's booming e-commerce industry. Nigeria, Africa's most populous and rapidly growing country with around 206 million people, presents substantial opportunities for online businesses (Emembolu *et. al.*, 2022). E-commerce sales in Nigeria have exceeded 3.2 trillion naira (approximately 7.6 billion euros), driven by a rising internet penetration rate of about 54% of the population, with a considerable number of daily internet users engaging in online shopping (Statista, 2024). The e-commerce sector contributes over 12% to Nigeria's GDP and is projected to grow by over 15% in the coming years, indicating a promising future for this industry in Nigeria (Okolie & Ojomo, 2020). The research on this industry can provide both descriptive and prescriptive value. Descriptively, it familiarises consumers with various marketing strategies employed by businesses, thus creating consumer education about the forces influencing their purchasing behaviour. Prescriptively, it guides consumers on how to make informed and rational purchasing decisions within a continuously evolving business landscape.

Review of Literature

Digital Pricing Strategies in Consumer Behaviour: Conceptual Clarification

The four fundamental aspects of marketing, as outlined by Ali and Anwar, (2021), traditionally encompass the product, promotion, placement, and price. Among these elements, pricing holds a distinct position as it represents the stage at which a company endeavours to actualise the value it has generated. Even with flawless execution of the first three elements, a poorly conceived pricing strategy can lead to overall business failure due to its attached value proposition. According to Krämer and Kalka, (2017), drawing from Borden (1964), pricing has always been a crucial component of marketing, which is noted further, by Kim *et. al.*, (2021), that pricing is the sole element among the traditional marketing components responsible for revenue generation. Ji *et. al.*, (2022) illustrate this with the case of Apple, highlighting how their decision to price music per song, instead of by album, played a significant role in their global success, reflecting a more consumer-friendly pricing strategy for music products. Thus, the concept of pricing in marketing, rooted in historical barter trade, has evolved significantly, as seen through different scholarly perspectives. Gupta *et. al.*, (2021), in alignment with the presumption of Feurer *et. al.*, (2019), coined pricing as a pivotal marketing mix element that directly impacts revenue objective through value proposition, with customers being exceptionally sensitive to it, compared to other traditional marketing components. In today's digital era, the emergence of digital pricing in e-commerce reflects a vital facet of contemporary marketing strategies, where businesses tailor pricing methodologies specifically for the online marketplace. The digital economy's evolution is reshaping traditional pricing models to align with online transaction dynamics and consumer behaviours. This, against the bedrock of conventional pricing strategies, makes digital pricing harness digital platforms and data analytics to optimise pricing decisions swiftly, enabling companies to adapt rapidly to market shifts, consumer preferences, and competitive pressures in real-time (Calvano *et. al.*, 2020). Consequently, the digital environment demands agile and responsive pricing strategies to uphold competitiveness and profitability amidst industry phased out pressure.

Pricing plays a pivotal role in business success, as demonstrated in the Apple case discussed by Chang and Guo, (2021), highlighting how strategic pricing can effectively differentiate a product or service in a competitive market. Yan *et. al.*, (2020) identify key reasons why customers may reject a product due to pricing: if the product seems too expensive or beyond reach; if customers who were initially willing to pay a certain price resist purchasing due to price increase; and if perceptions of unfair or deceptive pricing leads to customer dissatisfaction and reluctance to make a purchase. In such instances, it becomes evident that the chosen pricing strategy has not resonated with consumers. However, Xi and Zhang, (2023) criticises conventional pricing strategies for its efficacy by having limited impact in attracting Gen Z's customer segments, if a product's price is significantly out of a consumer's budget. Thus, the landscape of pricing strategies has evolved significantly due to the influence of data analytics and globalisation, transforming traditional approaches into digital ones aimed at enhancing revenue and brand loyalty. Major corporations like Amazon, Uber, Alibaba, Netflix, and Spotify leverage digital pricing as a core element of their e-commerce strategies, utilising advanced algorithms and consumer data to optimise revenue generation. This shift towards digital pricing is not limited to tech giants; small and medium enterprises are also embracing these strategies to bolster their market presence. The COVID-19 pandemic accelerated digital adoption in Nigeria, pushing businesses, including educational institutions and traditional enterprises, to pivot online for sustainability (Lei *et. al.*, 2015). This digital transformation intensified competition, prompting enterprises to re-evaluate pricing strategies to effectively attract and retain customers. Moreover, the scalability of digital platforms provides unprecedented opportunities for businesses to expand their customer base (Li *et. al.*, 2020), albeit amidst heightened competition, necessitating a strategic reassessment of pricing methodologies to capture market share and boost engagement.

In e-commerce, developing effective pricing strategies involves a comprehensive analysis of various critical factors. Wu *et. al.*, (2020) stress the significance of considering variables like time scale, weather conditions, customer relationships, and demand elasticity when establishing price ranges for products and services. Conversely, Sarkar *et. al.* (2023) identifies essential drivers for digital pricing strategies, encompassing a firm's profit policy, where higher-cost operations may lead to elevated prices; the perceived value of a product, where unique features like quality and efficiency can justify premium pricing; branding, allowing elite positioning and higher pricing; cost considerations for maintaining profitability; competitive dynamics, balancing pricing against market rivals; market size, which mitigate competitive pressures; and the product life cycle stage, affecting pricing strategies over time. This underscores the intricate nature of pricing decisions, combining economic principles with strategic marketing concepts to navigate competitive landscapes and consumer behaviours in the digital age. The term "digital" describes pricing by indicating its fluctuation based on data analytics amidst internal and external drivers. As elucidated by Saharan *et. al.* (2020), online stores may increase prices due to low stock, reacting to competitors, or to meet specific sales targets, reflecting the uncertainty and multiple influences behind modern pricing changes.

Consequently, Meng *et. al.* (2021) describe digital pricing as dynamic pricing, a strategy that adjusts product prices in the digital age based on both external and internal factors.

Academic literature documented several digital pricing approaches, coined as algorithms in pricing or dynamic pricing strategies, commonly employed by e-commerce vendors. Luo *et. al.* (2018) and Mansouri and Hosseini (2018) highlighted several effective techniques: Segmented Pricing, where different consumer segments are offered different prices, often charging higher prices to high-value customers; Time-based Pricing, which involves charging more for faster services (such as same-day delivery) or offering discounts to early-bird customers; Peaking Pricing, where prices increase during high-demand periods or peak hours; Penetration Pricing, a strategy of entering the market with lower prices to gain significant market share; Random Market Fluctuations, adjusting prices based on random factors; and Competition Driven Pricing, adapting prices based on competitors' actions. In contrast, Liu and Ke (2020) introduces product-mixing strategies, which involve optional pricing (offering optional features at additional cost), captive pricing (selling main products alongside necessary accessories), and product lining (offering a range of related products with varying features and prices). Zhu and Lin (2019) mentions promotional pricing strategies like special event pricing (discounts during events), sample product pricing (offering smaller samples to promote sales), and loss leader pricing (selling products below cost to attract customers) as key elements of digital pricing strategies in marketing. These strategies are critical for businesses seeking to maximise revenue and market penetration while responding dynamically to consumer behaviour and competition in the tech-savvy landscape.

Cachon and Daniels (2017) and Bertini and Koenigsberg (2021) discuss price algorithms amidst the evolution of platforms like Uber and Lyft, which utilise "self-scheduling" providers allowing flexibility in work hours. These platforms employ dynamic pricing strategies, such as Uber's surge pricing, which adjusts prices based on demand. While surge pricing has drawn criticism over concerns for both consumers and providers (Zhao *et. al.*, 2021), Cachon and Daniels (2017) argue for it, claiming it is beneficial to all parties involved, especially when labour costs rise. This finding motions that surge pricing can optimise platform profits and efficiently allocate resources during peak demand, benefiting providers and consumers alike. Bertini and Koenigsberg (2021) support this assertion by noting the increasing popularity of pricing algorithms in modern platforms, of which e-commerce giants maximise profit and resource allocation, contrary to common criticisms of surge pricing for being less cost and revenue effective.

Moreover, Brown and MacKay, (2023) and Seele *et. al.* (2021) address the rising trend of businesses utilising pricing algorithms to maximise revenues. According to Brown and MacKay, (2023) ideas, pricing algorithms leverage artificial intelligence and machine learning to adjust prices in real-time based on factors like supply, demand, and competitor activities. However, this constant price fluctuation can potentially harm a company's brand perception and customer satisfaction. To mitigate this risk, Seele *et. al.*, (2021) propose four strategies: defining appropriate use cases for algorithmic pricing, communicating its benefits to customers, appointing a responsible system owner, setting guardrails to prevent extreme price swings, and intervening manually when necessary. On the other hand, Castillo *et. al.* (2017) explain how surge pricing in ride-hailing platforms like Uber and Lyft is driven by the inefficient allocation of drivers caused by an overburdened dispatch system. This results in drivers wasting time and reducing their earnings, leading to negative feedback loops and decreased welfare for both drivers and passengers. This understanding of these issues by e-commerce counterparts is essential for optimising markets and ensuring the benefits of new technologies are realised without detrimental consequences.

Without being prejudiced by the assumption of "*ceteris paribus*" coined as "all things being equal", today's e-commerce giants' marketing problem centres on consumer price sensitivity in the digital era. In response, Robert *et. al.* (2006) introduced an equational method to assess consumer price sensitivity using historical data, particularly by analysing how changes in past prices impact current pricing decisions. This mechanism allows for a deeper understanding of consumer behaviour in response to price fluctuations. While this model serves as a foundational framework, Robert *et. al.* (2006) acknowledged that real-world pricing sensitivity involves multiple variables beyond historical price changes. The function described by Robert *et. al.,* (2006) represents a simplified version of the broader price sensitivity function, which considers a more comprehensive set of factors influencing consumer behaviour towards pricing in the digital age. The below equation (1) define the consumer price sensitivity amidst digital age:

$$CPS\ (P_x) = CMR_x * \{1 - [\text{Arc-Tan}\ (\alpha * (P\text{-final} - P\text{-ref})) * 2/\pi]\} \cdots\cdots (1)$$

Where:

'CPS (P_x)' denote the Consumer Price Sensitivity at a given price level,

'CMR_x' denote the contribution margin ratio assigned by the e-commerce giants,

'Arc-Tan' denote the arc tangent function which is used to transform a linear difference in price (P-final – P-ref) into an angle measure,

'P-ref' denotes a reference price derived from prior data,

'P-final' represents the ultimate transaction price determined by current data,

'α' is the coefficient empirically set based on historical and real-time sales data,

'2/π' denotes a scaling factor applied to the result of the arctan function.

The price sensitivity approach exemplifies modern methods of employing vast datasets for pricing optimisation, underscoring the growing role of big data analysis in shaping pricing strategies. It holds significant importance for e-commerce firms by providing a structured approach to understanding how changes in pricing impact consumer behaviour, crucial for optimising profitability and competitiveness in online markets (Ye *et. al.*, 2023). While the equation integrates key behavioural variables including the consumer's reference price; it allows firms to model and predict consumer responses. By leveraging this equation, e-commerce businesses can tailor pricing strategies, balancing revenue objectives with consumer demand elasticity to maximise sales and market share effectively (Yin & Han, 2021). Therefore, understanding and applying such mathematical models is fundamental for driving strategic pricing decisions in the dynamic landscape of e-commerce. However, the equation concept pertains to digital pricing strategies rooted in extensive data analytics, as showcased by Robert *et.*

al. (2006) visual representations as depicted in Figure 1 which alternatively illustrate the sensitivity process in consumer behaviour:

Figure 1: Dynamic Pricing System in Digital Age (Robert et al., 2006)

The price sensitivity system comprises three distinct processes involving input, processing, and output stages (Golrezaei, Nazerzadeh, & Randhawa, 2020). The input area involves ten types of sensors for external data capture, which is then filtered and distributed to 100 processors for analysis. Upon the completion of the analysis, results are channelled through 20 devices to influence the latest price decisions. This interconnected system efficiently manages sensor data intake, processing through a vast array of processors, and dissemination of analysed outputs to impact pricing strategies based on real-time information. Consequently, in alignment with Shiller (2014), price sensitivity demonstrated that the vast datasets of consumer behaviour can offer significant advantages to marketers. By analysing mass datasets, detailed insights into individual consumer behaviour can be uncovered, which in turn can facilitate the development of hedonic estimates of consumer reserved values. Shiller (2014) highlights the potential for e-commerce firms to leverage this data to implement personalised pricing strategies. Specifically, Shiller (2014) mentions that approximately 5000 web-browsing variables were scrutinised to estimate individual reserved values, of which the integration of economic models with machine learning techniques is proposed as a solution to address challenges associated with big data analysis in pricing in the future. This suggests a promising approach where blending economic frameworks with advanced computational methods could effectively tackle complexities arising from large-scale data analysis in pricing within product life cycle stages.

Empirical Review and Hypothesis Development

Empirical studies in marketing literature noted mixed findings on how pricing strategies impact the consumer purchase decisions across various countries, economies, and industries. Diyaolu *et. al.* (2022) adopted survey methodology to showcase how price discount, as a sales promotion tool, affects customer patronage in the food and beverage industry, highlighting a significant impact for positive purchase behaviour. Similarly, Ali and Anwar (2021) explored how pricing strategies affect consumer purchasing decisions using a cross-sectional survey approach, emphasising the positive influence of penetration pricing and competitive pricing. Kimsanova, Sanaev, and Herzfeld (2024) adopted a case study approach to examine the dynamics of food demand during price instability, motioning its positive effect on consumer patronage in Kyrgyzstan, revealing preferences for accessible and good-quality products at reasonable prices. Gebremichael (2022) adopted the PLS-SEM survey approach to highlight the pricing strategy's impact on customer experience and loyalty within hospitality industries, emphasising the importance of price value and reputation. Al-Talidi (2020) conducted quantitative research to analyse the significance of psychological pricing policies in Saudi Arabia, demonstrating its positive impacts on consumer behaviour. Similarly, Ahmad, Majeed, and Salih (2019) motioned positive effects of psychological pricing in Iraq, using survey approach, guided by positivism as a philosophy, noting nine-ending prices as influential effect on consumer behaviour. Samo *et. al.* (2018) adopted a qualitative and exploratory approach to study the efficacy of charm pricing in Pakistan, highlighting differences in perception between urban and rural consumers. Zhang, Deng, and Xu (2017) explored online price promotion effects on purchasing intention using quantitative strategy, emphasising the role of complementary products in shaping pricing impact on consumer behaviour. Kumar and Pandey (2017) embarked on a qualitative study to motion the role of socio-demographic factors in influencing consumers' response to psychological pricing, while Thomas and Morwitz (2009) highlighted the efficacy of consumer interpretations of prices ending in .99, emphasising the impact of word-of-mouth communication. Tawalbe and Abu-Rumman (2015) analysed the positive effect of marketing-oriented pricing on product mix strategies in Jordan telecoms, using deductive reasoning guided by quantitative research. Lin, and Bowman (2022) highlighted how price promotions affect customer brand loyalty and sales performance in retail industry using survey approach, revealing a complex relationship between variables where promotions stimulate purchases but do not necessarily enhance loyalty. However, Jha (2013) adopted a survey approach to explore the positive impact of pricing strategies on consumer purchase behaviour in Ranchi, emphasising how different pricing tactics influence consumer choices in the Indian retail market. Singh and Basu (2023) systematically reviewed the online consumer behaviour, revealing the critical role of rapid advancement of technology in shaping pricing strategy towards consumer behaviour and shopping habits amidst global competition. This aligns with the contributions of Singh and Suryavanshi (2018) on how pricing strategies specifically influence e-commerce consumer behaviour in India, highlighting the positive nuanced interplay between pricing tactics and consumer responses. Yang and Xia (2021) systematically reviewed the pricing strategies in the sharing economy. Their findings revealed a nuanced landscape, highlighting the significance of dynamic pricing, personalised pricing, and pricing transparency. Dynamic pricing, often based on demand fluctuations, emerges as a prevalent strategy, offering businesses flexibility and the ability to optimise profits. Personalised pricing, tailored to individual characteristics or behaviours, is identified as a strategy with potential to enhance customer satisfaction and loyalty. Pricing transparency, crucial for building trust, is shown to positively influence consumer decision-making. However, challenges such as algorithmic biases and regulatory concerns underscore the need for further research and industry regulation.

Despite these studies, significant assertions collectively illustrate how pricing and market factors contribute to purchasing patterns and brand preferences, the pricing strategies of e-commerce brands remain inadequately studied within the context of Gen Z's online purchasing behaviour in Nigeria, a key player in Africa's digital economy. Thus, the below hypothesis is developed from the research objective:

H_{01}: There is no significant relationship between promotional pricing and online patronage of Gen Z's consumers in Nigeria, To statistically ascertain the cause-effect relationship of the research variables, the below sub-hypotheses are conceptualised from the main hypothesis:

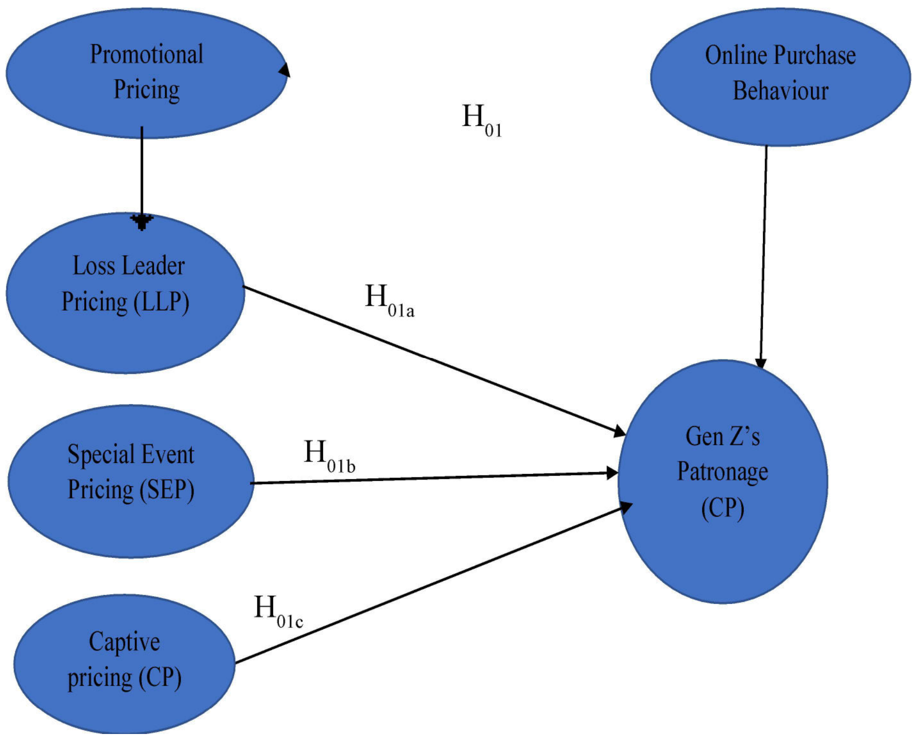


Figure 2: Conceptual Framework (Authors, 2024)

Furthermore, Khaniwale (2015) investigated forces that drive consumer buying behaviour, demonstrating that internal and external factors significantly shape consumer behaviour. Al-Salamin and Al-Hassan, (2016) discovered that the prices of well-known brand products negatively affect the purchasing process, particularly among young consumers with limited incomes. In contrast, Boztepe (2012) highlighted the positive influence of environmental factors like green product features and pricing on consumer behaviour. Radha and Aithal (2024) observed that price discounts can shift brands from a consumer's hold set to consideration set, although different discount types do not significantly alter attitudes and purchase intentions. Moon (2006) emphasised the impact of individualism and product type on purchase intentions, rather than price itself. Alford and Biswas (2002) noted that consumer sale proneness affects various outcome variables, while price consciousness mainly influences search intentions. Mathur and Gangwani (2021), Fitri and Mardikaningsih (2023), and Loh and Hassan (2022) emphasised the roles of brand awareness, price fairness, and perceived risk in shaping consumer attitudes towards purchase decisions, especially with private label brands. However, Vessal, De-Giovanni, and Hassanzadeh (2022), *Sahoo et. al.* (2022) and Tang, You, and Cao (2024) emphasise the efficacy of penetration pricing strategies in capturing a substantial market share and triggering favourable word-of-mouth recommendations, thus encouraging consumers to make positive purchase choices. This approach not only facilitates market entry but also cultivates a base of satisfied customers who become advocates for the product or service.

Despite the prescriptive value of these studies in underscoring collectively the significance of pricing tools across different industries, economies, and regions, pricing of e-commerce counterparts is underexplored among the digital age generation, especially within the Gen Z's context of online buying decision in Nigeria, as a giant of Africa. Thus, the below hypothesis is developed from the research conceptual and empirical review:

H_{02}: Product mix pricing has no significant influence on online satisfaction of Gen Z's consumers in Nigeria,

To statistically ascertain the relationship between the variables, the below sub-hypotheses are conceptualised from the main hypothesis:

H_{02}

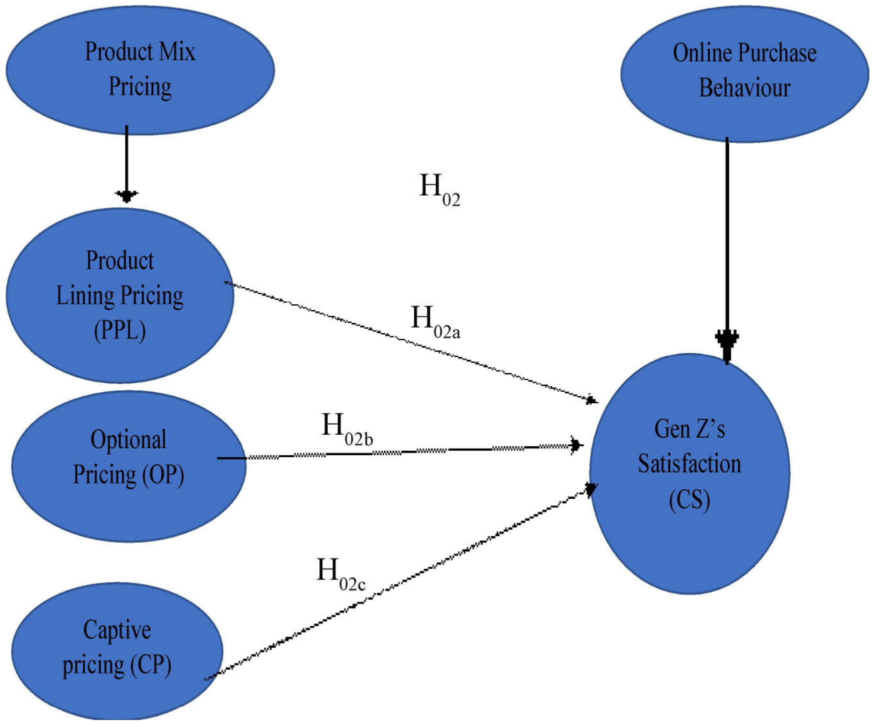


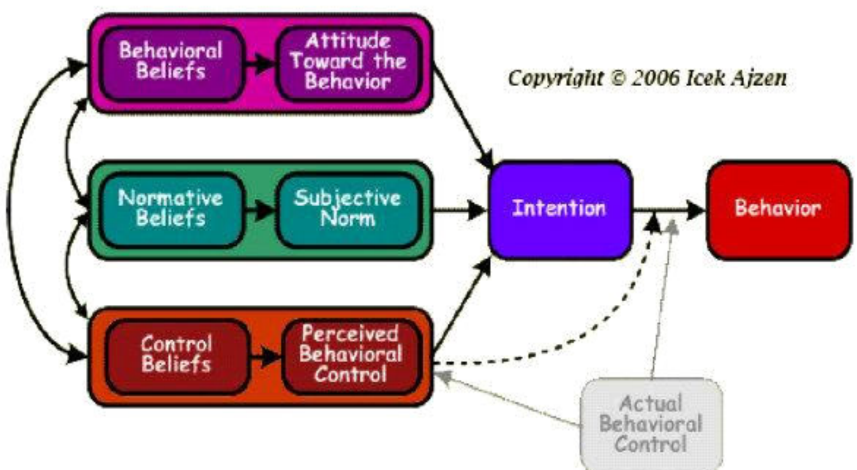
Figure 3: Conceptual Framework (Authors, 2024)

By adopting the PLS-SEM approach to ascertain the cause-effect relationship, the research findings offer valuable insights for marketers. At first, it helps in understanding consumer reactions to marketing strategies, facilitating more effective implementation of pricing strategy in the future. This will foster a deeper grasp of consumer behaviour aids in enhancing product differentiation and market segmentation strategies, crucial for gaining competitive advantage in the market. By offering an empirical and theoretical documentary, the PLS-SEM approach underscores the importance of critical analysis of path measurement in understanding consumer behaviour in formulating effective marketing and pricing strategies in the digital age.

Theoretical Framework

Given the diverse impact of digitalisation in the e-commerce industry, several theoretical frameworks offer valuable insights into understanding its influence on customer purchasing decisions. The Diffusion of Innovation Theory by Everett Rogers (1962) posits that innovation adoption occurs in stages, elucidating how new technologies are adopted and diffused in society (Sachdeva, Kapur, & Singh, 2016). This theory is relevant in understanding how digitalisation in pricing strategies is embraced by marketers to influence positive online purchase behaviour among Gen Z consumers. This aligns with the Technology Acceptance Model (TAM) introduced by Fred Davis (1989), which suggests that the market acceptance of technology depends on its perceived ease of use and usefulness (Wicaksono, & Maharani, 2020). TAM provides insights into the factors that affect individuals' acceptance and usage of technology in consumer behaviour, shedding light on the efficacy of digital pricing strategies in enhancing online patronage. Furthermore, the Social Capital Theory by Robert D. Putnam (2000) underscores the value of social connections and networks in facilitating information flow and resource access, particularly regarding brand information (Castaneda *et. al.*, 2015). This theory emphasises the importance of social collaborations (Oladipo, 2023). Social collaboration is crucial within the e-commerce sector in effectively implementing pricing strategies. Despite the efficacy of these theories in addressing how price shapes purchase intention within social, technology and people context, the research employed the Theory of Planned Behaviour to gain a nuanced understanding of how pricing strategies are adopted in the digital age, accepted by Gen Z consumers, and integrated into the purchase behaviour landscape in Nigeria's e-commerce industry.

The Theory of Planned Behaviour (TPB), developed by Ajzen in 1985, is a key psychological framework used to analyse and forecast human behaviour (Ajzen, 2015). It extends the Theory of Reasoned Action (TRA) by including the concept of perceived behavioural control. TPB was created to address the limitations of TRA, which focused solely on attitudes and subjective norms in predicting behaviour (Abdullah *et. al.*, 2018). TPB acknowledges that individuals may not always have full control over their actions, even if they have positive attitudes and strong social norms supporting a specific behaviour, such as attending e-commerce shows virtually (Arora *et. al.*, 2017). It emphasises the role of perceived barriers and the importance of skills in influencing behaviour. Despite its significance, TPB has been subject to criticisms and enhancements, such as the integration of factors like self-identity and emotions (Ashaduzzaman *et. al.*, 2022). However, TPB remains a fundamental tool for researchers and practitioners in understanding and shaping human behaviour, establishing its place in social psychology and behavioural science research. While digitalisation has become increasingly popular, the understanding of the psychological and social factors driving Gen Z's use of e-commerce platforms remains limited (Bhutto *et. al.*, 2019). Previous studies have indicated that individuals' past behaviours strongly predict their intentions and future actions on digital platforms. Budhathoki *et. al.* (2022) suggest that consumer's self-identity and sense of belonging are significant predictors of developing addictive tendencies towards digital pricing. Additionally, high-level social media usage is influenced by attitudes, social norms, and self-identity factors (Dorce *et. al.*, 2021). According to Lee *et. al.* (2021), intentions are considered reflections of the motivational factors shaping behaviour, indicating the level of effort individuals are willing to invest and the extent to which they plan to act on a specific behaviour. Kim and Han (2010) explain that the TPB posits that behavioural intention is determined by an individual's beliefs in three key areas as reflected in Figure 4.



According to Khan *et. al.* (2023), the behavioural belief in the context of Gen Z refers to their beliefs about the likely outcomes or consequences of engaging in a specific behaviour. Research on online contexts consistently indicates a significant correlation between attendees' attitudes and purchase intentions. Quantitative studies have shown that when Gen Z holds a more favourable attitude towards a particular social media behaviour, they are more likely to have the intention to engage in that behaviour (Farid *et. al.*, 2023; Ghifarini *et. al.*, 2018). This suggests that maintaining a positive attitude towards interacting with social media platforms, such as e-commerce platforms, is likely to increase the likelihood of forming an intention to engage with brands due to digital pricing strategies. However, the subjective norm in Gen Z's perception reflects the social expectations of influential individuals regarding certain attitudes (Hameed *et. al.*, 2019; Hamilton & Terblanche-Smit, 2018). Previous studies consistently show a positive relationship between subjective norms and the intention to engage with e-commerce brands (Han & Stoel, 2017). This indicates that when individuals perceive subjective norms to favour a specific digital act, they are more likely to intend to engage in that behaviour (Hsu *et. al.*, 2017; Lindblom & Lindblom, 2018).

Yakasai and Jusoh (2015) motion that favourable subjective norms, related to participating in e-commerce brands, via promotional and product mix-pricing, will increase individuals' intention to participate. Moreover, perceived behavioural control implies that the Gen Z's perception of factors can either facilitate or hinder their ability to carry out the intention to purchase. This perception plays a significant role not only in shaping the intention to buy but also in directly influencing the actual behaviour (Shalender & Sharma, 2021). Despite intending to engage in buying decisions influenced by dynamic pricing in the digital age, external factors beyond their control can hinder Gen Z from actually making the purchase. Prior research indicates that perceived behavioural control does not directly impact the behaviour of customer towards e-commerce brands (Sheoran & Kumar, 2022; Liobikienë *et. al.*, 2016), suggesting that despite Gen Z's strong perceived control over pricing across product mix, this may not always translate into actual purchasing behaviour. This aligns with Spence *et. al.* (2018) notion that while Gen Z may intend to engage in e-commerce trade due to digital pricing strategies, other external factors may influence their actual behaviour.

Social and behaviour critics support the suitability of the TPB as an ideal theoretical framework for understanding attitudes and behaviours related to pricing in the digital age (Manalu & Adzimatinur, 2020; Nimri *et. al.*, 2020; Setiawati *et. al.*, 2018). TPB's focus on attitudes suggests that individuals' attitudes towards using digital pricing strategy will influence their participation in e-commerce patronage (Madahi & Sukati, 2016). This is relevant in Nigeria, where technology adoption varies, and understanding these attitudes can help marketers tailor their pricing strategies according to the promotional events and product mix. Also, TPB's emphasis on subjective norms is crucial in collectivist societies like Nigeria, where social pressure and cultural factors strongly influence technology usage in the execution of marketing strategy in e-commerce industry (Maryam *et. al.*, 2022). TPB can help assess these influences on purchase choices according to the product mix offered in the e-commerce platform. However, TPB's consideration of perceived behavioural control allows for the nuanced interplay of individuals' perceived capabilities to adapt to pricing tactics in product offerings, which is essential in a rapidly changing digital landscape (Muça & Zeqiri, 2020). Lastly, as TPB recognises intentions as precursors to behaviour, understanding intentions to use pricing as the basis of decision in e-commerce industry can aid in forecasting and shaping participation rates (Ngah *et. al.*, 2020; Ogiemwonyi, 2022). Overall, TPB provides a robust framework for assessing the multifaceted aspects of digital pricing's impact on online purchase intention in Nigeria's e-commerce industry, by offering an explanation on how attitudes, norms, perceived control, intentions, and external influences affect the overall Gen Z's buying decisions.

Methodology

Research Design, Data Collection Approach and Instrument

Exploratory research design was employed, using an online survey distributed through Google Form to investigate the facts, perceptions, motivations, and behaviours of tech savvy individuals. This approach uncovered the consumer perception regarding the sociological and psychological variables underlying the study, within the dimension of digital pricing. This method was chosen for its ability to collect quantitative data suitable for advanced statistical analysis, aligning with the research paradigm. By targeting tech-savvy Gen Z's consumers, the online survey captured comprehensive perspectives, facilitating a thorough understanding of the subject matter (Latkovikj & Popovska, 2019). This method was ideal by allowing access to a large sample size, proving cost-effective for studying dispersed populations like Nigerians (Rice *et. al.*, 2017). It also provided a platform to explore sensitive topics, ensuring the acquisition of unbiased responses since the prototype validity test was established for its reliability (McKinlay, 2020). However, it facilitated the collection of valuable insights from a diverse population, thus enhancing the data objectivity, which was essential for general hypotheses testing including the pooled and panel regression hypotheses (Latkovikj & Popovska, 2019).

The authors designed a questionnaire instrument, following the model of Krosnick (2018), which accommodates a series of questions with predefined response options. The questionnaire incorporates a five-point Likert scale (Strongly Agree (SA) =5, Agree (A) =4, Undecided (UN) =3, Disagree (D) =2, Strongly Disagree (SD) =1) to allow respondents to express their preferences. This approach is advantageous for accommodating a large number of participants while facilitating diverse and quantifiable data collection. Despite requiring significant time investment during the design phase, this method is effective in mitigating issues such as inconsistent responses (Song, Son, & Oh, 2015). The survey, titled "Questionnaire on the Digital Pricing Strategy and Customer Buying Decision in the E-commerce Industry, Evidence from Nigerian Gen Z Consumers (DPS-CBD Q)," comprises two sections. Section A gathers demographic details from participants, while Section B systematically addresses the variables related to the research objectives. This approach is aligned with the research on whether digital pricing strategies influence customer buying decisions in the e-commerce industry, utilising the PLS-SEM approach.

Research Area, Participant and Sample Size

Amidst the burgeoning Africa's e-commerce industry recording over $17 billion market size in 2023, Nigeria stands out as a compelling research area due to its status as the continent's largest economy. Nigeria's e-commerce sector has experienced remarkable growth, with annual revenues exceeding $255 billion, representing 25.8% growth rate, surpassing the global average of 16.8% (Oyekanmi, 2023). The country's internet penetration has surged, with over 60 million Nigerians now online, primarily comprising a youthful population called Gen Z. This digital landscape has led to a significant rise in online orders, with over 300,000 transactions occurring daily, representing a penetration rate of 37.59%. This contributes over 10% to Nigeria's GDP, with a GDP per capita of $5,911 in 2023 (International Trade Administration, 2023). Despite facing infrastructural challenges, Nigeria's e-commerce market exhibits diverse dynamics, including varying income levels and cultural preferences, emphasising the critical role of pricing strategies in influencing customer buying decisions in this digital era.

Consequently, Gen Z, born between the mid-1990s and early 2010s, is a targeted respondent because they depict a demographic known for its digital nativity, significant purchasing power, and unique consumer behaviours (Sutia & Fahlevi, 2024). This implies that they are adept at navigating online e-commerce platforms, seeking value, and engaging with online store brands in innovative ways. To narrow down the research focus, this study targets Gen Z consumers of the top twelve global online store brands, including Amazon, eBay, AliExpress, Almart, Rakuten, Wildberries, Ozon, Flipkart, Samsung, Etsy, Jiji, Konga, and Jumia, as identified by Pool (2024). These brands were selected due to their global coverage of both consumable and non-consumable goods, widespread adoption of digital pricing strategies, and significant internet penetration in their marketing activities and also have e-commerce websites that attract a large number of Gen Z visitors (Chiu & Cho, 2021). However, given the lack of definitive statistical data on the Gen Z population supporting the researcher's intention of avoiding sample bias, a probability sampling approach based on Bill Golden's guidance is employed. This approach is chosen for its capacity to facilitate generalisation to a wider population (Pace, 2021), considering constraints such as the inability to survey the entire population, financial limitations, time constraints, and the need for efficient data processing. Consequently, the current research sample size of 384 Gen Z consumers were targeted which was determined as follows:

$$SS = \frac{Z^2 x\ (p)\ x\ (1 - p)}{C^2}$$

Where: SS = Sample Size, Z = Z-value (1.96 for 95% confidence interval), P = Population (expressed as 0.5), C = Confidence interval (expressed as 0.05 = +/- 5 percentage points)

$$SS = \frac{1.96^2 \text{ x } 0.5\ (1 - 0.5)}{0.05^2}$$

$$SS = \frac{3.8416 \text{ x } 0.5 \text{ x} 0.5}{.0025}$$

$$SS = \frac{0.9604}{.0025}$$

Therefore: SS = **384.16**

Data Analysis and Variable Measurement

Descriptive and inferential analyses were conducted using STATA and Smart-PLS software respectively. Descriptive analysis involved assessing the frequency, percentage, mean, standard deviation, and skewness to gauge Gen Z's patronage in e-commerce stores and the extent of digital pricing strategy implementation in sampled online store companies. The inferential analysis utilised structural equation modelling (SEM) with the partial least squares (PLS) version to analyse the moderating variable's effect. PLS-SEM was chosen due to its ability to analyse multiple structural equations simultaneously, accommodating numerous dependent and independent variables (Hair *et. al.*, 2014). It allows for the establishment of relationships between latent variables such as digital pricing strategies and customer buying decisions, which are not directly observable but inferred from measured indicators (Usakli & Rasoolimanesh, 2023). PLS-SEM is also valuable for exploring direct and indirect impacts, including the presence of mediating variables (Legate *et. al.*, 2023). This is particularly suitable for exploratory research seeking to uncover new insights and relationships in a dynamic and constantly evolving industry like e-commerce. Additionally, PLS-SEM enables effective evaluation of the reliability and validity of study constructs by calculating statistical tools like mean, median, adjusted regression (R^2), and correlation statistics of variables. It does not require data normality and can accommodate smaller sample sizes due to its robust assumptions, making it suitable for analysing data that may not meet strict assumptions of traditional methods like covariance-based SEM (Matthews, Hair, & Matthews, 2018). This is especially ideal for this research, which collected data from diverse respondents that may not conform to normality assumptions. However, the variables were adopted from the past literature as exemplified in research model and Table 1:

Y = F (X).. (1)

CBD (Y) = f (DPS).. (2)

DPS = (PMP, PP).. (3)

Thus, substituting equation (3) into equation (2) and then give equation (4)

CBD (Y) = $\alpha + \beta_1$PMP + β_2PP + e .... (4)

The below sub-equation were derived from the main equation:

CS (Y) = $\alpha + \beta_1$PLP + β_2CP + β........................... (4a)

CB (Y) = $\alpha + \beta_1$LLP + β_2SEP + β_3......................... (4b)

Table 1: Variable Measurement

Variable	Measurement	Proxies	Source
Independent (X)	Digital Pricing Strategy (DLP)	Product Mix Pricing (PMP) and Promotional Pricing (PP)	Aparicio *et. al.* (2017); Al-Tawalbeh, & Abu-Rumman (2015) and Chen *et. al.* (2020).
Dependent (Y)	Customer Buying Decision (CBD)	Customer Satisfaction (CS) and Customer Patronage (CP)	Djan & Adawiyyah (2020); Dash, Kiefer, & Paul, (2021); and Singh, Althuwaini, & Alflayyeh (2020).

Variable	Measurement	Proxies	Source
Construct (X_1)	Product Mix Pricing (PMP)	Product Lining Pricing (PLP), Captive Pricing (CP) and Optional Pricing (OP)	Lii & Lin (2020), Xin, Hao, & Xie, (2023) and Bauer & Jannach (2018).
Construct (X_2)	Promotional Pricing (PP)	Loss Leader Pricing (LLP), Special Event Pricing (SEP) and Sample Product Pricing (SPP).	Daly (2002), Jiao (2018), and Brata, Husani, & Ali (2017).

Source: Authors (2024).

Result Presentation and Discussion of Findings

The survey responses were analysed using both descriptive and inferential methods, focusing on 332 electronic responses, which constituted 86% of the total sample size of 384. This aligns with the suggestion of Guenther *et. al.* (2023) that a 70% sample rate can effectively represent PLS-SEM results for hypothesis testing. The demographic breakdown (as reflected in Table 2) shows a slight skew towards females (58.4%) compared to males (41.6%), indicating potentially different shopping behaviours and responses to pricing strategies among Gen Z consumers. However, the age distribution is balanced, with the majority falling within the 21-25 years category (48.2%), which aligns with the focus on Gen Z consumers born between the mid-1990s and early 2010s. The majority of the respondents are single (75.6%), typical for younger age groups and the Gen Z demographic. Education levels vary, with a significant proportion holding BSc/HND qualifications (58.4%), followed by O'Level (22.0%) and Master's (9.9%) qualifications. This diversity suggests varying levels of understanding and response to pricing strategies. The high online store patronage (82.5%) indicates a high level of familiarity and experience with online shopping platforms among the respondents, with a majority patronising online stores for 6-10 years (62.3%), suggesting a mature market in terms of online shopping experience.

Table 2: Demographic Characteristics of Gen Z's Respondents

Variable	Category	Frequency	Percentage
Gender	Female	194	58.4%
	Male	138	41.6%
	Total	**332**	**100%**
Age	15-20 years	79	23.8%
	21-25 years	160	48.2%
	26-30 years	57	17.2%
	31-35 years	21	6.3%
	35 years and above	15	4.5%
	Total	**332**	**100.0%**
Marital Status	Married	78	23.5%
	Single	251	75.6%
	Divorced	3	0.9%
	Total	**332**	**100.0%**
Highest Educational Level	A's Level	2	.6%
	ACA	4	1.2%
	AAT	2	.6%
	BSC/HND	194	58.4%
	Masters	33	9.9%
	O'Level	73	22.0%
	OND/NCE	20	6.0%
	PhD	2	.6%
	Undergraduate	2	.6%
	Total	**332**	**100.0%**
Online Store Patronage	Yes	274	82.5%
	No	58	17.5%
	Total	**332**	**100.0%**
Years of Patronage	1-5 years	53	16.0%
	6-10 years	207	62.3%
	11 years and above	7	2.1%
	Not applicable	65	19.6%
	Total	**332**	**100.0%**

Source: STAT Output (2024)

Result of Hypothesis Testing
Descriptive Analysis

Table 3: Descriptive Analysis and Normality Test

	Mean	Standard Deviation	Excess Kurtosis	Skewness	Observations
CP1	3.007	1.275	-1.048	-0.192	332.000
CP2	3.000	1.223	-0.976	-0.023	332.000
CS1	3.762	1.382	-0.540	-0.861	332.000
CS2	3.884	1.397	-0.290	-1.046	332.000
CS3	3.857	1.405	-0.332	-1.023	332.000
OP1	2.850	1.186	-0.878	-0.003	332.000
OP2	3.347	1.302	-1.056	-0.276	332.000
PLP1	3.211	1.336	-1.096	-0.272	332.000
PLP2	3.435	1.346	-0.944	-0.513	332.000
CP1	3.796	1.390	-0.340	-0.981	332.000
CP2	3.680	1.325	-0.639	-0.724	332.000
CP3	3.408	1.282	-0.903	-0.391	332.000
LLP1	3.000	1.223	-0.976	-0.023	332.000
LLP2	3.347	1.302	-1.056	-0.276	332.000
SEP1	3.463	1.420	-1.070	-0.528	332.000
SEP2	3.524	1.263	-0.632	-0.596	332.000
SPP1	3.299	1.253	-0.904	-0.354	332.000
SPP2	3.469	1.290	-0.737	-0.546	332.000

Source: Smart-PLS Output (2024)

Table 3 displays the mean and standard deviation results analysing the relationship between promotional pricing (measured as loss leader pricing (LLP), special event pricing (SEP), and sample product pricing (SPP) and product mix pricing (as measured by product lining pricing, optional pricing, and captive pricing), and online purchase behaviour [(measured as consumer patronage (CP) and consumer satisfaction (CS)] of Gen Z consumers. The mean scores, ranging from 3.796 to 3.000, all exceed 3 average benchmarks, indicating a significant association between the variables. This suggests that an increase in promotional and product mix-pricing notably affects online patronage of Gen Z consumers in Nigeria's e-commerce industry. However, the low standard deviation, ranging from 1.223 to 1.390, suggests minimal variability in consumer patronage and satisfaction concerning changes in the mean value of promotional and product mix pricing dimensions. This emphasises the need for advanced adoption of digitalisation in pricing policy reforms to promote online patronage of e-commerce stores among Gen Z consumers. Moreover, regarding normality, skewness values below +1.0 and kurtosis values within ±3.0 (Matore & Khairani, 2020), indicate a normal distribution. Table 3 confirms normalcy, with all variables falling within the ±1.0 skewness and ±3.0 kurtosis limits, suggesting that the variables considered for the hypotheses development are normally distributed. This suggests that promotional pricing practices among the online stores, including loss leader pricing, special event pricing, and sample product pricing, significantly influence Gen Z's patronage of e-commerce stores in Nigeria.

PLS-SEM Path Measurement

A) **H_{01}**: There is no significant relationship between promotional pricing and online patronage of Gen Z's consumers in Nigeria.

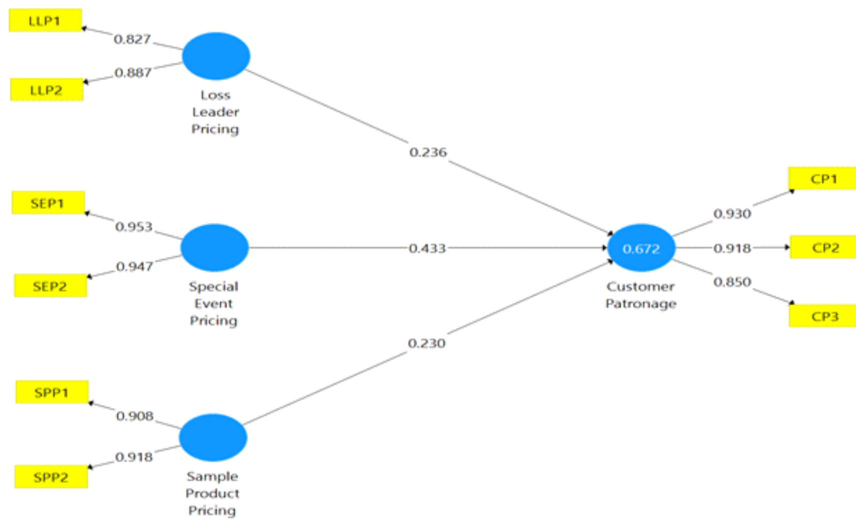


Figure 5: A SEM Path Model of Promotional Pricing on Consumer Patronage (Smart-PLS, 2024).

Figure 5 illustrates the significant positive impact of latent variables on consumer patronage, by surpassing the 5% threshold for significance level. This underscores the critical importance of adopting a pricing strategy that reflects the digital landscape of the business environment, as it can enhance patronage and strengthen Gen Z's loyalty. Specifically, the path measurement highlights that special event pricing has the most substantial effect (0.433), influencing consumer patronage by 91.8%. Therefore, e-commerce brands should prioritise offering cut-rate service with innovative product brand designs to bolster loyalty and subsequently increase patronage. Additionally, the study shows that sample product pricing (0.236) moderately influences consumer patronage by 85.0%. Thus, e-commerce businesses should offer samples to price-reluctant customers, by providing avenues to showcase product benefits, to leave a lasting impression on customers' memory and enhance patronage. Moreover, loss leader pricing (0.236) has a high effect on consumer patronage by 93%. This aligns with El-Said (2020) findings; this suggests that online store brands should enticingly set low prices on certain products, to encourage increased patronage that stimulate sales and potentially increase overall revenue.

B) H_{02}: Product mix-pricing has no significant influence on online satisfaction of Gen Z's consumers in Nigeria.

The results in Figure 6 demonstrate the impact of product mix-pricing, (measured by product lining pricing (PLP), captive pricing (CP), and optional pricing (OP)), on customer satisfaction (CS) in Nigeria's e-commerce industry. The analysis reveals that all latent variables significantly influence Gen Z's satisfaction at a significance level of 5% or higher. This underscores the importance of dynamic pricing strategies in the digital age for online store businesses, as it can enhance satisfaction that yields greater brand recognition and subsequently contribute to the overall sales performance. Specifically, the findings indicate that product lining pricing has the most substantial effect on online satisfaction of Gen Z's consumers (0.457, 93.7% high effect), emphasising the importance of offering a range of prices for variations of the same product which boost the overall satisfaction rate. Captive pricing (0.161, 96.21% high effect) also significantly impacts Gen Z's perceived satisfaction, highlighting the need for e-commerce businesses to choose a packaged product that will be priced low, and complementary products or services that will be priced expensive. Moreover, optional pricing strategy (0.252, 96.0% medium effect) plays a role in Gen Z's online purchase satisfaction, suggesting that businesses should foster customers' flexibility and choice by enhancing their perceived value of the optional product or service. These findings criticise the notion of Benhardy *et. al.* (2020) that optional pricing can harm brand image.

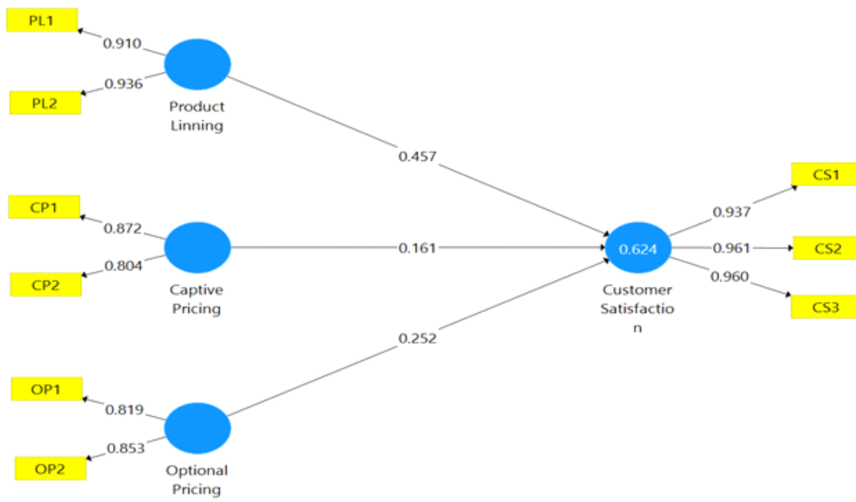


Figure 6: A SEM Path Model of Product Mix-Pricing on Customer Satisfaction (Smart-PLS, 2024)

Validity and Reliability Analysis

Table 4 outlines the reliability and validity results for the four latent variables in the study. Cronbach's Alpha values, indicating internal consistency, range from 0.743 to 0.883, surpassing the 0.7 threshold (Schrepp, 2020), signifying strong reliability. Composite reliability scores, reflecting consistency among latent variable items, range from 0.847 to 0.949, further supporting the variables' reliability which is above 0.70 threshold (Lai, 2021). Average Variance Extracted (AVE) values, measuring convergent validity, range from 0.735 to 0.902, surpassing the 0.5 threshold (Shrestha, 2021), indicating high validity. The diagonal values of the discriminant validity assessment range from 0.858 to 0.950, by above 0.85 threshold (Naveed *et. al.*, 2022), indicating that each variable is distinct from others. Variance Inflation Factor (VIF) values range from 2.063 to 3.359, below the threshold of 10 (Vörösmarty & Dobos, 2020), indicating no severe multicollinearity among variables. These findings affirm the reliability and validity of the variables in the analysis. Furthermore, the results for Hypothesis 1 show high internal consistency, robust composite reliability, and satisfactory convergent validity, supporting the suitability of these variables for the research study.

Table 4: Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	Discriminant Validity	Variance Inflation Factor
Captive Pricing	0.782	0.826	0.703	0.839	2.260
Customer Satisfaction	0.949	0.967	0.907	0.953	-
Optional Pricing	0.771	0.823	0.699	0.836	2.350
Product Lining	0.827	0.920	0.852	0.923	2.565
Customer Patronage	0.883	0.928	0.810	0.900	-
Loss Leader Pricing	0.743	0.847	0.735	0.858	2.063
Sample Product Pricing	0.800	0.909	0.833	0.913	2.991
Special Event Pricing	0.892	0.949	0.902	0.950	3.359

Source: Smart-PLS (2024).

Correlation Coefficient and Bootstrapping Analysis

Yusuf *et. al.* (2024) suggest that the impact of independent variables on the R^2 values of a dependent variable can be assessed using F^2 statistics, where values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. According to Table 5, the R^2 value for customer satisfaction (CS) is 0.624, indicating that 62.4% of the variance in CS is explained by the dimension of the promotional pricing model. Similarly, for customer patronage (CP), R^2 is 0.672, suggesting that 67.2% of the variance in CP is explained by the dimension of product mix pricing model. The adjusted R^2 values, although slightly lower, still suggest a good fit, though with a potential for slight overfitting due to close relationship with R^2 value. The F^2 values for CP, OP, and PLP with respect to CS are 0.031, 0.072, and 0.217, respectively, indicating small to moderate effects. For CP, the F^2 values for

LLP, SPL, and SEP are 0.161, 0.252, and 0.457, respectively, indicating moderate to large effects. All coefficients for CS and most coefficients for CP have t-statistics greater than 2, indicating statistical significance at the 5% level. Overall, these results suggest that while the model has good explanatory power for both CS and CP, some variables may have limited practical significance due to relatively small effect sizes.

Table 5: Coefficient and Bootstrapping Results

	R^2	Adjusted (R^2)	F^2	Original Sample	Sample Mean	Stand-ard Devia-tion	T-Stat-istics	P-Value
CS	**0.624**	**0.616**						
CP->CS			0.031	0.161	0.164	0.080	2.017	**0.044**
OP->CS			0.072	0.252	0.254	0.065	3.906	**0.000**
PLP->CS			0.217	0.457	0.454	0.086	5.328	**0.000**
CP	**0.672**	**0.665**						
LLP->CP			0.161	0.236	0.233	0.079	2.982	**0.003**
SPL->CP			0.252	0.230	0.238	0.102	2.243	**0.025**
SEP->CP			0.457	0.434	0.427	0.106	4.110	**0.000**

Source: Smart-PLS (2024)

Discussion of Findings

The fast-paced global economy, propelled by technological advancements, creates opportunities for marketers in the digital realm, intensifying competition in the e-commerce industry. Marketers now leverage this opportunity by adopting digital pricing strategies to offer a diverse range of products at dynamic prices, impacting consumer purchasing behaviour significantly. Price plays a crucial role in defining a product's value and is a key element of the marketing mix, generating financial resources and serving as an indicator of product success or failure. This aligns with research indicating that digital pricing strategies have a positive effect on Gen Z consumers' purchase decisions in Nigeria, with factors such as product line (45.7%), optional pricing (16.1%), and captive pricing (25.2%) significantly influencing customer satisfaction (62.4%). This aligns with past studies by Yang and Xia (2021) and Singh and Suryavanshi (2018); thus, this further underscores the importance of pricing strategy in enhancing customer satisfaction, emphasising its role in shaping the customer experience in various sectors. Also, the research indicates that loss leader pricing (23.6%), special event pricing (43.3%), and sample product pricing (23%) significantly influence customer patronage (67.2%). This motions the rejection of the null hypothesis and aligns with Jha (2013), who demonstrated that promotional pricing encourages more purchases. Similarly, Diyaolu, Adeleke, and Rasheed (2022) highlighted that promotional pricing has a positive effect on the overall customer behaviour, supporting the research motion that pricing in the digital age is evolving with technology advancement in the e-commerce industry.

The research underscores several critical implications. From a policy perspective, regulators and policymakers must monitor the rapid evolution of pricing strategies in the digital age and ensure that consumer protection measures are in place to prevent potential exploitation. This includes monitoring pricing practices that may be considered unfair or deceptive, particularly with regard to vulnerable consumer groups. Theoretical implications acknowledges a need to update traditional marketing paradigms to incorporate the dynamic nature of technology evolution. Critical concepts such as optional pricing, captive pricing, and sample product pricing challenge conventional pricing theories, highlighting the necessity for a re-evaluation of how pricing strategies are conceptualised and applied in the digital age. From a managerial standpoint, the findings emphasise the importance of agility and responsiveness in pricing decisions. Marketers should be proficient at analysing market trends and consumer behaviour to implement effective pricing strategies that enhance customer satisfaction and patronage. This necessitates a data-driven approach, utilising analytics and consumer insights to inform real-time pricing decisions. Finally, from an empirical perspective, the research contributes to the growing literature on digital pricing strategies, particularly within the context of Gen Z consumers in Nigeria's e-commerce industry. This supports the effectiveness of various pricing strategies in influencing consumer behaviour, enhancing the understanding of how digital pricing impacts purchasing decisions in emerging markets.

Despite the significance of the research, the research findings were criticised for perceived limitations. The use of electronic surveys might introduce response bias due to disparities in access or willingness among different segments of Generation Z in Nigeria to engage online, impacting the demographic composition and representation of consumer viewpoints. Additionally, focusing solely on Gen Z consumers in the e-commerce industry may not fully capture the diversity and complexity of overall consumer behaviour across the continent, where various regions exhibit distinct cultural, economic, and social dynamics influencing e-commerce brand preferences and purchasing behaviours. Furthermore, the reliance on a cross-sectional survey design may limit the ability to establish definitive causality between the construct variables; longitudinal studies or experimental designs would offer more robust evidence. Moreover, using self-reported data could introduce common method bias, potentially inflating correlations due to shared respondent perceptions rather than genuine associations among constructs. Future research could explore how e-commerce brands can effectively implement digital pricing strategies tailored for Generation Z consumers globally, considering cultural differences, digital engagement preferences, perceptions of e-commerce brands authenticity, and the effect of augmented reality and Artificial Intelligence (AI) driven customisation to refine marketing approaches.

Conclusion and Recommendation

Pricing is a crucial factor in business success, especially in the digital age, where strategic pricing can differentiate a product or service in a competitive market. However, if a product is perceived as too expensive, customers may refuse to purchase it, leading to dissatisfaction and reluctance to buy. Consequently, the PLS-SEM result acknowledges the significant impact of digital pricing strategies on the online purchasing behaviour of Generation Z consumers in Nigeria's e-commerce industry. The findings reveal that promotional pricing tactics, including loss leader pricing, special event pricing, and sample product pricing, have a substantial influence on consumer patronage, accounting for 67.2% of the variance in online purchase behaviour. Moreover, product mix-pricing strategies, such as product lining pricing, captive pricing, and optional pricing, significantly affect customer satisfaction, explaining 62.4% of the variance. These results underscore the critical role of pricing strategies in shaping consumer behaviour and driving e-commerce sales in a rapidly evolving digital landscape. The below action plans are recommended:

i. Online stores in Nigeria should incorporate product lining, optional pricing, and captive pricing in their product mix strategies, as these tactics can positively impact customer satisfaction and overall business performance.
ii. To enhance customer patronage in the e-commerce industry, online stores in Nigeria should effectively implement the loss leader pricing, special event pricing, and sample product pricing. These promotional strategies, if strategically deployed, can attract and retain customers, thereby positively influencing the overall business.
iii. Government should implement regulations to monitor and ensure fair pricing practices in the e-commerce industry. This can include guidelines on transparency in pricing, preventing price manipulation, and protecting consumers from deceptive pricing strategies.
iv. Industry regulators should create guidelines and standards for pricing strategies in the e-commerce sector. This can help ensure that businesses adopt fair pricing practices and prevent practices that may harm consumers or create unfair competition.
v. E-commerce brand stakeholders should strengthen relationships with suppliers and distributors to improve pricing strategies. This can involve negotiating better prices for products, optimising inventory management to reduce costs, and collaborating to offer competitive pricing to consumers.
vi. E-commerce brands should embrace data analytics to enhance pricing strategies. This can include dynamic pricing based on real-time market data, personalised pricing offers based on customer behaviour, and using Artificial Intelligence (AI) algorithms to optimise pricing for maximum profitability.

vii. Online stores should educate consumers about pricing strategies in the e-commerce industry to empower them to make informed purchasing decisions. This can include providing information about how prices are set, promoting price comparison tools, and offering tips for spotting deceptive pricing practices.

References

Abdullah, M. I., Sarfraz, M., Arif, A., & Azam, A. (2018). An extension of the theory of planned behaviour towards brand equity and premium price. *Polish Journal of Management Studies*, *18*(1), 20–32.

Ahmed, K., & Joshi, V. (2024). E-Commerce expansion in Indian retail: a strategic analysis of market penetration and competitive dynamics. *Frontiers in Management Science*, *3*(1), 12–20.

Ahmed, Y. A., Majeed, B. N., & Salih, H. A. (2020). Psychological pricing strategy and its influences on consumer's buying behaviour in Kurdistan Region. *Journal of Global Economics and Business*, *1*(3), 73–92.

Ajzen, I. (2015). Consumer attitudes and behaviour: the theory of planned behaviour applied to food consumption decisions. *Italian Review of Agricultural Economics*, *70*(2), 121–138.

Al-Tawalbeh, M., & Abu-Rumman, A. (2015). The impact of marketing-orientated pricing on product mix pricing strategies. *International Journal of Economics, Commerce and Management, III*, *1*, 1–18.

Alford, B. L., & Biswas, A. (2002). The effects of discount level, price consciousness and sale proneness on consumers' price perception and behavioural intention. *Journal of Business Research*, *55*(9), 775–783.

Ali, B. J., & Anwar, G. (2021). Marketing strategy: pricing strategies and its influence on consumer purchasing decisions. *International Journal of Rural Development, Environment and Health Research*, *5*(2), 26–39.

Al-Salamin, H., & Al-Hassan, E. (2016). The impact of competitive pricing on customer patronage in Saudi Arabia: Al-Hassa case study. *European Journal of Business and Management*, *8*(12), 62–79.

Al-Talidi, A. b. (2020). The *impact of psychological pricing policy on consumer behaviour*. Kingdom of Saudi Arabia: Ibn Rushd faculty for Administrative Sciences in Abha, Department of Higher Studies.

Anand, D., & Mantrala, M. (2019). Responding to disruptive business model innovations: the case of traditional banks facing fintech entrants. *Journal of Banking and Financial Technology*, *3*, 19–31.

Aparicio, J., Pastor, J. T., Vidal, F., & Zofío, J. L. (2017). Evaluating productive performance: a new approach based on the product-mix problem consistent with Data Envelopment Analysis. *Omega*, *67*, 134–144.

Arora, S., Singha, K., & Sahney, S. (2017). Understanding consumer's showrooming behaviour: Extending the theory of planned behaviour. *Asia Pacific Journal of Marketing and Logistics*, *29*(2), 409–431.

Ashaduzzaman, M., Jebarajakirthy, C., Weaven, S. K., Maseeh, H. I., Das, M., & Pentecost, R. (2022). Predicting collaborative consumption behaviour: a meta-analytic path analysis on the theory of planned behaviour. *European Journal of Marketing*, *56*(4), 968–1013.

Azad, S., & Shankar Singh, U. (2019). A study on the effect of pricing strategy on customer retention in Kurdistan. *International Journal of Supply Chain Management*, *8*(1), 98–112.

Bauer, J., & Jannach, D. (2018). Optimal pricing in e-commerce based on sparse and noisy data. *Decision Support Systems*, *106*, 53–63.

Benhardy, K., Hardiyansyah, H., Putranto, A., & Ronadi, M. (2020). Brand image and price perceptions impact on purchase intentions: mediating brand trust. *Management Science Letters*, *10*(14), 3425–3432.

Berlilana, B., Wahid, A. M., Fortuna, D., Saputra, A. N. A., & Bagaskoro, G. (2024). Exploring the Impact of Discount Strategies on Consumer Ratings: An Analytical Study of Amazon Product Reviews. *Journal of Applied Data Sciences*, *5*(1), 158–172.

Bertini, M., & Koenigsberg, O. (2021). The pitfalls of pricing algorithms: Be mindful of how they can hurt your brand. *Harvard Business Review*, *99*(5), 74–83.

Bhutto, M. Y., Zeng, F., Soomro, Y. A., & Khan, M. A. (2019). Young Chinese consumer decision making in buying green products: An application of theory of planned behaviour with gender and price transparency. *Pakistan Journal of Commerce and Social Sciences (PJCSS)*, *13*(3), 599–619.

Boztepe, A. (2012). Green marketing and its impact on consumer buying behaviour. *European Journal of Economic & Political Studies*, *5*(1).

Brata, B. H., Husani, S., & Ali, H. (2017). The influence of quality products, price, promotion, and location to product purchase decision on Nitchi at PT. Jaya Swarasa Agung in Central Jakarta. *Saudi Journal of Business and Management Studies*, *2*(4), 357–374.

Braun, V., Clarke, V., Boulton, E., Davey, L., & McEvoy, C. (2021). The online survey as a qualitative research tool. *International Journal of Social Research Methodology*, *24*(6), 641–654.

Brown, Z. Y., & MacKay, A. (2023). Competition in pricing algorithms. *American Economic Journal: Microeconomics*, *15*(2), 109–156.

Budhathoki, M., Zølner, A., Nielsen, T., Rasmussen, M. A., & Reinbach, H. C. (2022). Intention to buy organic fish among Danish consumers: Application of the segmentation approach and the theory of planned behaviour. *Aquaculture*, *549*, 737798.

Cachon, G. P., Daniels, K. M., & Lobel, R. (2017). The role of surge pricing on a service platform with self-scheduling capacity. *Manufacturing & Service Operations Management*, *19*(3), 368–384.

Calvano, E., Calzolari, G., Denicolo, V., & Pastorello, S. (2020). Artificial intelligence, algorithmic pricing, and collusion. *American Economic Review*, *110*(10), 3267–3297.

Can Zhong, Y., & Yi Na, M. (2024). How does cross platform externality impact pricing strategies? A two stage discriminatory pricing model analysis. *Managerial and Decision Economics*, *45*(3), 1454–1479.

Cao, X., Yuan, J., Wen, H., & Zhang, C. (2024). The pricing strategies under the online platform selling mode with information sharing. *Kybernetes*, *53*(3), 1181–1207.

Castaneda, M. G., Martinez, C. P., Marte, R., & Roxas, B. (2015). Explaining the environmentally-sustainable consumer behaviour: A social capital perspective. *Social Responsibility Journal*, *11*(4), 658–676.

Castillo, J. C., Knoepfle, D., & Weyl, G. (2017). Surge pricing solves the wild goose chase. *Proceedings of the 2017 ACM Conference on Economics and Computation*, 241–242.

Chai, L., Wu, D. D., Dolgui, A., & Duan, Y. (2021). Pricing strategy for B&M store in a dual-channel supply chain based on hotelling model. *International Journal of Production Research*, *59*(18), 5578–5591.

Chang, T., & Guo, Y. (2021). Research on Pricing Strategies of Chinese E-Business Platforms Based on Game Theory. *2021 3rd International Conference on Economic Management and Cultural Industry (ICEMCI 2021)*, 2534–2539.

Chen, C., Guo, Y., & Tong, L. (2020). Pricing multi-interval dispatch under uncertainty part II: Generalisation and performance. *IEEE Transactions on Power Systems*, *36*(5), 3878–3886.

Chen, L., Dong, T., Pang, M., Liu, Q., Wang, Z., & Rao, C. (2024). Logistics service strategy for e commerce supply chain: interactive impacts of cost reduction effort and fairness concern. *Managerial and Decision Economics*, *45*(2), 1067–1089.

Chen, Q., Wang, X., Yang, C., Jiang, Z., Qi, S., Zhang, J., Li, N., Wang, L., & Xiao, J. (2024). Reverse double auction mechanism: An efficient algorithm for E-commerce platform operations. *Electronic Commerce Research and Applications*, 101401.

Chiu, W., & Cho, H. (2021). E-commerce brand: The effect of perceived brand leadership on consumers' satisfaction and repurchase intention on e-commerce websites. *Asia Pacific Journal of Marketing and Logistics*, *33*(6), 1339–1362.

Daly, J. L. (2002). *Pricing for profitability: Activity-based pricing for competitive advantage*. John Wiley & Sons.

Dash, G., Kiefer, K., & Paul, J. (2021). Marketing-to-Millennials: Marketing 4.0, customer satisfaction and purchase intention. *Journal of Business Research*, *122*, 608–620.

Diyaolu, G. O., Adeleke, B. S., & Rasheed, D. G. (2022). Sales promotion and customer patronage of selected food and beverages companies in Lagos State, Nigeria. *International Academy Journal of Management, Marketing, and Entrepreneurial Studies*, *9*(1), 132–144.

Djan, I., & Adawiyyah, S. R. (2020). The effect of convenience and trust to purchase decisions and its impact on customer satisfaction. *International Journal of Business and Economics Research*, *9*(4), 269.

Dorce, L. C., da Silva, M. C., Mauad, J. R. C., de Faria Domingues, C. H., & Borges, J. A. R. (2021). Extending the theory of planned behaviour to understand consumer purchase behaviour for organic vegetables in Brazil: The role of perceived health benefits, perceived sustainability benefits and perceived price. *Food Quality and Preference*, *91*, 104191.

El-Said, O. A. (2020). Impact of online reviews on hotel booking intention: The moderating role of brand image, star category, and price. *Tourism Management Perspectives*, *33*, 100604.

Emembolu, I., Emembolu, C., Aderinwale, O., & Lobijo, E. (2022). Digital Entrepreneurship in Africa: Case Studies of Nigeria and South Sudan. In *Digital Service Delivery in Africa: Platforms and Practices*. 135–162. Springer.

Farid, M. S., Cavicchi, A., Rahman, M. M., Barua, S., Ethen, D. Z., Happy, F. A., Rasheduzzaman, M., Sharma, D., & Alam, M. J. (2023). Assessment of marketing mix associated with consumer's purchase intention of dairy products in Bangladesh: Application of an extended theory of planned behaviour. *Heliyon*, *9*(6).

Feurer, S., Schuhmacher, M. C., & Kuester, S. (2019). How pricing teams develop effective pricing strategies for new products. *Journal of Product Innovation Management*, *36*(1), 66–86.

Fitri, R., & Mardikaningsih, R. (2023). Factors Affecting Repurchase Intentions of Meat at Superindo: Product Variety, Perceived Risk, and Price Perception. *International Journal of Service Science, Management, Engineering, and Technology*, *4*(1), 11–19.

Gebremichael, A. H. (2022). Analysis on the effect of Marketing Mix on Customer Satisfaction and Loyalty in the Hospitality Industry of Ethiopia: Using Structural Equation Model. *The Journal of Contemporary Issues in Business and Government*, *28*(3), 471–484.

Gelder, K.V. (2024) *E-commerce Worldwide*, *Statista*. Available at: https://www.statista.com/topics/871/online-shopping/#editorsPicks (Accessed: 1 January 2024).

Ghifarini, A. F., Sumarwan, U., & Najib, M. (2018). Application of theory of planned behaviour in shrimp consumer behaviour analysis. *Independent Journal of Management & Production*, *9*(3), 984–1001.

Golrezaei, N., Nazerzadeh, H., & Randhawa, R. (2020). Dynamic pricing for heterogeneous time-sensitive customers. *Manufacturing & Service Operations Management*, *22*(3), 562–581.

Groenewald, E., & Kilag, O. K. (2024). E-commerce Inventory Auditing: Best Practices, Challenges, and the Role of Technology. *International Multidisciplinary Journal of Research for Innovation, Sustainability, and Excellence (IMJRISE)*, *1*(2), 36–42.

Guenther, P., Guenther, M., Ringle, C. M., Zaefarian, G., & Cartwright, S. (2023). Improving PLS-SEM use for business marketing research. *Industrial Marketing Management*, *111*, 127–142.

Gupta, V., Ivanov, D., & Choi, T.-M. (2021). Competitive pricing of substitute products under supply disruption. *Omega*, *101*, 102279.

Hair F., Jr, J., Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modelling (PLS-SEM) An emerging tool in business research. *European Business Review*, *26*(2), 106–121.

Hameed, I., Waris, I., & Amin ul Haq, M. (2019). Predicting eco-conscious consumer behaviour using theory of planned behaviour in Pakistan. *Environmental Science and Pollution Research*, *26*, 15535–15547.

Hamilton, B., & Terblanche-Smit, M. (2018). Consumer intention to purchase green vehicles in the South African market: A theory of planned behaviour perspective. *South African Journal of Business Management*, *49*(1), 1–7.

Han, G., Feng, Z., Chen, S., Xue, X., & Wu, H. (2024). Evaluating differential pricing in e-commerce from the perspective of utility. *Electronic Commerce Research and Applications*, 101373.

Han, T.-I., & Stoel, L. (2017). Explaining socially responsible consumer behaviour: A meta-analytic review of theory of planned behaviour. *Journal of International Consumer Marketing*, *29*(2), 91–103.

Hsu, C.-L., Chang, C.-Y., & Yansritakul, C. (2017). Exploring purchase intention of green skincare products using the theory of planned behaviour: Testing the moderating effects of country of origin and price sensitivity. *Journal of Retailing and Consumer Services*, *34*, 145–152.

International Trade Administration (2023) *Nigeria-Market Overview*, *www.trade.gov*. Available at: https://www.trade.gov/country-commercial-guides/nigeria-market-overview (Accessed: January 2024).

Jha, M. (2013). A study of consumer shopping behaviour in organised retail at Ranchi. *Indian Journal of Applied Research*, *3*(11), 271–272.

Ji, Y., Li, Y., & Tang, W. (2022). Service investment and pricing strategies in e-commerce platforms with seller competition. *International Journal of Information Systems and Supply Chain Management (IJISSCM)*, *15*(1), 1–21.

Jiao, J. (2018). Investigating Uber price surges during a special event in Austin, TX. *Research in Transportation Business & Management*, *29*, 101–107.

Khan, Y., Hameed, I., & Akram, U. (2023). What drives attitude, purchase intention and consumer buying behaviour towards organic food? A self-determination theory and theory of planned behaviour perspective. *British Food Journal*, *125*(7), 2572–2587.

Khaniwale, M. (2015). Consumer buying behaviour. *International Journal of Innovation and Scientific Research*, *14*(2), 278–286.

Khrais, L. T. (2020). Role of artificial intelligence in shaping consumer demand in E-commerce. *Future Internet*, *12*(12), 226.

Kim, G., Wang, W., & Ha, H.-K. (2021). Pricing strategy for own shipping service of E-commerce platform using Two-sided market theory. *Electronic Commerce Research and Applications*, *49*, 101088.

Kim, Y., & Han, H. (2010). Intention to pay conventional-hotel prices at a green hotel– a modification of the theory of planned behaviour. *Journal of Sustainable Tourism*, *18*(8), 997–1014.

Kimsanova, B., Sanaev, G., & Herzfeld, T. (2024). Dynamics of food demand during political instability: Evidence from Kyrgyzstan. *Agricultural Economics*, *55*(1), 41–53.

Krämer, A., & Kalka, R. (2017). How digital disruption changes pricing strategies and price models. *Phantom Ex Machina: Digital Disruption's Role in Business Model Transformation*, 87–103.

Krosnick, J. A. (2018). Questionnaire design. *The Palgrave Handbook of Survey Research*, 439–455.

Kumar, S., & Pandey, M. (2017). The impact of psychological pricing strategy on consumers' buying behaviour: a qualitative study. *International Journal of Business and Systems Research*, *11*(1–2), 101–117.

Lai, M. H. C. (2021). Composite reliability of multilevel data: It's about observed scores and construct meanings. *Psychological Methods*, *26*(1), 90.

Latkovikj, M. T., & Popovska, M. B. (2019). Online research about online research: advantages and disadvantages. *E-Methodology*, *6*(6), 44–56.

Lee, C., Lim, S., & Ha, B. (2021). Green supply chain management and its impact on consumer purchase decisions as a marketing strategy: Applying the theory of planned behaviour. *Sustainability*, *13*(19), 10971.

Legate, A. E., Hair Jr, J. F., Chretien, J. L., & Risher, J. J. (2023). PLS SEM: Prediction oriented solutions for HRD researchers. *Human Resource Development Quarterly*, *34*(1), 91–109.

Lei, J., Jia, J., & Wu, T. (2015). Pricing strategies in dual-online channels based on consumers' shopping choice. *Procedia Computer Science*, *60*, 1377–1385.

Li, C., Chu, M., Zhou, C., & Zhao, L. (2020). Two-period discount pricing strategies for an e-commerce platform with strategic consumers. *Computers & Industrial Engineering*, *147*, 106640.

Li, S. S., & Karahanna, E. (2015). Online recommendation systems in a B2C E-commerce context: a review and future directions. *Journal of the Association for Information Systems*, *16*(2), 2.

Li, W., & He, W. (2024). Revenue-increasing effect of rural e-commerce: A perspective of farmers' market integration and employment growth. *Economic Analysis and Policy*, *81*, 482–493.

Lii, Y.-S., & Lin, C. L. (2020). The Effects of Product Line Prices and Competitors' Prices on Consumers' Evaluations of Reference Price Advertisements. *Proceeding on Japan International Business and Management Research Conference (JIBM)*, *1*(1), 54–59.

Lin, C., & Bowman, D. (2022). The impact of introducing a customer loyalty programme on category sales and profitability. *Journal of Retailing and Consumer Services*, *64*, 102769.

Lindblom, A., & Lindblom, T. (2018). Applying the extended theory of planned behaviour to predict collaborative consumption intentions. *Collaborative Value Co-Creation in the Platform Economy*, 167–182.

Liobikienë, G., Mandravickaitë, J., & Bernatonienë, J. (2016). Theory of planned behaviour approach to understand the green purchasing behaviour in the EU: A cross-cultural study. *Ecological Economics*, *125*, 38–46.

Liu, J., & Ke, H. (2020). Firms' pricing strategies under different decision sequences in dual-format online retailing. *Soft Computing*, *24*(10), 7811–7826.

Loh, Z., & Hassan, S. H. (2022). Consumers' attitudes, perceived risks and perceived benefits towards repurchase intention of food truck products. *British Food Journal*, *124*(4), 1314–1332.

Luo, J., Zhang, H., & Li, H. (2018). Pricing strategies in online book industry: a comparative study. *Information Systems and E-Business Management*, *16*, 791–816.

Madahi, A., & Sukati, I. (2016). An empirical study of Malaysian consumers' channel-switching intention: Using theory of planned behaviour. *Global Business Review*, *17*(3), 489–523.

Manalu, V. G., & Adzimatinur, F. (2020). The effect of consumer ethnocentrism on purchasing batik products: Application of the extended theory of planned behaviour (TPB) and price sensitivity. *Budapest International Research and Critics Institute-Journal (BIRCI-Journal)*, *3*(4), 3137–3146.

Mansouri, S., & Hosseini, M. (2018). E-commerce, Marketing Strategies and a Variety of Pricing Methods. *Journal of Management and Accounting Studies*, *6*(03), 55–59.

Maryam, S. Z., Ahmad, A., Aslam, N., & Farooq, S. (2022). Reputation and cost benefits for attitude and adoption intention among potential customers using theory of planned behaviour: An empirical evidence from Pakistan. *Journal of Islamic Marketing*, *13*(10), 2090–2107.

Mathur, M., & Gangwani, S. (2021). Mediating role of perceived value on the relationship among perceived risks, perceived quality, and purchase intention of private label brands. *International Journal of Applied Management and Technology*, *20*(1), 4.

Matore, E. M., & Khairani, A. Z. (2020). The pattern of skewness and kurtosis using mean score and logit in measuring adversity quotient (AQ) for normality testing. *International Journal of Future Generation Communication and Networking*, *13*(1), 688–702.

Matthews, L., Hair, J. O. E., & Matthews, R. (2018). PLS-SEM: The holy grail for advanced analysis. *Marketing Management Journal*, *28*(1).

McKinlay, J. B. (2020). Advantages and limitations of the survey approach: understanding older people. In *Researching Health Care* (pp. 114–137). Routledge.

Meng, Q., Li, M., Liu, W., Li, Z., & Zhang, J. (2021). Pricing policies of dual-channel green supply chain: Considering government subsidies and consumers' dual preferences. *Sustainable Production and Consumption*, *26*, 1021–1030.

Moon, J. Y. (2006). Consumer purchase intention to buy mass customised products online: Effects of culture, product type and price. *Korean Management Review*, *35*(6), 1773–1795.

Muça, S., & Zeqiri, J. (2020). Purchase intention of customers towards luxury brands in North Macedonia: Theory of planned behaviour approach. *International Journal of Islamic Marketing and Branding*, *5*(2), 99–113.

Naveed, R. T., Alhaidan, H., Al Halbusi, H., & Al-Swidi, A. K. (2022). Do organisations really evolve? The critical link between organisational culture and organisational innovation toward organisational effectiveness: Pivotal role of organisational resistance. *Journal of Innovation & Knowledge*, *7*(2), 100178.

Neger, M., & Uddin, B. (2020). Factors affecting consumers' internet shopping behaviour during the COVID-19 pandemic: Evidence from Bangladesh. *Chinese Business Review*, *19*(3), 91–104.

Ngah, A. H., Jeevan, J., Salleh, N. H. M., Lee, T. T. H., & Mhd Ruslan, S. M. (2020). Willingness to pay for halal transportation cost: The moderating effect of knowledge on the theory of planned behaviour. *Journal of Environmental Treatment Techniques*, *8*(1), 13–22.

Nimri, R., Patiar, A., & Jin, X. (2020). The determinants of consumers' intention of purchasing green hotel accommodation: Extending the theory of planned behaviour. *Journal of Hospitality and Tourism Management*, *45*, 535–543.

Nogueira, G. P. M., de Assis Rangel, J. J., & Shimoda, E. (2021). Sustainable last-mile distribution in B2C e-commerce: Do consumers really care? *Cleaner and Responsible Consumption*, *3*, 100021.

Odeyemi, O., Elufioye, O. A., Mhlongo, N. Z., & Ifesinachi, A. (2024). AI in E-commerce: Reviewing developments in the USA and their global influence. *International Journal of Science and Research Archive*, *11*(1), 1460–1468.

Ogiemwonyi, O. (2022). Factors influencing generation Y green behaviour on green products in Nigeria: An application of theory of planned behaviour. *Environmental and Sustainability Indicators*, *13*, 100164.

Okolie, U. C., & Ojomo, A. H. (2020). E-commerce in Nigeria: benefits and challenges. *Humanities & Social Sciences Latvia*, *28*(2).

Oladipo, T.D. 2023. A Review of social capital as a concept. *ABUAD Journal of Social and Management Sciences*, *4*(2). 283-297.

Oyekanmi, T. (2023) *The E-commerce Sector in Nigeria: Industry Analysis*, *Business Africa Online*. Available at: https://businessafricaonline.com/e-commerce/ (Accessed: February 2024).

Pace, D. S. (2021). Probability and non-probability sampling- an entry point for undergraduate researchers. *International Journal of Quantitative and Qualitative Research Methods*, *9*(2), 1–15.

Pool, J. (2024) *The Top 12 e-commerce Sites in the World in 2024*, *Webretailer.com*. Available at: https://www.webretailer.com/marketplaces-worldwide/the-top-10-ecommerce-sites-in-the-world/#:~:text=Top%2010%20eCommerce%20Sites%20to%20Explore%201%201. (Accessed: 31 February 2024).

Radha, P., & Aithal, P. S. (2024). An exploratory analysis of variables shaping consumer decision-making in the purchase of kitchen appliances within Shopping mall environments. *International Journal of Management, Technology and Social Sciences (IJMTS)*, *9*(1), 148–168.

Ramdani, D., & Azzahra, G. A. (2024). Analysis of consumer preference to price strategies in the retail industry. *Journal of Student Collaboration Research*, *1*(1), 26–29.

Rice, S., Winter, S. R., Doherty, S., & Milner, M. (2017). Advantages and disadvantages of using internet-based survey methods in aviation-related research. *Journal of Aviation Technology and Engineering*, *7*(1), 5.

Sachdeva, N., Kapur, P. K., & Singh, O. (2016). An innovation diffusion model for consumer durables with three parameters. *Journal of Management Analytics*, *3*(3), 240–265.

Saharan, S., Bawa, S., & Kumar, N. (2020). Dynamic pricing techniques for Intelligent transportation system in smart cities: A systematic review. *Computer Communications*, *150*, 603–625.

Sahoo, D., Harichandan, S., Kar, S. K., & Sreejesh, S. (2022). An empirical study on consumer motives and attitude towards adoption of electric vehicles in India: Policy implications for stakeholders. *Energy Policy*, *165*, 112941.

Samo, A. H., Asif, Y., & Mujtaba, M. D. (2018). Role of charm pricing in purchase decision- A study of online consumers of Pakistan. *Journal of Business Administration and Management Sciences (JOBAMS)*, *2*(2), 327–336.

Sarkar, M., Ayon, E. H., Mia, M. T., Ray, R. K., Chowdhury, M. S., Ghosh, B. P., Al-Imran, M., Islam, M. D. T., Tayaba, M., & Puja, A. R. (2023). Optimising e-commerce profits: A comprehensive machine learning framework for dynamic pricing and predicting online purchases. *Journal of Computer Science and Technology Studies*, *5*(4), 186–193.

Sasu, D.D. (2023) *Topic: E-commerce in Nigeria*, *Statista*. Available at: https://www.statista.com/topics/6786/e-commerce-in-nigeria/#topicOverview (Accessed: 2 January 2024).

Schrepp, M. (2020). On the usage of Cronbach's Alpha to measure reliability of UX Scales. *Journal of Usability Studies*, *15*(4).

Seele, P., Dierksmeier, C., Hofstetter, R., & Schultz, M. D. (2021). Mapping the ethicality of algorithmic pricing: A review of dynamic and personalised pricing. *Journal of Business Ethics*, *170*, 697–719.

Setiawati, H., Hartoyo, H., & Simanjuntak, M. (2018). Analysis on intention of purchasing organic foods by the undergraduate students of IPB using the theory of planned behaviour approach. *Jurnal Manajemen & Agribisnis*, *15*(2), 198.

Shah, S. K., & Zhongjun, T. (2021). Elaborating on the consumer's intention–behaviour gap regarding 5G technology: The moderating role of the product market-creation ability. *Technology in Society*, *66*, 101657.

Shalender, K., & Sharma, N. (2021). Using extended theory of planned behaviour (TPB) to predict adoption intention of electric vehicles in India. *Environment, Development and Sustainability*, *23*(1), 665–681.

Shang, Y., & Zong, Y. (2024). Role of e-commerce for promoting sustainability in the mining sector. *Resources Policy*, *90*. 104794.

Sharma, M., Sharma, M., & Mehta, A. (2024). E-commerce and social media marketing: Impact of advertising, brand and price on brand image of MSME. *Academy of Marketing Studies Journal*, *28*(1).

Sheoran, M., & Kumar, D. (2022). Conceptualisation of sustainable consumer behaviour: converging the theory of planned behaviour and consumption cycle. *Qualitative Research in Organisations and Management: An International Journal*, *17*(1), 103–135.

Shiller, B. R. (2013). *First Degree Price Discrimination Using Big Data*. Brandeis Univ., Department of Economics.

Shrestha, N. (2021). Factor analysis as a tool for survey analysis. *American Journal of Applied Mathematics and Statistics*, *9*(1), 4–11.

Singh, H., Althuwaini, S., & Alflayyeh, S. (2020). Retailscape impact on customer emotional responses and on customer patronage: The moderating role of customer motivation. *International Journal of Management (IJM)*, *11*(8).

Singh, K., & Basu, R. (2023). Online consumer shopping behaviour: A review and research agenda. *International Journal of Consumer Studies*, *47*(3), 815–851.

Song, Y., Son, Y.-J., & Oh, D. (2015). Methodological issues in questionnaire design. *Journal of Korean Academy of Nursing*, *45*(3), 323–328.

Spence, M., Stancu, V., Elliott, C. T., & Dean, M. (2018). Exploring consumer purchase intentions towards traceable minced beef and beef steak using the theory of planned behaviour. *Food Control*, *91*, 138–147.

Statista (2024) *Global E-commerce Revenue by Region*, *Statista*. Available at: https://www.statista.com/forecasts/1117851/worldwide-e-commerce-revenue-by-region (Accessed: 31 February 2024).

Sugiharto, B. H. (2024). The role of e-commerce for MSMEs as a digital marketing strategy in facing industrial revolution 4.0. *Management Studies and Business Journal (PRODUCTIVITY)*, *1*(1), 99–107.

Sutia, S., & Fahlevi, M. (2024). Brand image and customer behaviour in container food courts: The role of social media content and generational differences in Indonesia. *Uncertain Supply Chain Management*, *12*(3), 1549–1566.

Tang, M., You, T., & Cao, B. (2024). Advance selling strategy and pricing decisions with online reviews. *International Transactions in Operational Research*.

Thomas, M., & Morwitz, V. (2009). Heuristics in numerical cognition: Implications for pricing. In *Handbook of pricing research in marketing*. pp. 132–149. Edward Elgar Publishing.

Thota, V., Nagalakshmi, M., Kumar, K., Kumar, S., Momin, U., & Mishra, P. (2024). E-Commerce management and AI based dynamic pricing revenue optimisation strategies. *Migration Letters*, *21*(S4), 168–177.

Usakli, A., & Rasoolimanesh, S. M. (2023). Which SEM to use and what to report? A comparison of CB-SEM and PLS-SEM. In *Cutting edge research methods in hospitality and tourism*. 5–28. Emerald Publishing Limited.

Vessal, S. R., De Giovanni, P., & Hassanzadeh, A. (2022). Technology and service investments in the presence of feature fatigue and word-of-mouth. *European Journal of Operational Research*, *301*(3), 923–941.

Victor, V., Thoppan, J. J., Fekete-Farkas, M., & Grabara, J. (2019). Pricing strategies in the era of digitalisation and the perceived shift in consumer behaviour of youth in Poland. *Journal of International Studies (2071-8330)*, *12*(3).

Vörösmarty, G., & Dobos, I. (2020). Green purchasing frameworks considering firm size: a multicollinearity analysis using variance inflation factor. *Supply Chain Forum: An International Journal*, *21*(4), 290–301.

Wicaksono, A., & Maharani, A. (2020). The effect of perceived usefulness and perceived ease of use on the technology acceptance model to use online travel agency. *Journal of Business and Management Review*, *1*(5), 313–328.

Wu, C.-H., Yan, Z., Tsai, S.-B., Wang, W., Cao, B., & Li, X. (2020). An empirical study on sales performance effect and pricing strategy for e-commerce: from the perspective of mobile information. *Mobile Information Systems*, *2020*, 1–8.

Wu, X., Zhang, F., & Zhou, Y. (2022). Brand spillover as a marketing strategy. *Management Science*, *68*(7), 5348–5363.

Xi, X., & Zhang, Y. (2023). The interplay between marketplace channel addition and pricing strategy in an e-commerce supply chain. *International Journal of Production Economics*, *258*, 108807.

Xiang, Y., Yang, J., Li, X., Gu, C., & Zhang, S. (2021). Routing optimisation of electric vehicles for charging with event-driven pricing strategy. *IEEE Transactions on Automation Science and Engineering*, *19*(1), 7–20.

Xin, B., Hao, Y., & Xie, L. (2023). Strategic product showcasing mode of E-commerce live streaming. *Journal of Retailing and Consumer Services*, *73*, 103360.

Yakasai, A. B. M., & Jusoh, W. J. W. (2015). Testing the theory of planned behaviour in determining intention to use digital coupons among university students. *Procedia Economics and Finance*, *31*, 186–193.

Yan, N., Liu, Y., Xu, X., & He, X. (2020). Strategic dual-channel pricing games with e-retailer finance. *European Journal of Operational Research*, *283*(1), 138–151.

Yang, M., & Xia, E. (2021). A systematic literature review on pricing strategies in the sharing economy. *Sustainability*, *13*(17), 9762.

Yao, A. Y., & Bao, Y. (2024). Leveraging visual cues and pricing strategies: An empirical investigation of the pre-owned luxury market. *Journal of Global Fashion Marketing*, *15*(2), 286–301.

Ye, X., Fu, Y.-K., Wang, H., & Zhou, J. (2023). Information asymmetry evaluation in hotel E-commerce market: Dynamics and pricing strategy under pandemic. *Information Processing & Management*, *60*(1), 103117.

Yin, C., & Han, J. (2021). Dynamic pricing model of e-commerce platforms based on deep reinforcement learning. *Computer Modeling in Engineering & Sciences*, *127*(1), 291–307.

Yusuf, M. S. A., Man, N., Haris, N. B. M., Ismail, I. A., Yee, S. S., & Bakar, T. H. S. T. A. (2024). Improvement model framework of urban agriculture programme in Malaysia: PLS-SEM analysis. *Sarhad Journal of Agriculture*, *40*(1).

Zhang, X., Chen, H., & Liu, Z. (2024). Operation strategy in an e commerce platform supply chain: Whether and how to introduce live streaming services? *International Transactions in Operational Research*, *31*(2), 1093–1121.

Zhang, Y., Deng, J., & Xu, Y. (2017). The effect of different price promotion ways on consumers' purchasing intention. *American Journal of Industrial and Business Management*, *7*(10), 1192.

Zhang, Z., Garimella, A., & Fan, M. (2024). Leveraging the Social Fabric to Improve Rural E-Commerce Access. *Production and Operations Management*, 10591478231224974.

Zhao, H., Yao, X., Liu, Z., & Yang, Q. (2021). Impact of pricing and product information on consumer buying behaviour with customer satisfaction in a mediating role. *Frontiers in Psychology*, *12*, 720151.

Zhou, C., Leng, M., Liu, Z., Cui, X., & Yu, J. (2022). The impact of recommender systems and pricing strategies on brand competition and consumer search. *Electronic Commerce Research and Applications*, *53*, 101144.

Zhu, L., & Lin, J. (2019). A pricing strategy of e-commerce advertising cooperation in the stackelberg game model with different market power structure. *Algorithms*, *12*(1), 24.

Zhu, S. (2024). How does e-commerce industry benefit from big data. *SHS Web of Conferences*, *181*, 1029.