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The effect of artificial intelligence and payment flexibility on operational performance: The enabling role of supply chain risk management

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This paper investigates the effect of artificial intelligence (product information, recommendation, and social media exposure) and payment flexibility on the operational performance of ecommerce retailers. The study is based on Transactional Cost Analysis, Material Flow, and Technology Integration theories. It considered a sample size of 270 members out of the population of 769 employees from five ecommerce companies operating in the region (Namshi.com, Noon, Joly Chic, Extra, and Styli). The analysis involved constructing a structural equation model to examine the trickle-down effect of the variables included in the study. The study concluded that artificial intelligence and payment flexibility are the core reasons that the retailers in the region are registering operational success in the retail market.

1. Introduction

The application of artificial intelligence is experiencing steady growth in the contemporary business environment. It is no longer a preserve for elite firms, as small and medium enterprises continue to appreciate the role played by this technology (Hansen & Bøgh, 2021). Its relevance is apparent across the board regardless of the business department of application. As a result, its effects have manifested in various functions such as business process engineering, supply chain management, financial decision making, and marketing. The supply chain function continues to be increasingly key to promoting firm competitiveness amidst global supply challenges. Uncertainties in the business world such as natural calamities, terrorism, war, and pandemics have taught commercial organizations to optimize their supply chains as a matter of necessity (Alicke & Strigel, 2020; Chu, Park, & Kremer, 2020). The integration of AI in the management supply chain functions seems to be an area that enjoys scholarly and practical attention. Nevertheless, information on the same is scanty due to the relatively new phenomenon of artificial intelligence. Social media exposure is a key determinant in the process of establishing the competitiveness of a commercial entity in the market. Almost half of the current generation is on social media. ("Number of social network users worldwide from 2017 to 2025," 2022) reports that 49% of the global population uses social media. The same source indicates that the average time people spend on these platforms is 144 minutes. According to (Adegbuyi, Akinyele, & Akinyele, 2015), firms engaging in strong social media activity seem to experience more customer reach, and their overall performance is high. Some argue that this notion manifests because by having a bigger audience on social media, firms can effectively position their brands and products in the mind of their customers. Consequently, this phenomenon results in more sales and customer loyalty, which is good for any business (van Asperen, de Rooij, & Dijkmans, 2018).

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Artificial intelligence has also been in use to process social media data and determine trends in the market. In this case, artificial intelligence and social media are both requisite elements in the promotion of business operational performance.
The mediating role of supply chain risk management on the interactions between artificial intelligence, social media, and their effect on operational performance is an area of research that is not fully explored. (Belhadi, Mani, Kamble, Khan, & Verma, 2021) only investigates the interactions between artificial intelligence and supply chain management. Another study by (Basri, 2020) examines the role of artificial intelligence integrated into social media on the performance of SMEs in Saudi Arabia. The study was guided by the following research questions. What is the effect of artificial intelligence on stimulation intensity? How does payment flexibility affect stimulation intensity? Does stimulation intensity have a significant effect on impulsive buying? What is the effect of impulsive buying on supply chain disruption? Does supply chain risk management completely mediate the relationship between supply chain disruption and operational performance? How significant is the effect of supply chain disruption on operational performance?

This study effectively contributes to the body of knowledge on the subject at hand by analyzing findings from primary research. It engages stakeholders in the retail business environment in the region to determine how effective artificial intelligence has been in enhancing the performance prospects of such businesses. Hence, primary research investigating the interactions between aspects of artificial intelligence in businesses, payment flexibility, and supply chain risk management can potentially explain the operational performance of contemporary business organizations in the retail sector.

2. Literature Review

Artificial intelligence heavily relies on product information for it to classify a product into specific groups. Most of the time it uses its features such as price, product category, usage, ingredients, and country of origin. The quality of predictions made by artificial intelligence are dependent on the amount and quality of product information. Some studies have investigated the effect of product information on the stimulation of buying behavior among customers. According to (Rajagopal, 2008), when product information is made available during point-of-sales promotions, it results in more purchase interest from customers in Mexico. The study adds that the use of point-of-sale promotion in arousing customer interest has become a prominent sales and marketing strategy among retailers in the said country. The satisfaction among customers treated to such an arrangement is high. The results are ease in acquiring new customers and enhancing the loyalty levels of present customers (van Esch & Stewart Black, 2021). These two outcomes have further made retailers engaging in these strategies gain an edge against rivals. This revelation is a major indication that product information is a significant antecedent to the arousal of customer interest, otherwise known as stimulation intensity.

The display of product information does not have to be to customers in a retail shop. (Khisa et al., 2020) find that many retail outlets have embraced the habit of displaying this information to prospective customers passing by the premises. The study reports that by doing so, businesses have succeeded in positively influencing buying behavior. This technique is known as visual merchandising where a business strategically displays a product in a manner that is provoking to instigate customer attention and their subsequent purchase interest (Adam, 2020). While the investigation was on an apparel store, its applicability traverses this industry. (Thomas, Louise, & Vipinkumar, 2018) further claims that not only does visual merchandizing spike customer interest, but it is also a trigger for impulse buying. The studies above seem to strongly suggest that the display of product information has a significant effect on buyer stimulation intensity.

Product recommendation systems are artificial intelligence systems that take in user data, process it, and intelligently determine what products a user may want. (Bag, Tiwari, & Chan, 2019) argue that online retail shops are currently adopting Retail 4.0, which is the digitization of customer retail experiences. The use of AI recommender systems is one way that the source considers an improvement on the previously dominant retail management systems. They take in user data in the form of reviewing polarity brands' social perception score, which then goes into sentimental analysis and network mining (Guo, Yin, Li, Ren, & Liu, 2018). Afterwards, the system carries out a regression analysis. This method has proven to be effective in triggering the interest in buyers to purchase particular products. While the study was specifically designed to analyze the buying behavior of customers of durable goods, it seems applicable to other product categories. Artificial intelligence significantly influences customer buying decisions to the extent of pushing them to engage in impulse buying (Jain & Gandhi, 2021). This notion demonstrates the power that AI has to influence buyer behavior through product recommendation systems. Product recommendation systems have also been responsible for determining the perceived value of products. (Yin & Qiu, 2021) report that recommender systems positively impact customer buying behavior by influencing related utility and perceived hedonic value. These two consequently influence the purchase intention of a consumer, which is a prelude to their purchase behavior. While both the perceived hedonic and utility values significantly and positively influence purchase patterns, the study finds that the perceived hedonic value is more effective in influencing purchase decisions. This section’s review suggests that product recommendation has become an integral part of customer stimulation mechanisms in the retail market because of its formidability in influencing customer purchase decisions.

Artificial intelligence systems also rely on social media data obtained from various sites. Using tools such as Python’s Selenium, one can scrape a social media site and collect user information that can be used in improving the recommendation engine. (Ioanas, 2020) argues that social media exposure not only provides a platform for customers to preview details of a product. On top of providing detailed information on products, this exposure also helps customers to provide and or read independent reviews. Left to businesses, it is easy to find ways of manipulating customers by providing fancy but inaccurate information about their products. However, the source relishes social media exposure because of its ability to allow criticism and accolades in equal measure. Ultimately, the information and reviews found on these sites become the tools that users employ to empower their purchase decisions (Erkan & Evans, 2018). Some firms have even designed their websites to accept the social interaction of users. This information is critical in feeding the AI recommendation engine with products that have great reviews by users. The benefits of the approach seem to outweigh the corresponding risks.

Sometimes, the effect of social media exposure on buyer behavior depends on the stage at which a consumer is while consulting. (Chowdhury, 2019) finds a statistically significant effect of social media exposure on buying behavior during the problem recognition and post-purchase steps. During problem or need recognition, a customer finds out that they need a solution to an existing problem. Post-purchase is the stage that comes after a customer has purchased and or consumed the product in question. During this stage, a customer may leave a review of their experience purchasing or consuming the product in question (Voramontri & Klieb, 2019). It is quite interesting that the study did not find social media as important during the information search stage. Many people find it easy to visit these platforms to clarify information that they find confusing or unavailable elsewhere.

Payment flexibility is another issue of concern, as it can influence buyer behavior if not well considered. Cashless systems have dominated the e-commerce market because of the digital nature of the stores in question. Even with digital payment systems, some require debit/credit cards and those that are online wallets. According to (Greenacre & Akbar, 2019), these cashless methods gained traction with time because of the convenience that comes with their usage. Essentially, a business with more payment methods is likely to attract more customers to it. Some customers buy out of convenience rather than out of need. Getting to such prospects is only possible if the array of payment methods allowable on the system conforms with the ones wielded by customers (Alheet, 2018). Some of the most common payment methods are Visa, MasterCard, PayPal, and Payoneer. When combined with artificial intelligence technologies, the effectiveness of payment flexibility is advanced. The use of QR codes in confirming payment transactions fast-tracks this process and enhances security. In this way, a customer can scan the QR code from the ecommerce website from their mobile wallet application to execute and or confirm the payment.

Payment flexibility is particularly an issue of concern to international customers. In a world that is becoming increasingly global, (Njoroge, 2021) argues that e-commerce platforms should appreciate the variety of payment methods that are convenient to different sets of customers. In some countries, mobile payment systems are at an advanced level to warrant their inclusion into the global payment infrastructure. A good example is the Mpesa product by Safaricom PLC Kenya, which is the first mobile payment application in the world (Chebichiy & Odhiambo, 2020). The convenience of such payment options makes them indispensable to global e-commerce giants such as Alibaba and Amazon. These firms try to keep updated with the latest payment gateway technologies emerging around the world. It is a salient indication that payment flexibility is a major determinant of buyer behavior stimulation intensity.

It is an expected phenomenon that when stimulation intensity in the purchase behavior of customers exceeds the average threshold, impulse buying sets in. While this notion may be true, (Katakam, Bhukya, Bellamkonda, & Samala, 2021) cautions that some factors would ultimately lead to impulse buying. The factors discussed in the source are store ambiance and salesperson interactions. The study finds that these sources are particularly influential during the first store visits by customers. However, the customers did not show similar purchase behavior in their subsequent visits. In (Ahmad, Ali, Malik, Humayun, & Ahmad, 2019), several factors were found to be influential in determining customer purchase behavior, some of which are impulse buying tendencies, positive mood, and fashion involvement. On the other hand, the study found that self-esteem and hedonism did not significantly impulse buying behavior among customers. (Jain & Gandhi, 2021) argue that artificial intelligence actively promotes impulse buying by affecting purchase duration, providing product information, recommending products, and enhancing human interaction with products. This review shows that depending on the factors, impulse buying may emanate from stimulation intensity.

Whenever customers' desire to buy a specific product is triggered, they are more likely to buy that product even if it was not in their plan. In the study by (Badgaiyan & Verma, 2014), materialism, shopping enjoyment, and impulsive buying tendency significantly influence impulse buying (Badgaiyan, Verma, & Dixit, 201). Additionally, collectivism, extraversion, and conscientiousness impact buying behavior too (Arpaci, Baloğlu, & Kesici, 2018). It is clear from these findings that cultural and personal factors all influence the impulsiveness of individuals while they are shopping. These factors seem to raise the desire in customers to own and enjoy specific products based on instantaneous emotions of want. Therefore, it is clear from this review that the factors that result in impulsive buying behavior are mostly subjective and sentimental. To induce these feelings, a retailer may need to communicate with the inner feelings of individuals through various messaging options.
Some studies have established the link between impulse buying and supply chain disruption. (Jiang & Cai, 2021) find that the impact of impulse buying on supply chain agents is not monotonic. The study suggests that rational pricing decisions and the provision of high-value products are the primary solutions to leveling demand for products and their supply. The outcome of leveling these two aspects is profitability (Qaisar, Sial, & Rathour, 2018). Impulse spending is an encouraging phenomenon

among retailers because it is one of the goals of promotional campaigns. The study recommends that supply decision-makers should not just encourage more impulse buying, but instead offer more value in products that attract the most interest in this fashion. This approach ensures that customer satisfaction is enhanced rather than simply expecting customers to buy more of the merchandise. The latter may result in unexpected results such as product returns inwards and remorse from buyers. Artificial intelligence can be a useful tool in limiting the effects of supply chain disruptions by leveraging its predictive capabilities, especially in the short term (Belhadi et al., 2021). The result is a more resilient supply chain that is highly responsive to external shocks.

Impulse buying stemming from media-driven panic buying may often result in supply chain disruption. (Kaur & Sharma, 2020) investigate this notion and threat perception and consumer psychology are significant causes of this kind of buying behavior. When the media promotes messaging to the effect that a certain product may run out of stock, customers may buy more of it even if they do not truly need it. The study further reports that the income level of consumers affects their ability to participate in impulse buying. This notion is logical because consumers with more humble income sources may be unable to buy impulsively because of their limited potential. However, their wealthier counterparts do not have this problem. Hence, their impulsiveness during shopping manifests easily. Impulsive buying on its own may not cause supply chain problems (Arafat, Hussain, Kar, Menon, & Yuen, 2020). However, if coupled with panic buying, the locality may experience supply chain disruption in the near future.

In mitigating possible supply chain integration, some management teams have solicited the help of supply chain risk management principles in a bid to sustain operational performance. Findings from (Munir, Jajja, Chatha, & Farooq, 2020) indicate that supplier and customer integration techniques proved effective in enhancing operational performance. The study also found that the role of internal integration is mediated by the relationship between supplier and customer integration. The source reports that supply chain management has a partial mediation effect on how internal integration impacts the operational performance of an entity. It also showed that SCRM mediates supplier and customer integration fully. These findings are key to the determination of the role played by supply chain risk management in mediating the relationship between supply chain disruption and operational performance.

Some factors determine the ability of an entity to use supply chain risk management practices in reducing supply chain disruptions, and thereby achieve operational integrity. The study by (Hohenstein, 2022) identified some of these factors and established that they can promote or disable a firm's agility to respond to supply uncertainties in the global market. Firms that are agile enough can respond fast to these uncertainties by sourcing from other suppliers and or using buffer stock. The source finds that whenever a supply chain is disrupted, the performance of a business remains firm if it can reconfigure supply chain risk management design that is responsive to such changes. Many organizations are integrating artificial intelligence technologies into their supply chain risk management decisions. According to (Baryannis, Dani, Validi, & Antoniou, 2019), technologies such as Petri nets, machine learning, and multi-agency systems positively impact risk mitigation activities in the management of supply chain risks. Hence, it is evident from this review that the mediating role of supply chain risk management is critically important in the administration of a firm's business performance amid supply-side disruptions.
Supply chain risk management helps to reduce the negative impact caused by supply chain disruptions to a business. (Munir et al., 2020) suggest that the stability of businesses in the wake of supply chain disruptions lie in their ability to effect proper supply chain risk management practices. Whenever a firm allows these disruptions to go unattended, the continuity of the business is also likely to be at stake. Hence, the application of risk management techniques such as multi-sourcing, keeping buffer stock, and creating lasting relationships with suppliers can make the difference between firms enjoying steady supply and those languishing in shortages.

Supply chain disruptions have a direct effect on the operational performance of a business entity. This dwindling performance may hit hard, especially if the disruption continues for an extended time. Findings from the study by (Gazali, 2020) suggest that panic buying is often the cause of supply chain disruption, as experienced during the COVID-19 pandemic. The identified factors were sensitivity to anxiety, price, availability of the product, and buyer exposure to social media platforms. These findings are almost similar to those established in (Kaur & Sharma, 2020), where panic buying was the primary cause of supply chain disruption. When such disruptions occur, businesses have no stock to sell or to use in the production of other goods and or services. When the phenomenon occurs for a long time, some businesses may have to close or undergo retrenchment to cut off unnecessary costs that make the entities less profitable.

Supply chain disruptions may occur in three forms, namely supply disruption, demand disruption, and process disruption. In a study by (Parast & Subramanian, 2021), the investigation established that all three forms of disruption have a resounding effect on form performance. Additionally, the paper indicated that disruptions have a significant effect on supply chain performance. However, the researchers caution that leaders ought to be wary when managing the risks of supply chain disruption. The process is different when seeking to enhance firm performance from when the goal is to enhance supply chain performance (Ateş, Melek, Suurmond, Luzzini, & Krause, 2022). The study made a substantive revelation that disruptions on the supply side are more devastating for an entity than if the disruptions emanate from the downstream. Indeed, if a firm lacks raw materials or inventory, it is almost impaired to carry out its core functions. The study suggests that management should be alert and highly responsive about any risks and signs of disruption anywhere in the supply chain.

3. Theoretical Background

3.1. TCA Model

The Transaction Cost Theory is a theory by Oliver E. Williamson, which posits that while buying goods, buyers incur more costs that the actual price of the product on sale (Rindfleisch, 2020; Schmidt & Wagner, 2019). Hence, it is incumbent upon the buyer to minimize these costs for an efficient purchasing process. For example, purchasing products from a physical store may require one to bear the transport cost to and from the retailer and the associated shipping costs where necessary (Wu, Ke, & Nguyen, 2018). It is for this reason that many find online shopping to be a more cost-effective purchasing model than visiting a physical store. For those that have to fuel their cars, the costs are even higher.

3.2. The Material Flow Theory

Another theory relevant to the study in context is the material flow theory. It is a model in supply chain management that maps the sourcing of materials/products to how they are processed in an organization and how they are dispatched/delivered to the end user (Xu, 2008). In the context of analysis, the retailer receives goods from producers and processes them to feature on the ecommerce platform. After a customer has paid for them, the goods are then processed for shipping to the customer's given address. When this flow is interrupted at any point because of bottlenecks, it is likely to result in supply chain disruptions.

3.3. The Technology Integration Theory

Business integration theory posits that there is a need to synchronize information technology with the goals, mission, and vision of a firm. When this model is in place, a firm is likely to be more efficient, effective, and profitable because of the consistent innovation initiatives implicit in this arrangement (Shaw, Ellis, & Ziegler, 2018). Businesses with strong technological integration practices tend to be more competitive in the market and their market leadership position is rarely challenged. As such (Ibrahim & Jebur, 2019) view technology integration as a competitive strategy that is applicable in the contemporary business environment.

4. Conceptual Framework and Research Hypothesis

4.1. Conceptual Framework

The Following figure shows the study's conceptual framework followed by hypothesis development.

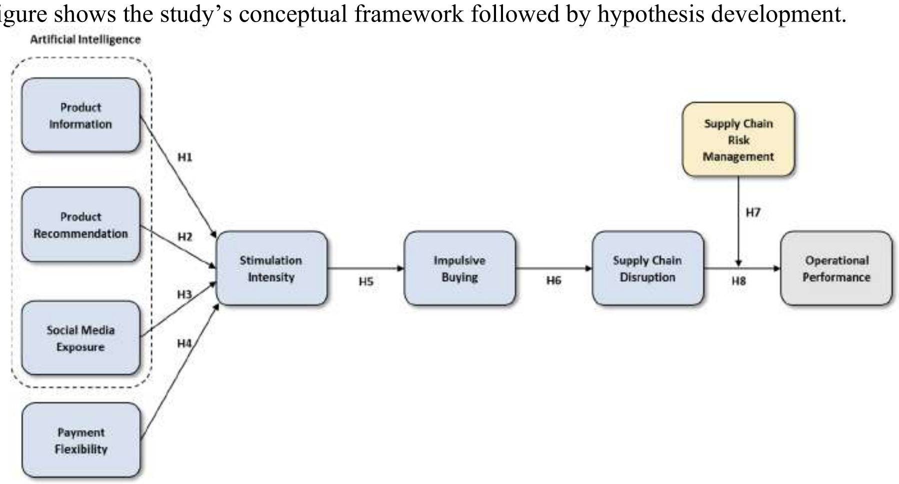

Fig. 1. Conceptual Framework

4.2. Hypotheses Development

4.2.1. Product information on stimulation intensity

The availability of product information can be critical to the enhancement of stimulation intensity. However, more information may not necessarily result in higher demand because there is a limit to the effect that it has on demand. When AI is used to provide relevant information on a firm's products, the likelihood of stimulating buyer purchase interest is high. This notion is reflected in the paper by (Khisa et al., 2020). The mentioned study indicates that product information is crucial in empowering potential consumers with the details they need to make informed purchase decisions. As a result, we hypothesize that:

Hypothesis 1 (H1): *Product information has a significant positive effect on stimulation intensity.*

4.2.2. Product recommendation on stimulation intensity

AI-based product recommendation potentially influences demand because it exposes prospective customers to the right products. Regardless of this logical expectation, the quality of recommendation is critical. In other words, if the quality of recommendation is poor, this strategy may not significantly impact stimulation intensity. On ecommerce platforms, the use of product recommendation systems has become an industry standard (Hwangbo, Kim, & Cha, 2018). Such strategies seem to be positively impacting buyer interest because of their wide-spread adoption. Consequently, we hypothesize that:

Hypothesis 2 (H2): *Product recommendation has a significant positive effect on stimulation intensity.*

4.2.3. Social media on stimulation intensity

The effect of social media exposure on stimulation intensity stems partially from the fact that information on the products is available on these platforms, which consequently impacts stimulation intensity. Many firms have social media handles that they use to interact with the public and dispense information. Hence, this exposure provides an avenue through which users can be more informed about a product from independent parties (Voramontri & Klieb, 2019). Such information is usually more reliable than advertisement information, which often over-promises. For this reason, we hypothesize that:

Hypothesis 3 (H3): *Social media exposure has a significant positive effect on stimulation intensity.*

4.2.4. Payment flexibility on stimulation intensity

The ultimate process that marketing campaigns target is the actual purchase transaction. Since this process involves payment, buyers should be more interested in products for which payment methods conform to their current viable options. With more payment flexibility, customers have the assurance of payment convenience (Choi, 2020). Just like product information, payment there is a limit to which payment flexibility can impact stimulation intensity. For example, a firm with 15 payment methods and another with 20 may not different significantly in how they stimulate demand. This convenience is part of what draws customers to purchase products from a specific vendor. It is for this reason that we hypothesize that:

Hypothesis 4 (H4): *Payment flexibility has a significant positive effect on stimulation intensity.*

4.2.5. Stimulation intensity on impulsive buying

Stimulation intensity can result in impulsive buying because customers are willing to purchase the products. Because of the intensity, which results in high purchase intentions or willingness, the number of customers is consequently large. These many customers are drawn to an online store, and they are more likely to engage in more impulse buying. This notion is evident in (Sokić, Korkut, & Šestanović, 2020), where the source asserts that impulsive buying is a product of aggressive marketing techniques and the availability of extra money. Hence, we hypothesize that:

Hypothesis 5 (H5): *Stimulation intensity has a significant positive effect on impulsive buying.*

4.2.6. Impulse buying on supply chain disruption

Higher impulsive buying implies that customers are making more purchases than they intended. If this kind of purchase behavior reaches unprecedented levels, it may result in supply shortages among retailers. There is also the question of how much impulsive buying can trigger supply chain shortages and disruptions. While impulsive buying results in more purchase intentions from buyers, such intentions are mostly not sufficient to cause significant shortages. This view is inconsistent with (Qaisar et al., 2018). The author argues for the significant causal relationship between the two variables. Consequently, we hypothesize that:

Hypothesis 6 (H6): *Impulse buying has an insignificant positive effect on supply chain disruption.*

4.2.7. Supply chain risk management on the causal relationship between supply chain disruption and operational performance

These risk management techniques are measures employed by management to mitigate the gravity of disruptions on a business. Their role is to ensure that regardless of the situation in the upstream supply chain, the downstream end does not experience disruptions. Some of the key risk management techniques are keeping buffer stock, sourcing from multiple suppliers, and producing in-house. (Kumar et al., 2018) report supply stability among businesses engaging in supply chain risk management techniques. Supply chain risk management practices stabilize operational performance regardless of supply chain shocks. For this reason, we hypothesize that:

Hypothesis 7 (H7): *Supply chain risk management has a significant positive mediating effect on the causal relationship between supply chain disruption and operational performance.*

4.2.8. Supply chain disruption on operational performance

Supply chain disruptions have a direct effect on a business's operational performance, especially if they occur on the upstream end. Nevertheless, supply chain disruptions on the downstream end may negatively impact operational performance because the products barely reach customers. (Wong, Lirn, Yang, & Shang, 2020) claim that business continuity can be jeopardized if management does not heed the call to manage supply chain disruptions. This negative causal relationship is what makes it hard for businesses to thrive when the market is experiencing supply chain shocks. Therefore, we hypothesize that:

Hypothesis 8 (H8): *Supply chain disruption has a significant negative effect on operational performance*

5. Research Methodology

5.1. Item Measurement and Questionnaire Design

The study adopted the structural model approach because of the several levels of causal relationships in which this investigation took interest. Table 1 below is a breakdown of the questions relevant to the different constructs and variables included in the study.

Table 1
Questionnaire Items

Construct	Items	Survey Questions	Inspiring Source
Product Information	PI1	Products sold in the store have detailed information to inform buyer decisions	(Jain & Gandhi, 2021)
	PI2	Search results include succinct information to help customers in selecting their preferred products	(Jain & Gandhi, 2021)
	PI3	Search results are relevant to the terms used in the search	(Jain & Gandhi, 2021)
Product Recommendation	PR1	The algorithm used to recommend products is accurate enough	(Jain & Gandhi, 2021)
	PR2	Product recommendation is more of an item-item rather than user-user basis	(Jain & Gandhi, 2021)
	PR3	The algorithm uses machine learning methods to improve its accuracy as more data is captured	(Jain & Gandhi, 2021)
Social Media Exposure	SME1	The store capitalizes on social media exposure to advertise its products	(Voramontri & Klieb, 2019)
	SME2	The store has active social media pages on major platforms such as Facebook and Twitter	(Voramontri & Klieb, 2019)
	SME3	Posts made on social media by the company receive heavy interaction from users	(Voramontri & Klieb, 2019)
Payment Flexibility	PF1	The store allows multiple payment methods on its ecommerce platform	(Greenacre & Akbar, 2019)
	PF2	The payment process is highly intuitive that even the non-tech-savvy persons can follow	(Greenacre & Akbar, 2019)
	PF3	All payment methods allowed on the platform are fast and instant	(Greenacre & Akbar, 2019)
Stimulation Intensity	SI1	The store has an avalanche of purchases from its online platform	(Bag et al., 2019)
	SI2	Customers flock into the store's site by using external links	(Bag et al., 2019)
	SI3	The click-through rate of links posted on third-party sites is high	(Bag et al., 2019)
Impulsive Buying	IB1	Many customers purchase products they did not search for on the ecommerce site	(Jain & Gandhi, 2021)
	IB2	Products placed on offer receive much attention and purchase from users	(Jain & Gandhi, 2021)
	IB3	Discounted and highly-rated products receive the biggest purchase interest	(Jain & Gandhi, 2021)
Supply Chain Risk Management	SCRM1	The store effectively conducts risk identification	(Chu et al., 2020)
	SCRM2	The store effectively conducts risk assessment	(Chu et al., 2020)
	SCRM3	The store effectively does risk mitigation	(Chu et al., 2020)
Supply Chain Disruption	SCD1	The frequency of supply chain felt by the store is high	(Parast & Subramanian, 2021)
	SCD2	When supply chain disruption occurs, the store's mitigation response is poor	(Parast & Subramanian, 2021)
	SCD3	Products in high demand and necessities encounter supply chain disruption	(Parast & Subramanian, 2021)
Operational Performance	OP1	The financial performance of the store is high	(Parast & Subramanian, 2021)
	OP2	The growth of the firm's customer base has been increasing	(Parast & Subramanian, 2021)
	OP3	Customer satisfaction at the store is high	(Parast & Subramanian, 2021)

5.2. Structural Model

The following figure shows the structural model run by AMOS.

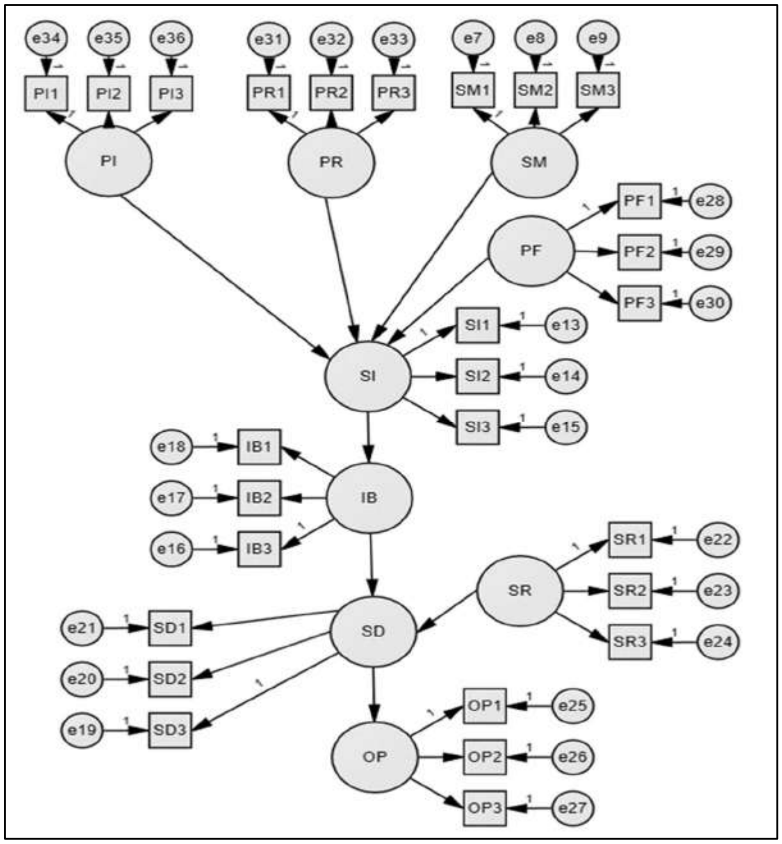

Fig. 2. The Structural Model

5.2. Sampling and Data Collection

The study engaged with employees of Namshi.com, Noon, Joly Chic, Extra, and Styli, which are arguably the country's biggest and widely used online shopping sites. The total population was 769. The sample size computed using the Yamane formula below.

$$n = \frac{N}{1 + N * (e^2)}$$

where:
n = sample size
N = population size
e = margin of error (0.05)
The result of the substituting the variables in the formula is as follows

$$n = \frac{769}{1 + 769 \times (0.05^2)} \approx 263$$

Hence, the minimum sample size is 263. In reaching out to the respondents, the researcher contacted the retailer via their social media pages with the suggestion of conducting a survey. Upon acceptance, the researcher issued the survey instrument to the contact persons, who were then responsible for distributing the questionnaire links to the other employees. A total of 270 employees managed to fill the online questionnaire, and this number is the ultimate sample size for the study. The contact persons indicated that they shared the link with 285 employees. Therefore, the response rate was 94.7%. After the questionnaire filling was complete, the researcher entered and cleaned the data using IBM SPSS software. The software used to build the structural model was IBM SPSS AMOS.

6. Data Analysis

6.1. Assessment of the Measurement Model

In the assessment of the measurement model, the analysis considered four tests of reliability, namely indicator reliability, internal consistency, convergent validity, and discriminant validity.

6.2. Indicator Reliability

Indicator reliability measures the ability of construct variables to explain the target variable's variance. In this case, the path-weighting scheme was preferred to the factorial scheme because of the former's reliability. Hence, this analysis used the factor loadings and error values to calculate the indicator reliability of the construct variables in this study. A reliability score of 0.70 was considered the minimum threshold, which is consistent with (Cheah, Sarstedt, Ringle, Ramayah, & Ting, 2018). Even though some of the variables scored values below 0.70, findings reveal that the average value in this regard was 0.71, which implies that they averagely passed this test as shown in Table 2.

Table 2
Variables indicators

Construct	Items	Factor Loading	Composite Reliability	Indicators	Cronbach's Alpha	AVE
Product Information	PI1	0.559	0.63	3	0.772	0.639
	PI2	0.919				
	PI3	0.262				
Product Recommendation	PR1	0.521	0.71	3	0.815	0.688
	PR2	0.535				
	PR3	0.929				
Social Media Exposure	SM1	0.345	0.59	3	0.740	0.629
	SM2	0.253				
	SM3	1.002				
Payment Flexibility	PF1	0.804	0.77	3	0.803	0.730
	PF2	0.756				
	PF3	0.617				
Stimulation Intensity	SI1	0.769	0.68	3	0.762	0.648
	SI2	0.574				
	SI3	0.582				
Impulse Buying	IB1	0.575	0.66	3	0.778	0.629
	IB2	0.542				
	IB3	0.751				
Supply Chain Risk Management	SC1	0.328	0.84	3	0.816	0.673
	SC2	0.953				
	SC3	0.987				
Supply Chain Disruption	SC1	0.876	0.69	3	0.704	0.691
	SC2	0.786				
	SC3	0.221				
Operational Performance	OP1	0.944	0.78	3	0.785	0.764
	OP2	0.883				
	OP3	0.286				

6.3. Internal Consistency

The internal consistency of an instrument explains the ability of questionnaire items to explain the latent variables in which they occur. The test statistics used in making this determination is Cronbach's Alpha. The minimum acceptable level of the alpha is 0.70 (Cheah et al., 2018). Findings reveal that the average alpha stands at 0.775, which conforms to the minimum acceptable level for internal consistency. As shown above Table 2, a summary of the results obtained from SPSS after running the relevant reliability test.

6.4. Convergent Validity

Convergent is a measure of a research instrument validity to determine whether the parent variables correlate well with their respective questions. Ideally, the questions constituting a construct variable should have significant correlation with the construct variable. Otherwise, it would imply that the selected question variables do not necessarily contribute to the construct variable in question. To measure this outcome, the study considered the Average Variance Extracted, which is shown above in the AVE column in Table 2. The rule of thumb is that these values should be greater than 0.6 (Sürücü & MASLAKÇI, 2020). It was met for all the construct variables under investigation as shown in above in Table 2.

6.5. Discriminant Validity

Discriminant validity is the degree to which the indicators of a variable explain their intended target variable more than they explain other variables in the model. In a model with several construct variables, the questions belonging to one construct variable should not explain another variable better than they explain their intended construct variable. Using the Fornell-Larcker Criterion inspired by (Yusoff, Peng, Abd Razak, & Mustafa, 2020) and as shown in Table 3, the study constructed the table below showing the correlations between the questions of the respective constructs. Findings suggest that all construct variables passed this test.

Table 3
Correlations of constructs and questions

	PI	PR	SM	PF	SI	IB	SD	SR
PI	0.838							
PR	0.796	0.773						
SM	0.756	0.734	0.792					
PF	0.718	0.698	0.752	0.803				
SI	0.683	0.663	0.715	0.763	0.723			
IB	0.648	0.630	0.679	0.725	0.687	0.720		
SD	0.616	0.598	0.645	0.688	0.653	0.684	0.683	
SR	0.585	0.568	0.613	0.654	0.620	0.650	0.649	0.629

6.6. Assessment of the Structural Model

Below is the structural equation model created from IBM SPSS Amos. As shown in Figure 3, the key to the main variables is as follows: PI = Product Information, PR = Product Recommendation, AI = Artificial Intelligence, PF = Payment Flexibility, SM = Social Media Exposure, SI = Stimulation Intensity, IB = Impulse Buying, SD = Supply Chain Disruption, SR = Supply Chain Risk Management, OP = Operational Performance.

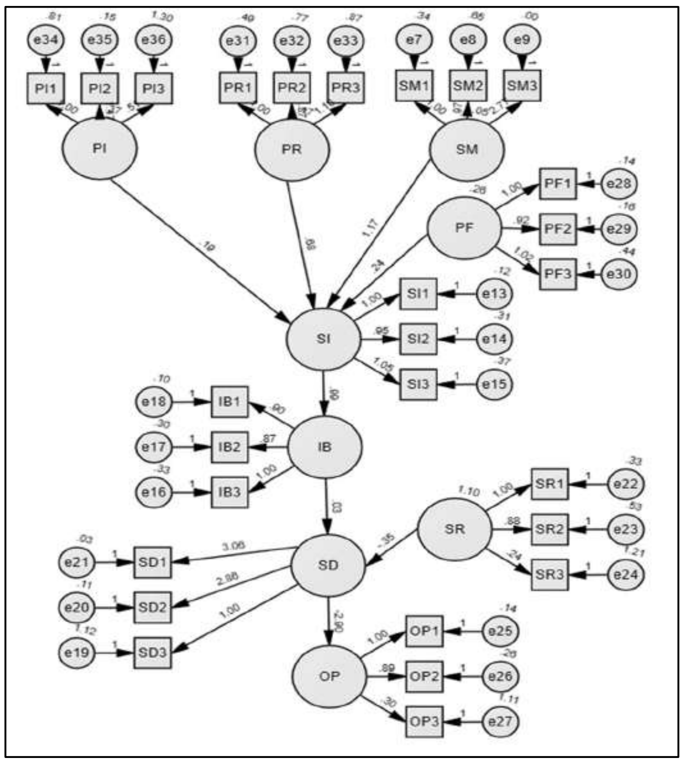

Fig. 3. Assessment of Structural Model

6.7. Model Fit Indices

Findings indicate that the model is significant, as it scored a chi square value of 58 (p=0.000, df=168). These findings imply that there is minimal likelihood of obtaining discrepancies from the model as shown in Table 4.

Table 4
Model Fit Indices

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	58	532.271	168	0.000	3.168
Saturated model	378	0	0		
Independence model	27	7241.112	351	0.000	20.63

The inspection of the individual elements in the model is even more interesting. The model summary in Table 5 shows that the study finds that the effect of product information and product recommendation on stimulation intensity scores r squared coefficients of 0.173 (F=55.896, p=0.000) and 0.556 (F=335.273, p=0.000), respectively. The effect of social media exposure scored r squared of 0.380 (F=164.436, p=0.000). Payment flexibility also significantly affected stimulation intensity with an r squared of 0.430 (F=164.436, p=0.000). Below is a summary of the overall effect of product information, product recommendation, social media exposure, and payment flexibility.

Table 5
Model Summery

Summary Stats							
R-Squared				**Adj. R-Squared**	**F Score**	**Sig/*p*-value**	
0.799				0.796	263.170	0.000	
Coefficients							
Hypothesis	**Path**	**R-Squared**	**F Score**	**Beta**	***t*-stat**	***p*-value**	**Decision**
H1	PI → SI	0.173	55.896			0.000	Supported
H2	PR → SI	0.556	335.273			0.000	Supported
H3	SM → SI	0.380	164.436			0.000	Supported
H4	PF → SI	0.430	164.436			0.000	Supported
H5	SI → IB	0.938	4060.266			0.000	Supported
H6	IB → SC	0.007	1.767			0.185	Rejected
H7	SD → OP			-0.905	58.947	0.000	Supported
H8	SR → SD → OP			-0.936	21.460	0.000	Supported

Stimulation intensity affected impulse buying, and this effect scored an R Squared coefficient of 0.938 (F=4060.266, p=0.000). Impulse buying had an insignificant effect on supply chain disruption, as its R Squared was 0.007 (F=1.767, p=0.185). Supply chain disruption on its own negatively influenced the operational performance of the firm, as it scored a beta coefficient of -0.905(p=0.000, t=-58.947). With the mediation of supply chain risk management, the effect of supply chain disruption declined from a beta of -0.936 (t=-21.460, p=0.000).

7. Discussion

This study has established that artificial intelligence (represented by product information, social media exposure, and product recommendation) and payment flexibility have a significant effect on operational performance. The effect of product information on stimulation intensity was found to be significant, which is also the case in the study by (Khisa et al., 2020). Similarly, this investigation found that product recommendation engines significantly and positively impact stimulation intensity. These findings are also consistent with those established in (Bag et al., 2019). The source claims that online retailers adopt Retail 4.0 technologies, and that these technologies have resulted in more purchase interest from the public. The study also established that social media exposure positively impacts stimulation intensity, which is also the case made by (Ioanas, 2020). The source argues that social media provides a platform for user reviews, which if good, promotes sales. Payment flexibility was found to be a significant predictor of stimulation intensity; a notion that features prominently in the research by (Njoroge, 2021). By cross referencing with the findings made in the previous studies, it is evident that artificial intelligence and payment flexibility all significantly impact stimulation intensity.

The study also captured the effect of stimulation intensity on impulse buying. Findings indicated that the effect was not only significant but also positive. This causal relationship is reported in (Badgaiyan et al., 201), where the source claims that materialism and shopping enjoyment significantly affect impulse buying. This study did not find any significant causal relationship between impulse buying and supply chain disruptions. Hence, these findings are quite inconsistent with those established in (Kaur & Sharma, 2020). (Gazali, 2020) claims that impulse buying caused by panic purchasing can lead to inadvertent supply shortages. The mediating effect of supply chain risk management was clear in this study, as it influenced the causal relationship between supply chain disruption and operational performance. Without the mediation, supply chain disruptions negatively impact performance. However, with the mediation of supply chain risk management practices, this effect is subverted to become positive.

8. Implications

The findings established herein seem to imply that the variables under investigation are significantly associated. While some of the causal relationships are positive, others are negative. This revelation is a wake-up call to management teams to exploit these associations for the benefit of their organizations. The findings also imply that artificial intelligence is a highly reliable tool in advancing the interests of online-based retailers. The establishment of the effects of AI features, namely product information, product recommendation, and social media show that there are still viable opportunities for retail organizations to exploit. While supply chain disruptions can have a significant negative effect on the overall performance of a business, the introduction of supply chain risk management is an effective remedy.

9. Limitations

The study faced a number of limitations that could have caused challenges in the data collection, compiling, analysis, and reporting processes. Firstly, it was possible that the contacted respondents would not answer the call to participate in the research. It would have resulted in a sample size that is not representative of the population in question. For this reason, the researcher instructed the contact persons at the five companies to send the survey link to more than enough respondents. Secondly, there was the risk that some respondents may leave the questionnaire unfinished. For this reason, the researcher made the questionnaire brief and indicated at the beginning of the instrument the importance of finishing the survey. Thirdly, there was also the risk that one person would inadvertently or intentionally fill the questionnaire multiple times. To curb this possible eventuality, the researcher required an email id for each respondent willing to participate in the survey.

10. Conclusions and Future Research

This study has established that artificial intelligence and payment flexibility have a significant effect on the performance of the investigated ecommerce platforms. This effect is wired through other variables, namely stimulation intensity, impulse buying, supply chain disruption, and supply chain risk management. Hence, the optimization and proper management of these variables should result in improvements at the online retailer. While supply chain disruption negatively affects operational performance, supply chain risk management can help greatly in mitigating these challenges. The study did not find a significant causal relationship between impulse buying and supply chain disruption. However, this notion may need further investigation in light of the effects of panic-based impulse buying. Future research should consider examining the direct effect of product recommendation on impulse buying. Additionally, future researchers need to investigate the direct effect of social media marketing on impulse buying.

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