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# Future of Retailing in Metro Manila: DIY Homeowners' Acceptance and Use of Technology in an Omnichannel Retailing

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## ABSTRACT

This paper investigates the multifaceted realm of consumer behavior within Metro Manila's hardware industry, focusing on omnichannel factors that shape purchase intentions. Drawing from Venkatesh *et al.*'s 2003 Unified Theory of Acceptance and Use of Technology (UTAUT) model, the researcher adapted the theoretical framework by eliminating moderators and substituting Facilitating Conditions with Habit and Perceived Security. To unravel the intricacies of consumer preferences, a quantitative approach was employed, utilizing a survey instrument administered to 400 DIY homeowners-representing a cross-section of the target population. The research methodology incorporated Slovin's formula for sample size determination, ensuring a robust and representative dataset. Additionally, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to analyze the data and derive meaningful insights. This methodological approach allows for a refined exploration of the relationships between variables, offering a quantitative foundation for answering the research questions. The results elucidate the pivotal roles of Performance Expectancy and Perceived Security in positively influencing Purchase Intent. Notably, the study unveils a significant positive relationship between Purchase Intent and Usage Behavior, emphasizing the consequential impact of intention on subsequent consumer actions. This comprehensive exploration provides valuable insights for industry practitioners seeking to refine their omnichannel strategies in the hardware sector. By deciphering the intricate interplay of factors influencing consumer behavior, businesses can optimize their approaches, fostering greater engagement and loyalty among DIY homeowners in Metro Manila. This research contributes significantly to the evolving discourse on omnichannel dynamics, offering a nuanced perspective grounded in empirical evidence and a modified UTAUT framework.

## INTRODUCTION

### Consumer Acceptance and Behavior in Online Retailing

Online purchasing acceptability and behavior have been studied extensively in recent years. Online commerce's ease, usefulness, and enjoyment affect customers' inclination to utilize it (Venkatesh *et al.*, 2012). Customers who find online shopping easy, helpful, and enjoyable are likelier to use it. Trust is another factor in online buying acceptance. Venkatesh *et al.* (2012) said clients must trust online transactions to preserve their personal and financial data. E-commerce companies may build client trust by providing secure payment methods, simple return policies, and transparent buy progress updates. Several factors influence online shoppers. Online shoppers seek, evaluate, and make purchases (Khusaini & Ambarumanti, 2019). Consumers use and dispose of products after purchasing and evaluating internet merchants. Human, contextual, and situational factors influence online purchase behavior. Personality, opinions, and attitudes are individual factors; social norms and cultural values are environmental variables. The consumer's temperament, time constraints, and items being purchased are situational factors.

### Modern Retailing Business Model: Omnichannel Retailing

To fulfill customers' changing requirements, merchants should offer a smooth, engaging, and dependable omnichannel experience (Juaneda *et al.*, 2016). Omnichannel commerce provides a consistent consumer experience across all touchpoints, including online, in-store, and mobile. This method involves channel integration and consumer behavior tracking to customize the experience and boost sales. Retailers may improve customer relations and sales by satisfying consumer demands. Omnichannel selling lets companies contact customers everywhere and tailor their shopping experience. Omnichannel commerce provides several benefits over single-channel purchasing. Hence many retailers prefer it (Verhoef, 2021). Omnichannel selling may boost revenue and customer loyalty by providing more product research and buying options. As firms can track client demand across several channels, inventory management and supply chain operations may improve. Omnichannel commerce may improve customer relationships by offering personalized experiences and direct touch.

An omnichannel paradigm may include online, physical, mobile, and social media touchpoints. Retailers must manage customer touchpoints to provide a consistent customer experience across channels. Omnichannel buying includes product browsing online, social media research, personalized marketing messaging, customer service interactions, and multichannel purchases. Merchants must ensure that each customer touchpoint matches

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their brand and message and provides a personalized experience to manage consumer touchpoints successfully. This demands a deep awareness of customer preferences, habits, and desires and the ability to use data and analytics to adapt experiences. To improve and optimize touchpoints, merchants must monitor and evaluate them. Customer surveys, social media monitoring, and data analytics can do this. Omnichannel is relevant in retailing in post-pandemic recovery. It relies on the supply chain to manage items and information across numerous channels and touchpoints. Retailers must integrate inventory management systems and order fulfillment processes to fulfill orders quickly and accurately across channels (Salvietti *et al*., 2022). Implementing a ship-from-store method to fulfill online orders from real locations may help optimize inventory levels and save transportation expenses.

**Global Context**

E-commerce and the importance of digital channels in the customer journey have created the global omnichannel ecosystem. People expect to buy and interact with firms through mobile devices, social media, and other digital touchpoints. Retailers and businesses worldwide focus on omnichannel to stay competitive and meet customer needs. The COVID-19 pandemic forced companies to adapt to shifting consumer preferences, including a growing focus on online and mobile purchases. Companies must have the technology and infrastructure to manage cross-border transactions (Jia *et al*., 2022).

**The Philippine Context**

Philippine retailer SM has successfully implemented an omnichannel approach. Their capabilities include allowing customers to purchase items online and then later picking up in-store or deliver directly to their homes. The company's loyalty program lets customers earn and spend points online and in-store. Many Philippine companies are adopting omnichannel strategies, investing in mobile apps and social media marketing to reach customers on their preferred channels. Some firms also adopt virtual and augmented reality to make purchasing more engaging. In the Philippines, omnichannel strategies provide benefits, but infrastructure, logistics, and cross-border restrictions must be addressed. The Philippines will continue to embrace omnichannel strategies to satisfy consumers' changing requirements.

**Research Topic**

As seen by an increase in e-commerce customers after Covid, the digital transformation of the Philippines forced merchants to adopt an omnichannel strategy to succeed. Merchants in the US, Europe, and Asia use it. Companies that are willing to take a chance and invest in software and systems are researching and putting these trends into practice to reach and please consumers. Using local research makes it simpler for business owners to decide on a plan in the Philippines. Technology for e-commerce is essential for business success. Due to the rapid development of information technology, e-commerce may increase sales. The study will demonstrate how omnichannel commerce has evolved into a modern and cutting-edge business method in the Philippines, especially Metro Manila. This could be examined and addressed depending on how much influence and relevance it can have on customers and businesses (SMEs & major enterprises). The researcher looks into the attitudes and actions of consumers with previous purchases online. To be more precise, the clients are DIY (do it yourself) homeowners who have already made at least one online hardware-related transaction. The unified theory of acceptance and use of technology, or UTAUT, was developed by Venkatesh *et al.* (2003). It helped the researcher alter and include the preexisting model in the study. One of the most frequently referenced ideas in the literature on information systems (IS) is the UTAUT. It applies to a wide range of contexts and populations outside of IS. The original UTAUT model uses four basic elements (social influence, performance expectation, enabling conditions, and effort expectation) and four modifiers (gender, age, voluntariness, and experience) to describe organizational technology use and behavioral intention. The UTAUT model would be used for this study to evaluate how corporate transformation for sustainable development and operations is driven by customer sophistication. The researcher will eliminate the moderating variables – gender, age, experience and voluntariness of use from the Venkatesh *et al.* (2003) model. "Facilitating Conditions" will be replaced by "Habit" and "Perceived Security." Lastly, the researcher will analyze the mediating effect of purchase intent between the variables "Performance Expectancy," "Effort Expectancy," "Social Influence," "Habit," and "Perceived Security" on customers' "Usage Behavior." The model is now in line with the desired research goals. This updated UTAUT model investigates how respondents embrace and use technology to interact with hardware merchants and comprehend their behavior. The improved UTAUT model focuses on the trends and patterns in consumer behavior that affect buying decisions. The researcher intends to contribute to the solution by utilizing the modified UTAUT model to analyze what influences DIY homeowners' technology adoption and identify their acceptance and behavior, resulting in an effective omnichannel retailing business model.

**Statement of the Problem**

Online buying and the obstacles of evaluating and choosing items online have grown in recent years. Performance expectancy measures how well a product meets or exceeds customer expectations. Online product evaluations are challenging because customers need help to touch the product. They can only try the product after buying. This makes it hard for customers to judge the product's quality, durability, and reliability, causing reluctance when buying. Customers' effort expectancy is how easy and convenient they think using a process will be. Online buying is convenient, but users may need help navigating websites, purchasing, and customer support. Buyers may abandon their buying basket and find a more straightforward platform if the process is relatively easy and time-consuming. Habit is the propensity to repeat actions that have been learned to do automatically. Customers may be resistant to online purchasing and prefer to shop in stores. To get customers to shop online, online retailers must make it easy. Social influence is how others' thoughts and actions affect a person's choices. Customer reviews and ratings may impact purchases. Negative or unreliable reviews may deter people from buying the goods, costing the business sales. Perceived security is the extent customers trust internet businesses with their personal and financial data. Customers may be wary about providing personal information or making transactions if a website or platform seems insecure. Online shoppers are wary of data breaches and identity theft. Online merchants must improve consumer experience to solve these issues.

High-quality products, fast customer service, and privacy and data protection can build customer trust (Haque & Mazumder, 2020). To lower effort expectations, retailers must have easy-to-use websites, checkout processes, and customer service. Personalization, prizes, and promotions can build consumer loyalty. Finally, retailers must provide good customer service and respond to complaints to build an excellent online reputation. Analyzing and choosing things online takes much work. Customers need help with performance expectancy, effort expectancy, habit, social influence, and perceived security. Online retailers must provide a convenient customer experience, credible product information, and transparent security measures to create customer trust and loyalty. They may boost sales, customer satisfaction, and reputation. Thus, the conceptualized research questions in this study are the following:

- What are the significant factors that influence DIY homeowners' Purchase Intent on hardware products online in terms of the following technological recognitions:
  1. Performance Expectancy
  2. Effort Expectancy
  3. Habit
  4. Social Influence
  5. Perceived Security
- What is the significant effect of Purchase Intent on DIY homeowners' Usage Behavior?

**Objectives of the Study**

In order to better understand customer behavior and improve the online shopping experience, use patterns derived from consumers' purchase intentions must be carefully analyzed. The goals of usage behavior analysis are to gain knowledge about how users interact with online platforms, identify areas for improvement, and increase the possibility of a successful transaction. Included are service, convenience, price, and quality. Retailers can examine user behavior to determine what customers want, why they buy, and how they utilize online platforms. This involves creating a user-centric design that is optimized for mobile devices, providing personalized recommendations and offers, and making it easy for users to find what they are looking for (Huang, 2021). Customers can require assistance paying for goods or services or with security and privacy concerns. By analyzing user behavior, retailers can identify and remove these hurdles by upgrading their websites or providing safe payment options. By examining usage, retailers can also discover patterns in consumer behavior. This includes information on product kinds, purchase frequency, and merchant engagement channels. This information can help retailers improve their marketing, product recommendations, and consumer interaction. With this, the researcher aims to achieve the following research objectives:

- To identify the significant factors that influence DIY homeowners' Purchase Intent on hardware products online in terms of their technological recognitions.
- To identify the significant effect of Purchase Intent on DIY homeowners' Usage Behavior?

**Scope and Delimitations of the Study**

Researchers may focus on specific research issues and avoid potential biases or inaccuracies by considering the study's scope and limitations (Akanle *et al.*, 2020). In this study, the behavior and approach of consumers on how they use and utilize their respective technological devices are observed. This is in line with their intention to purchase products online. The study will revolve around the modified UTAUT model and the new set of variables (Performance Expectancy, Effort Expectancy, Habit, Social Influence, Purchase Intent, and Usage Behavior). Participants are DIY homeowners residing in Metro Manila, Philippines. Four hundred respondents resulted from calculating Slovin's formula as the sample size. They were asked to fill out survey forms consisting of 49 questions using a 5-point Likert scale. The researcher created a digital survey form using Google Forms with the assistance of the internet. The digital survey form was extremely useful in providing a seamless and convenient method of responding to the form. The online connectivity allowed quick communication between selected respondents and the researcher to explain and request comments and approval. The study would not cover certain hardware store companies but rather obtain only insights from their customers. Digitalization and e-commerce customer behavior may also impact the findings. The study's results may not apply to future advancements in these areas. It simplifies data collection and analysis. Online surveys, social media monitoring, and site analytics help academics quickly get enormous volumes of data. This allows researchers to collect data from additional sources, improving research accuracy. The data is examined and computed by the university's accredited statistician using the most recent statistical software available to ensure that the results are as accurate and error-free as possible. Early in 2022, this research paper was drafted. However, the actual coverage period during which the researcher collected responses from participants was February 4-April 15, 2023. Because of the time constraints, any events in the industry before and after this timeframe do not reflect in the respondents' responses. This study involved no significant financial outlay or subscription. The majority of the literature has been gathered from open-access online papers.

**Significance of the Study**

Customers will gain the most from this study. The problem with businesses in Metro Manila, Philippines, nowadays is that they are more focused on making sales than on establishing devoted patrons and attaining steady, sustainable growth. This study will aid companies in understanding the effects of technology adoption and customer attitudes toward it. Organizations nowadays must concentrate on customer value in a competitive marketplace. But providing excellent customer value calls for more than just making a profit on goods of outstanding quality. Businesses will be able to improve internal processes, software, and systems that can help organizations reduce costs and streamline operations by switching to an omnichannel retailing business model. Automating manual processes and eliminating duplication is necessary for businesses to increase customer satisfaction. Customers would encounter fewer obstacles and have their questions and complaints quickly addressed with an integrated internal system and processes. Customer loyalty and satisfaction could rise. Businesses may tailor their goods and services by compiling information about customer preferences, behavior, and purchasing patterns. Omnichannel retailing offers seamless buying across channels. Customers can browse products online and then visit a store to try or buy them. Channel integration guarantees a consistent brand experience, smooth transitions, and the ability to continue buying. Customers are more satisfied and loyal to a company when they believe it understands and cares for them. By integrating client data across email, phone, and social media platforms, businesses can engage with customers consistently and promptly. Customers may be more satisfied and devoted if they perceive the company as prompt and responsive. Providing excellent customer service is the secret to long-term success in today's corporate environment.

The principles of omnichannel still need to be better understood by businesses today. This study could help them implement internal processes correctly and show them how they can significantly impact company sustainability and expansion. Integration boosts productivity and efficiency (Lipnicki *et al.*, 2018). Integrating systems and processes decreases duplication, boosts efficiency, and enhances accuracy. This can save costs and increase revenue. Confusion and delays may result from errors and disparities across many systems. System integration promotes data consistency and accuracy across departments, enhancing decision-making and minimizing mistakes. Integrating systems promotes teamwork and knowledge sharing among employees. Improving decision-making and innovation can assist businesses in remaining competitive. Additionally, it enhances business control and visibility. Managers may make better judgments and respond to market developments more quickly with the help of real-time data and analytics provided via system integration. By enhancing efficiency, productivity, customer service, and operations, integration can help businesses compete in a rapidly changing environment. Companies should integrate their systems and processes to be competitive. Last but not least, technological advancements have changed business practices, including customer behavior research. Businesses may improve their products and services by using technology to collect vast amounts of data on customer preferences, needs, and behaviors. Data collection aids businesses in understanding customer behavior. Due to digital technologies, consumers leave a ton of data when they shop online. This information includes past purchases, surfing patterns, social media activity, and customer reviews. Businesses can use this information to tailor their products and services and better understand customer behavior and preferences. Companies can study customer behavior with advanced analytics and machine learning. These tools assist businesses in seeing patterns and trends that human analysts overlook in their enormous data sets. These cutting-edge analytics tools can help enterprises better understand customer behavior and make choices about product design and marketing. Technology may go beyond data collection and analytics to customize customer experiences. Thanks to information systems learning, organizations may tailor client experiences based on preferences and behavior. E-commerce websites may use algorithms to make product recommendations based on consumer demographics, browsing history, and past purchases (Kietzmann *et al.*, 2018). This level of personalization can increase customer satisfaction and deepen relationships. For a complete picture of the customer journey, technology may enable businesses to track consumer behavior across channels and touchpoints. Thanks to omnichannel marketing, customers can interact with businesses through social media, email, physical stores, and contact centers. Companies can track these contacts and behaviors using technology to learn more about their customers and enhance marketing and customer service. Companies can use technology to evaluate consumer behavior. Through data collection, advanced analytics, personalization, and omnichannel monitoring, technology aids businesses in understanding customer preferences, needs, and behaviors. Companies should make technological investments to foster innovation, growth, and customer satisfaction.

## LITERATURE REVIEW

### Evolution Omnichannel Retailing

Omnichannel retailing had evolved from multichannel retailing when customers had several outlets to buy items but needed a consistent customer experience (Chopra, 2018). Omnichannel retailing, which provides a consistent consumer experience across all channels, emerged from the merger of online and offline channels in e-commerce. Mobile devices and social media have also helped omnichannel shopping evolve, giving customers more access to merchants and personalized experiences. Omnichannel commerce has forced merchants to adopt innovative supply chain technology and procedures to meet customer demands for real-time inventory visibility, flexible order fulfillment, and shorter delivery times. Omnichannel commerce provides advantages, but retailers must invest in technology, build out their supply chains, manage a variety of channels, and handle customer interactions. Retailers quickly adopted innovative fulfillment methods, including curbside pickup and contactless delivery during the COVID-19 epidemic. To compete in the multichannel world, merchants must adjust their tactics as technology advances. The transmission of information and goods between a retail channel and a customer can happen in several ways. These transactions can happen online or in-store. Products can be picked up or delivered. Figure 1 shows four omnichannel retail possibilities Bell *et al.* (2014) proposed based on these exchange methodologies.

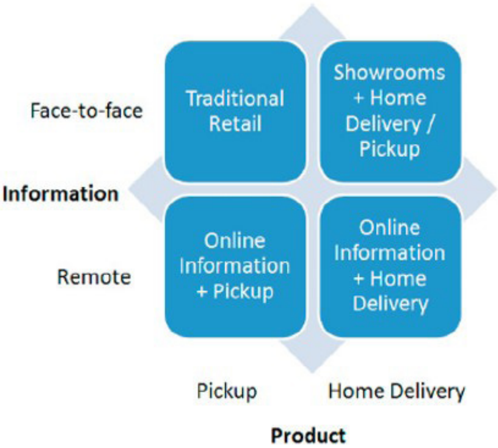


**Figure 1:** Methods for Information and Product Exchange (Bell *et al.*, 2014)

### Demystifying Omnichannel Retailing

Hickman *et al.* (2020) address omnichannel retailing, which integrates many channels into the shopping experience. Omnichannel commerce is necessary because consumers want a consistent experience across channels. Merchants must invest in IT solutions to create a seamless omnichannel experience. Data analytics helps personalize the omnichannel experience and boost consumer loyalty. The efficiency of an omnichannel experience depends on channel integration, consistent branding and message, inventory management, logistics, and delivery. To maintain a similar experience across channels, personnel training is necessary. Studies of successful omnichannel retailers show best practices. They explore how Nike, Sephora, Nordstrom, and Best Buy have leveraged inventory management technologies to provide a seamless, customized experience across channels. Omnichannel retailing's constraints include expensive technology implementation costs and continuous system and training investments. Before adopting omnichannel commerce, retailers should weigh the pros and cons. In Figure 2 below, four elements affect omnichannel: brand familiarity, personalization, perceived channel value, and technical readiness. Retailers must understand these characteristics to handle omnichannel initiatives. According to Hickman *et al.* (2020), Omnichannel is a seamless integration of numerous channels. The authors define omnichannel as online, in-store, and mobile channels that allow customers to interact with retailers.

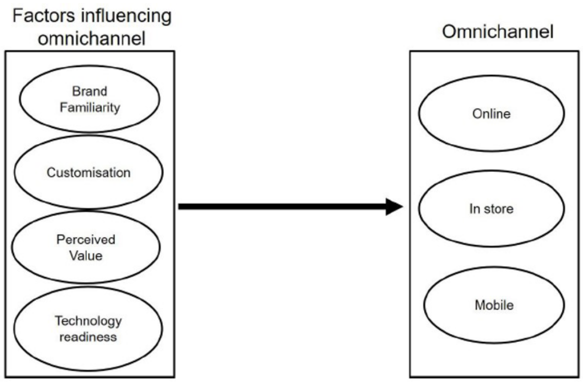


**Figure 2:** Integration of Multiple Channels (Hickman *et al.*, 2020)

### The Future of Retailing

Omnichannel retail is the future because consumers want a customized and quick purchasing experience. Integrating channels may boost revenue, enhance consumer happiness, and customize purchases, according to Lohiya and Mirijamdotter (2021). Although switching to an omnichannel strategy is difficult, the advantages exceed the expenses and merchants that need to implement it risk falling behind their competition. Thus, omnichannel retailing is the future of retail. Retailers must comprehend the emphasis, management, and integration of their operational strategies and examine their present characteristics to set future goals. Data integration creates new data sources. Complete channel integration improves customer experience and employee morale by coordinating digital and physical teams (Lohiya & Mirijamdotter, 2021).

Hilken *et al.* (2018) believe omnichannel commerce is the future of retail and that AR technology can improve it. To suit consumers' evolving wants and tastes, merchants must embrace an omnichannel strategy. AR technology may make omnichannel commerce more engaging and immersive, improving consumer experience and loyalty. Despite its implementation challenges, AR-enhanced omnichannel commerce might help companies who want to remain competitive in the rapidly evolving retail sector.

**Dynamic Capabilities**

Cross-channel integration and omnichannel commerce need dynamic capabilities. Dynamic capabilities allow a business to integrate, grow, and restructure internal and external competencies to adapt to fast-changing surroundings. Dynamic skills are crucial to omnichannel strategy success (Höcker *et al.*, 2018). A case study of IKEA's dynamic capabilities showed how sensing, seizing, and transforming helped the company better understand customer needs, respond quickly to market changes, and develop new competencies and business models to support omnichannel retailing. Firms need three skills, according to Teece (2007). The first is sensing market shifts, challenges, and opportunities. To do so, organizations must constantly monitor possibilities and dangers. The second capacity is to grab opportunities or overcome problems, which entails keeping up with technology and complementing assets. Finally, organizations must be agile and adaptable to spot and seize new possibilities when they grow and add assets. In a dynamic market, Teece (2007) believes enterprises must continually reconfigure and adapt.


**Figure 3:** Firms' Dynamic Capabilities (Teece, 2007)

Eriksson *et al.* (2022) examined grocery retail's omnichannel logistics transition from a dynamic capabilities viewpoint. Grocery merchants need dynamic skills to compete in the omnichannel market. To handle omnichannel logistical complexity and coordination, they stressed sensing, seizing, and transforming capabilities, cooperation, and integration across all channels and stakeholders in the grocery retail ecosystem. Dynamic capability is used in a cross-channel integration process, so integrating existing frameworks inside dynamic capabilities is essential.

Mirsch *et al.* (2016) examined dynamic capacities in omnichannel transitions. They cited a German retailer's successful omnichannel shift. The retailer's effective shift required detecting, seizing, and converting skills and supply chain ecosystem stakeholder engagement and coordination. According to the literature, dynamic skills are necessary for cross-channel integration and omnichannel commerce. Companies must continually create and use dynamic skills to understand consumer demands, adapt rapidly to market changes, develop new competencies, and manage omnichannel strategy complexity and coordination. Omnichannel integration and strategy are called spanning capabilities. For an omnichannel strategy to work, channel integration must be done well. In light of the potential IT-business separation, this is crucial. Figure 4 shows Koch's (2010) categorization of transformative processes, which this study used to determine the dynamic capabilities needed for omnichannel management.

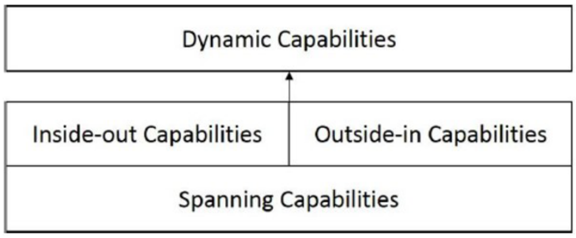


**Figure 4:** Categorization of Dynamic Capabilities (Koch, 2010)

**Touchpoints**

Zimmermann & Auinger (2020) identified the brand-owned touchpoints that impact the digital retail consumer experience. Digital merchants should focus on the website, social media, mobile app, and email. Digital businesses should modify their marketing efforts to certain phases of the consumer journey since touchpoints change. Holmes & Brewer (2020) explored merchants' difficulties in offering consistent and effective customer support across channels. They found unclear wording in shop customer service rules might confuse and frustrate consumers, impacting loyalty and satisfaction. The authors advise shops to emphasize customer experience, prevent ambiguity in regulations, particularly customer service policies, and make their automated systems visible and simple. These studies help companies build a consistent consumer experience across all digital retail touchpoints.

**Customer Satisfaction and Loyalty**

There is an increase in omnichannel commerce. Rahman *et al.* (2022) propose omnichannel commerce may boost customer satisfaction and loyalty. Omnichannel interactions improve consumer satisfaction and loyalty. Omnichannel commerce lets customers buy online and pick up in-store, saving time. Omnichannel data can customize purchases, focus marketing, and improve customer service. Omnichannel commerce may increase customer loyalty by reducing out-of-stock and product availability. Combining channels may expand shopping possibilities.

Cuesta-Valiño *et al.* (2023) examine multichannel supermarket loyalty and strategic digitization. Digital channels may increase client loyalty. Mobile apps, click-and-collect, and personalized promotions improve supermarket omnichannel experiences. Digitization boosts customer loyalty and profits. They suggest data analytics may enhance supply chain, marketing, and shopping.

**Sales Growth Performance**

Paz & Delgado (2020) studied customer experience and omnichannel behavior in several sales environments. The authors examined customer behavior in traditional shops, online channels, and both. Customers with a pleasant omnichannel experience were more inclined to buy, indicating that merchants investing in a smooth and enjoyable shopping experience across channels will see sales increases. In omnichannel contexts, shoppers who felt in control were more inclined to buy. This implies that allowing customers to personalize their goods may boost sales. The need for a good, seamless omnichannel shopping experience to boost revenues. Retailers that successfully connect physical and digital channels and provide customers freedom and autonomy will likely realize the highest sales and customer loyalty gains.

Feng *et al*. (2022) examined the benefits of high store visitation costs in an omnichannel with Buy Online, Pick Up In-Store (BOPS) services. BOPS affects customer behavior, especially during rush hour or in busy metropolitan locations. The research found that BOPS services may boost revenue for merchants. Customers were more inclined to buy more when ordering in person. Additionally, the availability of BOPS services increased the likelihood of consumers purchasing in the first place, as it provided an added convenience factor. Retailers may profit from integrating BOPS services into their omnichannel strategies, especially in high-cost markets. It may boost sales and customer loyalty by offering online shopping and in-store pickup.

**Purchase Intent**

Rajan *et al*. (2017) examined Indian omnichannel shoppers' purchase intent drivers. The research examined how omnichannel shopping, which integrates numerous channels into the shopping experience, affected customers' purchase intentions. They found numerous variables strongly affected omnichannel shopping purchasing intent. These aspects were quality, brand reputation, selection, price competition, simplicity of use, and convenience.

QR codes affect omnichannel consumer experience and purchase intention (Kjeldsen *et al*., 2023). QR codes, a sort of barcode read with a smartphone camera, might improve customer experience and buying intention in omnichannel shopping. It improved customer experience and purchase intention in omnichannel shopping. QR codes enhanced consumers' purchasing experiences by providing immediate product information, feedback, and discounts. The research also revealed that QR codes improved consumers' purchase intention by making it easy and fun to engage with things and buy them. In omnichannel retail, QR codes may improve consumer experience and buying intention. Retailers may boost consumer satisfaction and sales by making product information and incentives easily accessible.

**Security Risks**

Retailers acquire client data via RFID and MLA (Farshidi, 2016). These tools optimize store layouts and marketing. These tools also threaten clients' privacy. RFID and MLA technologies can track consumers' movements in the store and capture personal data from mobile devices. These privacy issues can lead to unwanted access, hacking, and data sharing or selling without consent. Thus, retailers must prioritize client data security and create clear privacy rules.

Gregorczuk (2022) explored retail analytics' security vulnerabilities. Retailers optimize shop layouts, inventory, and marketing using this data. Retail analytics may acquire and utilize personal data without authorization, leading to data breaches and cyberattacks. Retailers must emphasize consumer privacy and openness regarding data gathering and usage to avoid legal and ethical issues.

**UTAUT Integration**

UTAUT is a comprehensive and established paradigm for studying user acceptability and adoption of technology. Researchers may quantify performance expectation, effort expectancy, social impact, and enabling circumstances by adding UTAUT into investigations. This may

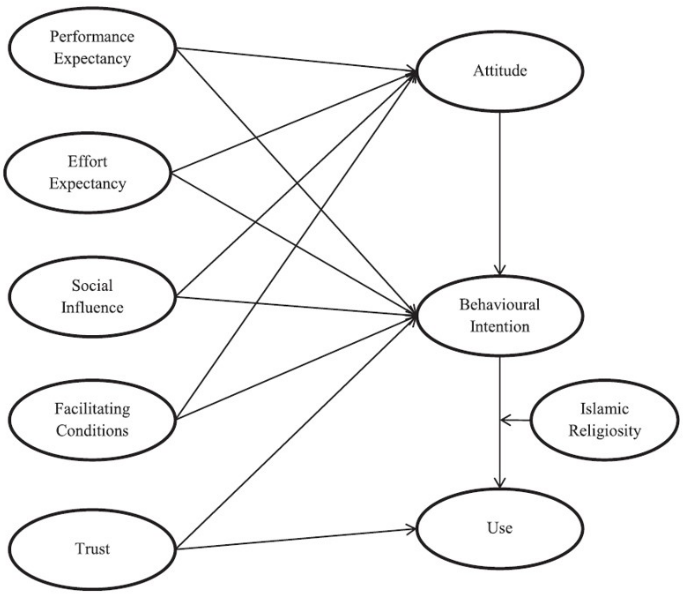


**Figure 5:** Modified UTAUT model of Alkhowaiter's (2022) GCC mobile payments

inform technology design and adoption efforts. Thus, UTAUT may help researchers comprehend technology adoption and analyze technology usage more thoroughly. Sharifian *et al*. (2014) noted that UTAUT might offer a comprehensive and proven paradigm for studying user acceptance and adoption of technology. UTAUT lets researchers quantify performance expectations, effort expectancy, social impact, and enabling environments, which affect technology adoption and usage. This may inform technology design and adoption efforts. Thus, UTAUT may help researchers comprehend technology adoption and analyze technology usage more thoroughly. Alkhowaiter's (2022) paper on GCC m-payment usage and behavioral intention uses UTAUT. The UTAUT framework examines how Gulf Cooperation Council (GCC) nations adopt and employ mobile payment technologies. UTAUT says Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions affect technology adoption. Trust and Islamic religiosity are added to the UTAUT framework to explain GCC m-payment adoption better. UTAUT provides a theoretical framework for identifying and studying GCC countries' m-payment technology uptake and acceptance characteristics. Figure 5 below depicts Alkhowaiter's (2022) conceptual framework, modifying the original UTAU model of Venkatesh *et al* (2023), in evaluating GCC nations people.

**Habit**

Habit is the extent to which using mobile internet has become an automatic teacher behavior due to repeated and frequent use (Nikolopoulou *et al*., 2021). It is the degree to which behavior has been entrenched in an individual's daily routine to the point where it is done automatically without much thinking. In their research, habit significantly increased instructors' mobile internet usage intention, according to the research. The more often instructors use mobile internet, the more likely they will continue. According to the authors, this discovery affects the design of teacher mobile internet interventions. Interventions should encourage instructors to use mobile internet often to form a habit. It shows that habit predicts teacher technology uptake and use. Understanding habits may help educators and policymakers create technology-in-education solutions that work.

Wilson & Lankton (2013) define a habit as a habitual activity that becomes unconscious. IT habit is the unthinking use of a system or application. The authors believe habit, experience, and intention drive IT usage. They think customers with a strong habit of utilizing an IT system or application will continue using it even if they do not want to. Habitual behavior requires less cognitive work and motivation. Academics and practitioners must grasp habits to maintain IT. They use habit to create therapies that last. Frequent training or reminders may help users establish good IT systems or application habits. Habit predicts ongoing IT behavior; more research is needed on habit and technology adoption and usage.

**Performance Expectancy**

As defined by Isaac *et al*. (2019), performance Expectancy is workers' belief that accessing the Internet would help them work more efficiently and effectively. It is how much employees think the Internet will help them access important information, communicate with coworkers and customers, and finish work on time. Performance Expectancy is the perceived value of the Internet in helping workers accomplish their job goals.

**Effort Expectancy**

Hunde *et al*. (2023) defined Effort Expectancy as health science students' perception of e-learning technology's ease or difficulty. It relates to their view of the effort needed to understand and operate the e-learning system efficiently. E-learning system complexity, simplicity of use, user interface, and computer literacy all affect effort expectation. Effort Expectancy is the perceived ease of using e-learning technology, which affects students' behavioral intention to utilize it.

**Social Influence**

In Gao's (2023) research, social influence refers to how friends, family, instructors, and classmates affect an individual's use of smart education technology. It relates to how much a person thinks others expect them to use the technology and will be impacted by their thoughts or suggestions. Societal influences may be good or detrimental, including societal standards, peer pressure, and interpersonal connections. Social influence is perceived pressure or influence from others that may alter an individual's desire to continue utilizing smart education technologies.

In Sarosa's (2019) research, social influence refers to how friends, family, and supervisors affect an individual's technology choice. It relates to how much a person thinks others expect them to use the item and will be impacted by their advice. Societal influences may be good or detrimental, including societal standards, peer pressure, and interpersonal connections. In other words, social influence is the perceived pressure or effect of others on an individual's decision to use a mandatory gadget.

**Behavioral Usage Intent**

Usage intent is someone's desire to utilize a technology or system. In Al-Mamary's (2022) study, usage intent refers to the extent to which Saudi undergraduate university students intend to use learning management systems (LMS) based on their perceptions of its usefulness, ease of use, social influence, and other factors, as assessed by the UTAUT model. The research examines the use of intent to identify characteristics that influence university students' LMS adoption, which may guide technology integration initiatives in higher education.

Usage intent is someone's desire to utilize a technology or system. Based on the UTAUT, Ayaz & Yanartaş's (2020) research defines usage intent as users' willingness to accept and employ electronic document management systems (EDMS). The research examines performance expectation, effort expectancy, social impact, and enabling variables that affect EDMS adoption and use. The research gives insights into the major factors of EDMS acceptability and adoption by assessing use intent, which may influence strategies for successful technology use in diverse corporate settings.

**Usage Behavior**

Instead of intending to utilize a technology or system, people use it. According to the UTAUT, behavioral use determines technology adoption success. Performance, Effort, Social Influence, and Facilitating Conditions affect behavioral use, according to UTAUT. Gunawan *et al.* (2019) utilize the UTAUT technique to uncover the characteristics that impact micro, small, and medium firms' adoption and use of e-money. This helps organizations to establish plans to increase e-money acceptance and use, resulting in increased success and advantages.

Instead of intending to utilize a technology or system, people use it. Alyoussef's (2022) research examined university students' behavioral utilization of the flipped classroom strategy to improve learning. The study uses the UTAUT and the Technology Acceptance Model (TAM) to examine students' acceptance of the flipped classroom approach to understanding better how technology can be used to improve student outcomes. This study's behavioral use analysis may assist in shaping future educational policy by revealing the flipped classroom's practical efficacy.

**Theoretical Framework**

**Conceptual Framework**

Venkatesh *et al.* (2003) created the UTAUT model, as shown in Figure 6, to describe and predict technology adoption behavior. The model suggests that performance expectation, effort expectancy, social influence, and enabling factors affect users' technology usage intentions and behaviors. The UTAUT offers a comprehensive framework for studying technology adoption behavior. UTAUT's four core constructs-performance expectation, effort expectancy, social influence, and enabling conditions-predict technology adoption. UTAUT has also been extensively adopted and evaluated in many situations, making it a credible and valid framework for investigating technology adoption behavior. Researchers may benefit from the enormous body of literature on this model and make meaningful comparisons by utilizing UTAUT. The UTAUT predicts technology adoption behavior well. UTAUT's capacity to explain and forecast consumers' technology uptake and use makes it exploratory. Researchers, practitioners, and policymakers benefit from its complete and integrated understanding of the elements that affect users' acceptance and usage of IT. UTAUT is used in healthcare, education, e-commerce, and social media. UTAUT also shows how circumstances can help or impede technology uptake and use. UTAUT suggests that users' intents to use technology depend on technology's perceived ease of use and utility. Thus, IT system designers and developers can use this knowledge to construct user-friendly, useful systems that suit users' needs. UTAUT emphasizes social influence and enabling factors in technology uptake and use. It implies that significant others, adequate resources, and infrastructure are essential to technology adoption and deployment. This knowledge can help governments and organizations foster technology uptake and utilization. UTAUT is a powerful theoretical framework providing a comprehensive and integrated view of technology acceptance and use. Its exploratory powers and importance lay in its ability to explain and anticipate technology uptake and use in many situations and provide insights into how to support or hinder it.

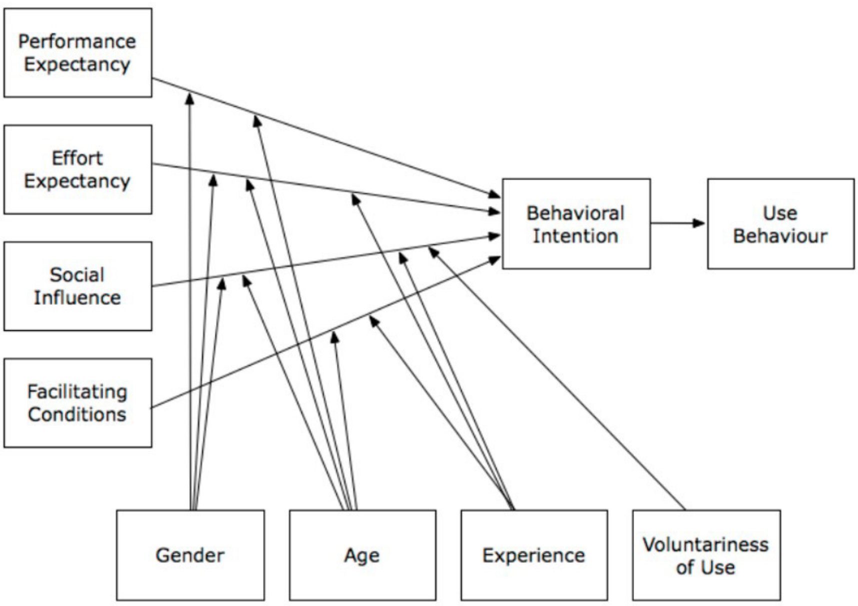


**Figure 6:** Unified Theory of Acceptance and Use of Technology (Venkatesh *et al.*, 2003)

**Operational Framework**

Figure 7 depicts the author's research-based paradigm. Venkatesh *et al.*'s (2003) UTAUT model is upgraded to accommodate technology-based consumer interactions. Performance Expectancy assesses utility, convenience, and productivity. Effort Expectancy measures usability. Social influence measures acceptability. The frequency of usage of technology for personal and work purposes is measured by Habit. Perceived Security is measured by how confident customers are in online payments. Consumer intention behavior is replaced by Purchase Intent, which is the consumer's likelihood to buy a product or avail of a service shortly. It indicates a consumer's intent to buy a product or service based on their needs, preferences, attitudes, and external influences. Lastly, usage behavior is the approach of customers after purchases. Personal preferences, requirements, motivations, and context affects user behavior. Modifying the UTAUT model to determine online buyers' usage behavior provides a complete knowledge of the elements affecting online buying behavior. Businesses can optimize their online platforms, create personalized experiences, build trust, and encourage long-term customer engagement by considering all the variables. This helps businesses succeed in the fast-paced digital industry.

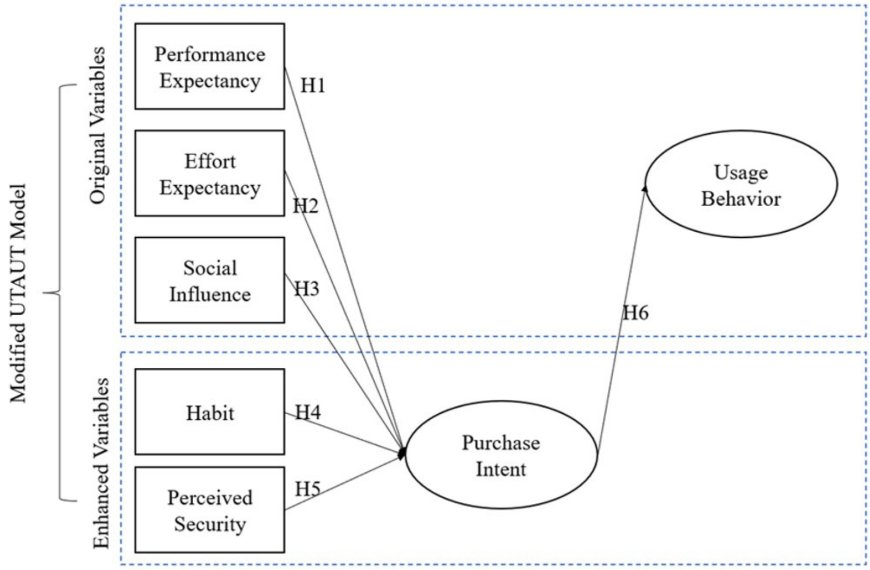


**Figure 7:** Author's own Operational Framework Model for the Study

**Hypotheses**

Performance Expectancy increased purchase intention and behavioral usage of freemium mobile games (Abdillah *et al.*, 2022). In other words, customers who thought the games were helpful, simple to use, and fun were more inclined to buy and utilize them. Improving game performance expectations might help freemium mobile game makers attract and keep consumers. Developers may achieve this by offering high-quality features and gameplay that fit customers' demands. For instance, they may ensure the games are simple to learn and use, have entertaining and tough levels, and provide appealing in-app purchases and prizes. The COVID-19 pandemic has changed people's everyday lives, including using technology for work, education, and leisure. The research implies that consumers' expectations about technology's effectiveness might affect their uptake and usage during times like the COVID-19 pandemic.

**H01: Performance Expectancy is Not Significantly Affecting Purchase Intention**

Effort expectation positively affects purchasing intention. San Martín and Herrero (2012) discovered that consumers who thought rural tourism internet purchases were simple (low effort expectation) were likelier to buy tourism items online. Ease of use is a crucial element in online purchase intention, and improving online platforms' usability and user-friendliness may raise buy intention. These initiatives may involve redesigning the website, streamlining the purchase process, and giving clear and straightforward information about tourist goods and services. Online tourist platforms must improve their user-friendliness to boost purchases.

**H02: Effort Expectancy is Not Significantly Affecting Purchase Intention**

Users who perceived a high social effect (i.e., the influence of other users or social networks) were likelier to prefer the metaverse and make purchases in Ifland (Lee & Kim, 2022). Social impact shapes metaverse users' opinions and buying inclinations. Friends, family, celebrities, and online groups may impact users' impressions of the metaverse's utility and worth. It emphasizes the necessity for metaverse marketers and developers to employ social influence to increase sales and brand loyalty.

**H03: Social Influence is Not Significantly Affecting Purchase Intention**

Habit, or automatic and habitual technology usage, has been shown to influence consumers' purchase intentions

(Yee & Abdullah, 2021). Consumers who regularly use technology are more likely to appreciate it and buy associated products. Education researchers must consider habit when forecasting users' purchasing intention and usage of educational devices. Continuous and regular usage of instructional technologies may help consumers accept and employ them. Habit predicts users' purchase intention and usage of educational technology using the UTAUT paradigm (Yee & Abdullah, 2021). The study shows how habit may improve users' adoption and usage of educational technology and emphasizes the importance of habit in education research.

**H04: Habit is Not Significantly Affecting Purchase Intention**

Customers who felt more secure using NFC-based mobile payment systems were more likely to enjoy the technology and utilize it in the future (Jalayer *et al*., 2017). Restaurant customers' acceptance and usage of NFC-based mobile payment systems depends on perceived security. Restaurant owners and payment suppliers must emphasize security and convey it to customers to promote their usage. The UTAUT model research shows that perceived security predicts restaurant customers' acceptance and usage of NFC-based mobile payment systems.

**H05: Perceived Security is Not Significantly Affecting Purchase Intention**

The research of Chen *et al*. (2021) showed that purchasing intention positively affects user behavior. In particular, customers with a stronger buy intention toward novel e-commerce platforms were more inclined to use them. Purchase intention predicts e-commerce platform use. Purchasers are more inclined to use the platforms and become loyal consumers. E-commerce platforms should provide high-quality items, user-friendly interfaces, and compelling promotional offers to increase consumers' buying intention, according to the research.

**H06: Purchase Intent is Not Significantly Affecting Usage Behavior**

## METHODOLOGY

### Research Design

E-commerce and online purchasing have changed consumer behavior. Using technology, businesses can evaluate consumer behavior, including buying habits and preferences. Targeted marketing and customized advertising can leverage this data. Social media and messaging apps have also enabled new business-consumer contact channels. In the digital age, businesses need technology to study consumer behavior. Quantitative research uses surveys to find consumer behavior patterns. This research is valuable for determining demographic and purchasing behaviors that affect consumer behavior. Quantitative studies provide objective, measurable data to test theories, identify patterns, and establish demographic generalizations. DIY homeowners have provided the quantitative data needed to complete this study.

Moreover, causal research linked variables. It helps researchers infer technology adoption and purchase intentions. Causal research identifies variable-cause correlations. It can help firms understand consumer behavior, such as how pricing or marketing efforts affect purchases. The methods are excellent for collecting data on large populations and examining variable-cause correlations (Goertzen, 2017). Quantitative and causal research can identify customer behavior, depending on the research issue and goals. To improve marketing and sales, firms must understand consumer behavior, which may need a mix of research methodologies Madhavan & Kaliyaperumal (2015).

### Research Participants and Locale

DIY homeowners who have bought hardware online are the target respondents. DIY homeowners undertake house improvements without employing contractors. They like saving money, gaining new talents, and decorating their home. The researcher characterizes DIY homeowners as someone tech-savvy and environmentally mindful. They seek eco-friendly and energy-efficient products for their initiatives. They study, shop, and share DIY projects online. They want a memorable buying experience. They want to buy from brands that understand their requirements, offer guidance and support, and celebrate their DIY successes. The budget ahead. Pricing calculators, how-to videos, and reviews help them estimate project costs and processes. They are multigenerational. DIY confidence, not age, gender, or income, limits them. Quality trumps price for them. Durable, distinctive, and customized products weigh more. The participants' ages range from 24 to 74. They have been working for at least three years or are self-employed. The survey was conducted between February 4 to April 15, 2023. The locale of the study is in Metro Manila, where most businesses and residential renovations are found.

### Sampling Design

This study used purposive sampling in selecting participants. Purposive sampling, a non-probability sampling method, selects research participants for a specified reason. Purposive sampling selects individuals who can best answer the study topic or hypothesis. Qualitative research uses purposive sampling to get in-depth knowledge about a phenomenon (Creswell, 2014). Survey research often uses Slovin's method to calculate the sample size. When the population number is unknown or big, it is beneficial. In this case, the total population is unknown. There needs to be available data on the number of customers buying hardware products online living in Metro Manila. The researcher used the population of Metro Manila, which is 13,484,482 – based on the latest 2022 PSA statistics, with a 5% margin of error. This resulted in a total of 400 respondents. Below is the formula used.

$n=N/(1+N(e)^2)$ $n=(13{,}484{,}482)/(1+13{,}484{,}482\ (0.05)^2)$
$n=(13{,}484{,}482)/33{,}712.205$ $n=399.98$ or 400
Where: n = sample size
N = Total number of households in a study site
e = Accepted error
Slovin's formula is suitable for quantitative, causal, and cross-sectional business investigations (Adam, 2020). Slovin's formula estimates the minimum sample size needed to generate a statistic with an acceptable margin of error.

**Instrumentation**

Participants completed a lengthy Google Forms survey on technology adoption and use-one page for respondent's demographic information and seven major elements for variables. The main variables are performance expectancy - assessing how much a user thinks technology will increase their work or daily performance or simplify activities. Respondents assess their agreement or disagreement with statements on the technology's usefulness and possible Influence on productivity. Effort expectations - asks users how much physical and mental work they expect utilizing a new technology or system. This concept measures the perceived ease of use of technology, considering aspects like learning time and energy, mental and physical effort, and system complexity. Social Influence - evaluate how much friends, family, and coworkers think they should utilize technology. These statements evaluate social norms, peer pressure, and faith in others' advice. Habit evaluates prior technology use frequency, habitually, and perceived difficulty of altering present usage habits. Perceived Security - measures how safe and trustworthy people think technology is. These statements evaluate technological reliability, the perceived danger of unwanted access or data breaches, and privacy protection. Purchase Intention - measure the individual's perceived need for the technology, desire to pay for it, and Intention to buy it soon. Lastly, Usage Behavior - measures users' post-adoption behavior.

The questionnaire was adapted from Venkatesh *et al.* (2003) and Baabdullah *et al.* (2019) for the elements that comprise the variables Performance Expectancy, Effort Expectancy, and Social Influence. The research conducted by Verplanken and Orbell (2003) and Venkatesh *et al.* (2012) served as the basis for Habit's instrument. The authors Tiwari *et al.* (2021) and Walrave and Ponnet (2020) were the ones who provided the questionnaire for perceived security. Moon and Kim (2001) and Davis (1989) provided the instrument for the Purchase Intent items. Last but not least, the items for the Usage Behavior came from Al-Maghrabi *et al.* (2011) and Moon & Kim (2001). These statements evaluate the diversity of activities and integration into the user's lifestyle. The instrument has 49 items, each of which is assessed on a scale of 1 (never), 2 (rarely), 3 (sometimes), 4 (often), and 5 (always).

**Table 1:** Adapted Instruments Used by Author

| Variable | Measure | Source |
|---|---|---|
| Performance Expectancy | I am able to utilize my mobile phone, laptop, or other technological gadgets in accomplishing my tasks. | (Venkatesh *et al.*, 2003; Baabdullah *et al.*, 2019) |
| | I am confident in my ability to use the technology to achieve desired performance outcomes. | |
| | Using the technology will enhance my personal satisfaction and enjoyment. | |
| | The technology will help me complete tasks that I was previously unable to accomplish. | |
| | Surfing the internet is beneficial in acquiring information and data. | |
| | The technology will help me better meet the needs of my personal life and hobbies. | |
| | The technology provides a high level of convenience for me | |
| Effort Expectancy | Learning how to use the technology will be easy. | |
| | I am confident in my ability to remember how to use the technology after I have learned it. | |
| | It is simple/easy for me to navigate and use my mobile phone, computer, or laptop | |
| | I can explore the internet and look for websites with ease | |
| | I believe that I will not need much training to use the technology effectively. | |
| | It is simple/easy for me to navigate and use my mobile phone, computer, or laptop | |
| Social Influence | I am influenced by the opinions of others when it comes to using technology. | |
| | I am more likely to use technology if I see others using it. | |
| | I am influenced by the social norms surrounding technology use in my community. | |
| | The approval of people I respect is important to me when deciding whether to use technology. | |
| | I am more likely to use technology if it is popular or trendy. | |

| | | |
|---|---|---|
| | Peer pressure affects my decision to use technology. | |
| | The opinions of celebrities and public figures influence my technology use. | |
| Habit | I always use my mobile phone, laptop, or computer in accomplishing my tasks | (Verplanken & Orbell, 2003; Venkatesh *et al.*, 2012) |
| | The use of the internet to visit websites and social media sites has become a routine for me | |
| | Using gadgets is something that I do automatically | |
| | My daily use of technology helps produce quality outputs | |
| | Usage of technology in my life is something I cannot live without | |
| | The alternative of using technology anywhere around is impossible | |
| Perceived Security | I feel that my personal information is secure when using technology. | (Tiwari *et al.*, 2021; Walrave & Ponnet, 2020) |
| | I am confident that the technology I use has effective security measures in place. | |
| | I feel that my online transactions are secure when using technology. | |
| | I am confident that the technology I use protects me from online threats such as viruses or malware. | |
| | The security of the technology I use impacts my overall satisfaction with it. | |
| | I am willing to take extra steps such as setting up two-factor authentication to improve the security of the technology I use. | |
| | The perceived security of technology impacts my willingness to share personal information with it. | |
| | I am more likely to use technology if it has a clear and transparent privacy policy. | |
| | I am more likely to use technology if it has a high level of encryption and data protection. | |
| Purchase Intent | I intend to utilize my mobile gadgets such as phones, laptops and computers to purchase products online | (Moon & Kim, 2001; Davis, 1989) |
| | I intend to purchase my basic necessities and luxury goods online instead of going to the store. | |
| | I intend to spend time analyzing, explore, and eventually purchasing products online | |
| | I intend to get discounts and promotions when I purchase products online | |
| | I intend to view other people's experiences, their ratings, and feedbacks from similar purchases to mine | |
| | I Intend to upgrade my buying patterns by purchasing products online | |
| Usage Behavior | I enjoy purchasing products online | (Al-Maghrabi *et al.*, 2011; Moon. & Kim, 2001) |
| | I will continue to purchase products online in the future | |
| | I feel comfortable using my technological gadgets in purchasing products online | |
| | I have explored some creative ways of using technology to purchase products | |
| | My basic and luxury necessities are being fulfilled and satisfied by using the technology continuously in purchasing purchase products | |
| | I am becoming more confident in paying products for my purchases online | |
| | The convenience I get from getting information on my purchases online is excellent | |
| | I am more likely to recommend purchasing products online to my relatives and colleagues | |

The researcher opted to assess the validity and reliability of 400 sample responders. It was examined using WarpPLS version 7.0, a free statistics program. This paper's constructions must be reliable and valid to be rigorous, trustworthy, and appropriately describe the phenomena under investigation. Without accurate measurements, the study's findings and conclusions may be wrong, diminishing its value. Table 2 shows that Cronbach alpha and composite reliability were examined to verify measurement stability and consistency in the research investigation. Bland and Altman (1997) claimed that a questionnaire or scale's Cronbach's alpha value of 0.5 or below indicates poor internal consistency reliability. Since they may measure different constructs, the items may require refining. The value between 0.5 and 0.7 indicates a moderate degree of internal consistency dependability, which may be sufficient for several study situations. The coefficient between 0.7 and 0.9 indicates strong internal consistency dependability, meaning the items assess the same underlying concept consistently. A value of 0.9 or greater indicates strong internal consistency reliability, which is ideal for most studies since it indicates high construct measurement consistency (Bland & Altman, 1997). Cronbach Alpha ranges from 0.861 to 0.963 for build internal consistency. Social influence had the lowest dependability and effort expectation the greatest. These data imply the constructs have strong to outstanding internal consistency dependability. Composite reliability and Cronbach alpha were assessed. Fornell and Larcker (1981) provided an appropriate composite reliability threshold. Most studies accept 0.7 or higher. A composite reliability rating of 0.8 or above implies acceptable internal consistency reliability, whereas 0.9 or higher suggests outstanding internal consistency reliability. Social influence had the lowest composite reliability and effort expectation the greatest. Hair *et al.* (2017) advise examining item standardized loadings on components to establish convergent validity in SEM. Standardized loadings vary from 0 to 1, where 0 denotes no measurement and 1 signifies flawless build measurement. Item loadings over 0.5 indicate convergent validity. In Table 2, all item loadings were over 0.5, ranging from 0.562 to 0.960, and all p-values were less than 0.001, indicating satisfactory convergent validity. Kline (2011) advises assessing concept convergent validity using the average variance extracted (AVE). The underlying concept explains AVE of a group of indicators. 0.5 or above means adequate convergent validity, whereas 0.7 or higher is strong. All structures in Table 2 had AVEs over 0.5. Social Influence had the lowest AVE rating, 0.553, while Effort Expectancy had the highest, 0.847. These numbers indicate high convergent validity, but discriminant validity should also be assessed to assure measure accuracy Kline (2011).

**Table 2:** Convergent validity and reliability measures.

| Constructs | Indicators | Item Loadings | p-value | Ave Variance Extracted | Composite Reliability | Cronbach's Alpha |
|---|---|---|---|---|---|---|
| Performance Expectancy | PE1 | 0.802 | <0.001 | 0.602 | 0.913 | 0.887 |
| | PE2 | 0.802 | <0.001 | | | |
| | PE3 | 0.842 | <0.001 | | | |
| | PE4 | 0.842 | <0.001 | | | |
| | PE5 | 0.799 | <0.001 | | | |
| | PE6 | 0.743 | <0.001 | | | |
| | PE7 | 0.562 | <0.001 | | | |
| Effort Expectancy | EE1 | 0.886 | <0.001 | 0.847 | 0.971 | 0.963 |
| | EE2 | 0.935 | <0.001 | | | |
| | EE3 | 0.959 | <0.001 | | | |
| | EE4 | 0.960 | <0.001 | | | |
| | EE5 | 0.944 | <0.001 | | | |
| | EE6 | 0.828 | <0.001 | | | |
| Social Influence | SI1 | 0.575 | <0.001 | 0.553 | 0.895 | 0.861 |
| | SI2 | 0.640 | <0.001 | | | |
| | SI3 | 0.766 | <0.001 | | | |
| | SI4 | 0.818 | <0.001 | | | |
| | SI5 | 0.852 | <0.001 | | | |
| | SI6 | 0.825 | <0.001 | | | |
| | SI7 | 0.684 | <0.001 | | | |
| Habit | H1 | 0.854 | <0.001 | 0.678 | 0.926 | 0.903 |
| | H2 | 0.865 | <0.001 | | | |
| | H3 | 0.894 | <0.001 | | | |
| | H4 | 0.879 | <0.001 | | | |
| | H5 | 0.762 | <0.001 | | | |
| | H6 | 0.662 | <0.001 | | | |
| Perceived Security | PS1 | 0.539 | <0.001 | 0.664 | 0.946 | 0.933 |
| | PS2 | 0.792 | <0.001 | | | |
| | PS3 | 0.870 | <0.001 | | | |
| | PS4 | 0.901 | <0.001 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | PS5 | 0.910 | <0.001 | | | |
| | PS6 | 0.905 | <0.001 | | | |
| | PS7 | 0.883 | <0.001 | | | |
| | PS8 | 0.795 | <0.001 | | | |
| | PS9 | 0.653 | <0.001 | | | |
| Purchase Intention | PI1 | 0.672 | <0.001 | 0.655 | 0.918 | 0.891 |
| | PI2 | 0.829 | <0.001 | | | |
| | PI3 | 0.890 | <0.001 | | | |
| | PI4 | 0.899 | <0.001 | | | |
| | PI5 | 0.837 | <0.001 | | | |
| | PI6 | 0.699 | <0.001 | 0.714 | 0.952 | 0.942 |
| Usage Behavior | UB1 | 0.721 | <0.001 | | | |
| | UB2 | 0.826 | <0.001 | | | |
| | UB3 | 0.863 | <0.001 | | | |
| | UB4 | 0.884 | <0.001 | | | |
| | UB5 | 0.885 | <0.001 | | | |
| | UB6 | 0.884 | <0.001 | | | |
| | UB7 | 0.842 | <0.001 | | | |
| | UB8 | 0.842 | <0.001 | | | |

*Note: All item loadings are significant at 0.001 (p<0.001).*

**Research Procedures of Data Collection**

For numerous reasons, the researcher needed original data from DIY homeowners. Primary data is the most dependable and accurate source of DIY homeowner needs, preferences, and behaviors. It prevents biases and inaccuracies from secondary data sources like reports, publications by obtaining primary data directly from them. Original data builds confidence with DIY homeowners. Engaging them in data collection shows valuing their thoughts and experiences.

The research also utilized mono-method data collection. Mono-method data collection and analysis uses one method. This approach focuses on data quality and consistency and avoids the risks of mixing methodologies, such as conflicting results, complexity, and ethical issues. It lets the researcher test ideas and make conclusions from surveys from quantitative data.

The data gathering method was a face-to-face approach to customers from the retail hardware stores of the researcher. The respondents are provided with tablets to complete the Google form survey. The results were uploaded and saved for analysis automatically in Google's back office. Introductory statements regarding the survey's topic and goals, respondent confidentiality, and the possible implications of their participation are included in the survey form. Gathering the 30 sample respondents were from February 4 to April 15, 2023

**Research Ethics Approaches**

The researcher collected informed consent from participants. It was crucial to weigh the advantages of the research against the hazards to participants and follow ethical procedures. Transparency and openness about research objectives, methodologies, and data sources were particularly important for trustworthiness. The researcher communicated clearly and honestly about the study's goal, data use, risks, and benefits. Participants were ensured of the safeguarding of data storage and sharing for data collection and usage to ensure confidentiality and anonymity. In the systematic study by Golder *et al.* (2017), authenticity was an ethical factor when conducting research.

**Data Analysis**

The researcher was guided by Venkatesh *et al.*'s (2003) UTAUT model to investigate relationships between existing and added study variables. PLS-SEM is a multivariate analysis method that tests complex correlations between observable and latent variables. It is ideal for exploratory research that seeks causal effects and predictive models when data does not match SEM assumptions such as normality, linearity, and large sample size. Formative measurement models can be modelled with PLS-SEM, where indicators cause latent variables. Ringle *et al.* (2015) introduce the latest edition of the SmartPLS software application for Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. PLS-SEM parameter analysis of the final model will be examined using SmartPLS software. SmartPLS is powerful and user-friendly for complex models and big data sets (Purwanto *et al.*, 2021). It handles reflective and formative structures, is quick, robust to non-normal data, and easy to use. Many high-impact journal articles have used SmartPLS, proving its legitimacy and utility in research. PLS-SEM analysis is straightforward with SmartPLS software. PLS-SEM is a multivariate statistical method for testing complex observed-latent correlations. Complex models, non-normal data, and formative measurements make PLS-SEM ideal for behavioral research. PLS-SEM can help DIY homeowners who buy online understand their motives, preferences, satisfaction, loyalty, and trust. SmartPLS program facilitates PLS-SEM analysis for researchers. SmartPLS program outperforms other PLS-SEM analysis software with characteristics like: PLS-Algorithm, PLSc, and GSCA are supported estimate methods.

- It evaluates models using GoF, SRMR, and HTMT.
- It tests mediation, moderation, multigroup, nonlinear, and higher-order hypotheses.
- It displays path coefficients, loadings, weights, R-squared values, effect sizes, p-values, confidence intervals, and bootstrapping findings.
- Its user-friendly interface lets researchers develop and edit models, import and export data, run studies, and generate results.

Thus, behavioral research on DIY homeowners' online purchase behavior requires SmartPLS software for PLS-SEM analysis. It helps researchers rigorously test and confirm theoretical models and assumptions.

## RESULTS AND DISCUSSION

This chapter holds significant importance in this scholarly investigation into omnichannel and consumer behavior, representing the culmination of an extensive research endeavor. This section provides a comprehensive analysis of a survey that was conducted, and the subsequent discussion scrutinizes each hypothesis with great attention to detail, offering valuable insights that are essential to the overall study. The narrative progresses along distinct axes, encompassing an examination of demographic profiles, a demonstration of descriptive statistics, an evaluation of collinearity, a scrutiny of the coefficient of determination, and a nuanced exploration of the direct interconnections between variables. Moreover, the discourse progresses to explicate the ultimate path coefficient in the structural model, thereby offering a consolidated comprehension of the complex interaction among variables that are fundamental to this inquiry.

### Demographic Profile

The demographic profile segment of the study provides a comprehensive snapshot of the participants involved, revealing insightful patterns and distributions within key demographic variables. In terms of gender, the study illustrates a notable gender distribution, with 65.75% identifying as male and 34.25% as female. Regarding age distribution, the majority of participants fall within the 45-54 age bracket (47.25%), followed by the 35-44 age group (18.5%). The remaining age categories include 24-34 (5.25%), 55-64 (24.5%), and 65-74 (4.5%). The residence distribution highlights a concentration within Metro Manila, where 100% of respondents reside, while none reside outside Metro Manila.

**Table 3:** Demographic Profile of Respondents

| | **Frequency** | **%** |
|---|---|---|
| **Gender** | | |
| Male | 263 | 65.75% |
| Female | 137 | 34.25% |
| **Age** | | |
| 24-34 | 21 | 5.25% |
| 35-44 | 74 | 18.5% |
| 45-54 | 189 | 47.25% |
| 55-64 | 98 | 24.5% |
| 65-74 | 18 | 4.5% |
| **Residence** | | |
| Within Metro Manila | 400 | 100% |
| Outside Metro Manila | 0 | 0% |
| **Work Status** | | |
| Currently Employed | 347 | 86.75% |
| Has Own Business | 48 | 12% |
| None of the Above | 5 | 1.25% |

In terms of work status, the majority of participants (86.75%) are currently employed, signifying a robust representation of the working demographic. A noteworthy 12% of respondents indicate having their own business, reflecting entrepreneurial diversity within the sample. A smaller fraction (1.25%) reports having none of the above-mentioned work statuses.

### Descriptive Statistics

The segment on descriptive statistics provides a detailed and illuminating portrayal of respondents' perceptions across key variables, shedding light on the nuanced dynamics within the study. The mean values, coupled with standard deviations, serve as a lens through which to discern the participants' collective stance on various aspects. Notably, a striking trend of strong agreement emerges across all measured dimensions. Performance Expectancy, with a mean score of 4.77 and a standard deviation of 0.42, reflects a robust consensus among respondents, indicating a high level of agreement regarding their expectations of system performance. Similarly, Effort Expectancy, boasting a mean of 4.75 and an SD of 0.43, signifies a pronounced unanimity on the

**Table 4:** Descriptive Statistics

| **Variables** | **Mean** | **SD** | **Interpretation** |
|---|---|---|---|
| Performance Expectancy | 4.77 | 0.42 | Strongly Agree |
| Effort Expectancy | 4.75 | 0.43 | Strongly Agree |
| Social Influence | 4.74 | 0.44 | Strongly Agree |
| Habit | 4.73 | 0.44 | Strongly Agree |
| Perceived Security | 4.76 | 0.43 | Strongly Agree |
| Purchase Intent | 4.73 | 0.45 | Strongly Agree |
| Usage Behavior | 4.76 | 0.43 | Strongly Agree |

perceived ease of system use. Social Influence, as gauged by a mean of 4.74 and an SD of 0.44, underscores the strong impact of social factors on participants' decision-making processes. The variable of Habit, with a mean of 4.73 and an SD of 0.44, reveals a prevailing inclination toward habitual use among respondents, indicative of established behavioral patterns. Participants exhibit a robust sense of Perceived Security, attested by a mean of 4.76 and an SD of 0.43, suggesting a high degree of confidence in the system's security features. Purchase Intent, with a mean of 4.73 and an SD of 0.45, signifies a strong inclination towards future purchasing behaviors among the study participants. Lastly, Usage Behavior, characterized by a mean of 4.76 and an SD of 0.43, encapsulates a resounding agreement on favorable and consistent patterns of system utilization. This uniformity in positive usage behavior signifies a collective affirmation of the system's appeal and functionality.

**Collinearity and Coefficient of Determination**

The collinearity assessment and coefficient of determination segment employ rigorous statistical scrutiny to elucidate the relationships among variables, offering valuable insights into the structural dynamics of the study. Following the principles outlined by Hair *et al.* (2017), the Variance Inflation Factor (VIF) values were examined, serving as a robust metric for assessing multicollinearity.

The VIF values, ranging from 1.343 to 1.835, exhibit a commendable absence of multicollinearity concerns. According to Hair *et al.* (2017), VIF values below 10 generally indicate a lack of significant multicollinearity. The calculated VIF values well below this threshold for all variables affirm the independence of the predictor variables in the model.

**Table 5:** Collinearity and Coefficient of Determination

| Variables | VIF | $R^2$ | $R^2$ Adjusted |
|---|---|---|---|
| Performance Expectancy | 1.653 | | |
| Effort Expectancy | 1.343 | | |
| Social Influence | 1.558 | | |
| Habit | 1.779 | | |
| Perceived Security | 1.449 | | |
| Purchase Intent | 1.820 | 0.293 | 0.284 |
| Usage Behavior | 1.835 | 0.331 | 0.239 |

Moving on to the coefficient of determination ($R^2$) and $R^2$ Adjusted, the results, particularly for Purchase Intent and Usage Behavior, echo the sentiments of Kock (2017) regarding the explanatory power of the model. Purchase Intent, with an $R^2$ of 0.293 and an $R^2$ Adjusted of 0.284, signifies a noteworthy 29.3% of the variance explained, showcasing a substantial predictive capability. Similarly, Usage Behavior, with an $R^2$ of 0.331 and an $R^2$ Adjusted of 0.239, attests to the model's ability to elucidate 33.1% of the variance, demonstrating a robust explanatory strength.

**Key Findings of the Study**

The exploration of path coefficients and their associated p-values within the context of the study unravels intricate relationships among key variables, offering nuanced insights into the dynamics governing consumer behavior. Each hypothesis, meticulously formulated to interrogate specific associations between predictor and outcome variables, has been scrutinized in the light of the derived results, illuminating the multifaceted landscape of the study.

Beginning with Hypothesis 1 (H1), which posited a connection between Performance Expectancy (PE) and Purchase Intent (PI), the obtained results exhibit a significant path coefficient of 0.265, accompanied by a p-value less than 0.001. This resoundingly rejects the null hypothesis, suggesting a robust and positive relationship between Performance Expectancy and Purchase Intent. The findings affirm the intuitive expectation that heightened perceptions of performance positively influence consumers' intentions to make a purchase.

In contrast, Hypothesis 2 (H2) explores the relationship between Effort Expectancy (EE) and Purchase Intent (PI). Despite a modest path coefficient of 0.041, the associated p-value of 0.203 fails to reach conventional significance levels, leading to the acceptance of the null hypothesis. This implies that Effort Expectancy, in this specific study, does not significantly predict Purchase Intent. The absence of a statistically significant relationship suggests that consumers' intentions to purchase may not be notably influenced by perceived effort in using the system.

Hypothesis 3 (H3) investigates Social Influence (SI) as a predictor of Purchase Intent (PI). Although the path coefficient stands at 0.077 with a p-value of 0.060, the decision to accept the null hypothesis indicates that, within the confines of this study, the relationship between

**Table 6:** Path Coefficients

| | Path Coefficients | β | p-values | Decision | Conclusion |
|---|---|---|---|---|---|
| H1 | PE→PI | 0.265 | <0.001 | Reject null | Not significant |
| H2 | EE→PI | 0.041 | 0.203 | Accept null | Significant |
| H3 | SI→PI | 0.077 | 0.060 | Accept null | Significant |
| H4 | H→PI | 0.027 | 0.294 | Accept null | Significant |
| H5 | PS→PI | 0.388 | <0.001 | Reject null | Not significant |
| H6 | PI→UB | 0.575 | <0.001 | Reject null | Not significant |

Social Influence and Purchase Intent may lack statistical significance. Further inquiry or a larger sample size may be requisite to draw more conclusive insights into this particular association.

Moving on to Hypothesis 4 (H4), examining the connection between Habit (H) and Purchase Intent (PI), the non-significant p-value of 0.294 suggests that habitual behavior may not be a substantial predictor of Purchase Intent within the parameters of this study. The findings indicate that, in this context, habitual tendencies may not play a statistically significant role in shaping consumers' intentions to make a purchase.

In contrast, Hypothesis 5 (H5) posits a link between Perceived Security (PS) and Purchase Intent (PI). The significant path coefficient of 0.388, coupled with a p-value below 0.001, categorically rejects the null hypothesis, underscoring a robust and positive relationship between Perceived Security and Purchase Intent. This implies that heightened perceptions of security significantly influence consumers' intentions to make a purchase.

Lastly, Hypothesis 6 (H6) explores the relationship between Purchase Intent (PI) and Usage Behavior (UB). The substantial path coefficient of 0.575, accompanied by a p-value below 0.001, emphatically rejects the null hypothesis, elucidating a strong and positive relationship between Purchase Intent and subsequent Usage Behavior. This finding accentuates the notion that intentions to purchase resonate strongly with actual usage, indicating a noteworthy translation of purchase intentions into tangible behavior.

**Path Coefficients of the Structural Model**

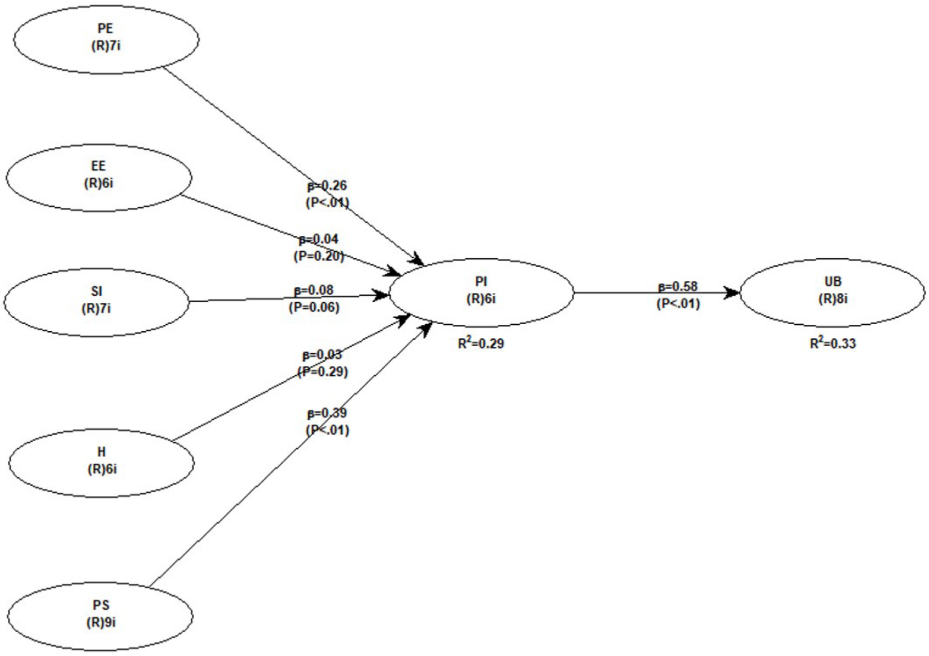


**Figure 8:** Final Structural Model

## CONCLUSIONS

The culmination of this study, exploring the influential factors shaping the Purchase Intent of do-it-yourself (DIY) homeowners in the realm of online hardware product acquisition, brings forth significant insights that contribute to the broader understanding of consumer behavior in the digital landscape. The investigation, guided by specific technological recognitions including Performance Expectancy, Effort Expectancy, Habit, Social Influence, and Perceived Security, as well as the consequential impact of Purchase Intent on Usage Behavior, was undertaken to address the formulated problem statements.

### Performance Expectancy Emerges as a Key Determinant

The analysis of Performance Expectancy within the context of DIY homeowners' online hardware product purchases reveals a pivotal role. The significant positive relationship between Performance Expectancy and Purchase Intent signifies that the perceived performance of the online platform strongly influences DIY homeowners' intentions to make a purchase. This underscores the importance of a platform's functionality and utility in shaping consumer decisions.

### Mixed Findings in Effort Expectancy, Habit, and Social Influence

Effort Expectancy, despite not exhibiting a statistically significant relationship with Purchase Intent, remains an essential dimension in understanding online purchasing decisions. The non-significant relationship may suggest that, in this specific context, ease of use may not be a primary driver of purchase intentions. Habit, similarly, does not emerge as a significant predictor of Purchase Intent, highlighting that habitual behaviors may not play a substantial role in shaping DIY homeowners' intentions to purchase hardware products online. Social

Influence, while not achieving conventional significance, demonstrates a marginal p-value, suggesting that further exploration or an expanded sample size could uncover a more definitive relationship.

**Perceived Security as a Crucial Factor**

The investigation into Perceived Security reveals its significant influence on Purchase Intent. The robust positive relationship implies that DIY homeowners' confidence in the security of the online platform significantly contributes to their intentions to make a purchase. This underscores the importance of instilling a sense of security to foster trust and confidence among online consumers.

**Purchase Intent's Impact on Usage Behavior**

The study affirms a robust and positive relationship between Purchase Intent and Usage Behavior. DIY homeowners who express stronger intentions to make a purchase online are more likely to translate those intentions into actual usage. This finding underscores the predictive power of Purchase Intent in shaping tangible consumer behavior.

## RECOMMENDATIONS

In the dynamic context of retail hardware stores in Metro Manila, practical recommendations and future research directions emerge from a comprehensive exploration of factors influencing customer purchase intentions in the omnichannel environment. To enhance current practices, optimizing online performance stands out as a strategic imperative, necessitating investments in user-friendly, responsive platforms that positively influence Performance Expectancy. Simultaneously, emphasizing perceived security through robust communication of security measures is vital to foster trust and contribute to positive purchase decisions. Leveraging social media engagement strategies and personalizing the shopping experience with tailored recommendations further underscore the importance of a customer-centric approach. Additionally, providing educational content for informed decision-making addresses the nuanced aspect of Effort Expectancy, enhancing the overall shopping experience.

Looking ahead, future research recommendations guide an extended inquiry into the evolving landscape. Longitudinal studies on habit formation offer a nuanced understanding of online shopping behaviors among DIY homeowners over time. Qualitative exploration of social influence seeks to unveil the intricacies that quantitative analyses may overlook, while investigating cross-channel interactions aims to comprehend holistic customer journeys. A comparative analysis across regions and strategies for post-purchase engagement open avenues for regional customization and loyalty-building initiatives. Establishing a systematic customer feedback mechanism, introducing loyalty programs, and leveraging personalized communication underscore the importance of ongoing customer engagement. Investing in efficient customer service and promoting omnichannel integration further solidify the foundation for sustained success and customer satisfaction in the omnichannel retail hardware industry in Metro Manila.

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