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Exploring Consumer Behavior in Instagram Purchasing Agent Services: An Integrated PLS-SEM Model of Satisfaction and Purchase Intention

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Abstract

This study investigates the determinants of purchase intention toward Instagram-based purchasing agent services in Indonesia within the context of social commerce. Drawing upon social commerce and consumer behavior literature, the study examines the effects of perceived service quality, personalization, customer satisfaction, product diversity, price, electronic word-of-mouth (eWOM), and hedonic value, while incorporating trust as a moderating variable. Data were collected from 203 Indonesian consumers who had prior experience purchasing products through Instagram purchasing agents. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The findings reveal that trust significantly strengthens the relationship between perceived service quality and customer satisfaction. Personalization also positively influences customer satisfaction, which subsequently enhances purchase intention. Furthermore, price, eWOM, and hedonic value demonstrate significant positive effects on purchase intention, with hedonic value emerging as the strongest predictor. However, product diversity does not significantly influence purchase intention. The results suggest that both functional factors and emotional experiences play important roles in shaping consumer behavior within social commerce environments. This study contributes to the growing literature on purchasing agent services and provides practical implications for purchasing agents seeking to enhance customer satisfaction, trust, and long-term purchase intention in increasingly competitive digital marketplaces.

JEL classification numbers: D12, L81, M31, M37, O33.
Keywords: Social commerce, Purchase intention, Purchasing agent, Trust, Hedonic value.

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1. Introduction

The internet, particularly through social media platforms, has become an integral part of daily life for a substantial proportion of the global population, with usage continuing to expand (Jashari and Rrustemi, 2017). Beyond facilitating personal interactions, it plays a pivotal role in enhancing global business competitiveness by enabling efficient information exchange and shaping customer relationship management (CRM) and long-term commercial performance. As noted by Khobzi, Lau, & Cheung (2019), social media provides innovative channels for global communication, connecting individuals not only with one another but also directly with firms. Moreover, the internet has emerged as a primary medium for information consumption and purchasing decisions, significantly influencing various dimensions of electronic commerce (e-commerce) (Pourkhani et al., 2019). According to data reported by Kepios (2023), growth in internet users has shown signs of slowing in recent months. Nevertheless, prevailing trends suggest that more than two-thirds of the world's population will be online by the end of 2023. As illustrated in Figure 1, the number of global internet users reached approximately 5.158 billion in January 2023, representing a 1.9% increase compared to January 2022.

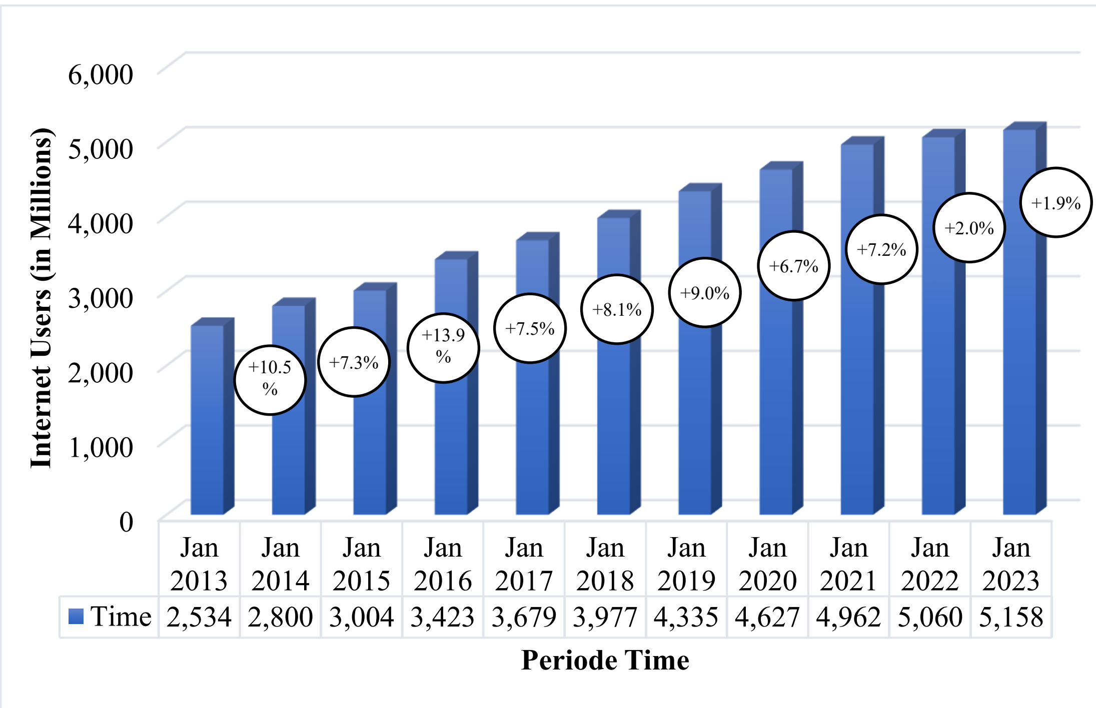

Figure 1: Internet Users Worldwide Over Time

Source: Kepios (2023)

Social media platforms have become increasingly significant for businesses, serving as essential channels through which customers discover, explore, and purchase products and services. Prior research highlights the evolving transformation from traditional e-commerce to social commerce (s-commerce) (Wu, Yang, & Gong, 2024). Social commerce leverages social media technologies to facilitate interpersonal interactions, enabling the exchange of commercial information and the execution of transactions through social communication. This transition extends beyond purely transactional activities, emphasizing the critical role of online social engagement. Platforms such as Instagram, with features like product tagging, and Facebook, with tools such as collection ads, exemplify how social media integrates commerce with interactive user experiences (Meng & Wang, 2024). Furthermore, s-commerce provides multiple advantages, including enhancing customer loyalty, attracting new customers, increasing sales performance, and strengthening brand recognition through accessible product information such as descriptions and pricing. Instagram is widely recognized as one of the most relevant and innovative developments in the social media landscape (Nedra, Hadhri, & Mezrani, 2019). This prominence is supported by global evidence: research conducted in 2022 by Global Web Index (GWI) indicates that Instagram ranks as the second most favored social media platform worldwide. The platform's influence is substantial, as a large proportion of users rely on Instagram to discover new products and services, which in turn shapes their purchasing decisions.

In emerging markets such as Indonesia, the job market has experienced notable growth in social commerce activities, particularly through Instagram. One prominent phenomenon is the rapid rise of purchasing agents—commonly referred to as "jasa titip" (jastip). This trend illustrates how Instagram is reshaping social commerce by enabling new forms of entrepreneurial activity. The platform not only transforms how online businesses operate but also creates economic opportunities for individuals to participate in the digital marketplace.

The concept of purchasing agents has gained widespread recognition and evolved into a prevailing business model. According to Kurniasih (2019), purchasing agents provide a personalized service in which consumers entrust them to acquire desired products, whether domestically, internationally, or during travel. This service typically includes an additional charge, commonly known as a service fee (Hapsari & Sirait, 2024).

The phenomenon of purchasing agents is not confined to Indonesia; it has also emerged in various international contexts. In Taiwan, for example, research by Tsou & Sun (2021) identified several purchasing agents who market Japanese products through social media platforms such as Facebook. In addition, other agents utilize multiple digital channels—including Instagram and Shopee—to sell sports-related products. However, the development of purchasing agents in Taiwan differs from that in Indonesia due to regulatory conditions. The Taiwanese government permits the sale of overseas products directly through e-commerce platforms, whereas the Indonesian government imposes restrictions to protect domestic industries. As a result, purchasing agents are relatively less prevalent in Taiwan, since consumers can conveniently access foreign products through official online marketplaces.

A further illustration can be found in China, where purchasing agents have also gained traction internationally. One notable case is Angela Zhang, who began her business as an international student in Australia in 2008. According to ABC News (2019), she initially focused on purchasing infant formula products but later expanded her offerings to include cosmetics, vitamins, snacks, toys, and clothing, particularly for items not readily available on e-commerce platforms. The same report highlights that purchasing agents have played a significant role in supporting companies such as Blackmores, contributing to approximately 25% of their business revenue. In contrast to these international cases, the purchasing agent trend in Indonesia demonstrates a broader scope. It involves not only sourcing products from overseas but also distributing local goods across different cities and provinces, thereby strengthening both domestic and cross-border social commerce activities.

Dincer & Dincer (2023) emphasize that purchase intention represents the most critical stage in any online transaction, particularly within the context of social commerce (s-commerce). The rapid growth of s-commerce has stimulated extensive research focusing on consumer-driven quality dimensions, including enjoyment, aesthetics, pleasantness, curiosity, trust, and emotional responses. Nevertheless, the existing literature remains limited in providing a comprehensive explanation of the determinants that influence consumers' purchase intentions on Instagram, especially in the context of purchasing agent services.

Building upon this gap, the present study conceptualizes purchase intention as the central outcome variable and examines multiple antecedents that may shape it. Specifically, seven key variables are incorporated: perceived service quality, personalization, customer satisfaction, product diversity, price, electronic word-of-mouth (eWOM), and hedonic value, with trust introduced as a moderating variable. This framework aims to provide a more integrated understanding of how these factors jointly influence consumer decision-making in s-commerce environments. Moreover, Instagram's interactive functionalities—such as Stories, product tagging, and real-time engagement—have become integral tools for businesses, further reinforcing the platform's significance in contemporary digital commerce. Overall, the dynamic interplay between social media and commerce continues to transform how firms operate, engage with customers, and market their offerings, positioning Instagram as a particularly powerful platform within the evolving digital business landscape.

2. Literature Review

2.1 Purchasing Agent

Some researchers have described purchasing agents as equivalent to personal shoppers; however, these two concepts differ fundamentally. Personal shoppers are typically employed by department stores or boutiques, although some operate independently or through online platforms. They specialize in assisting customers—often women—by providing advice on personal style, preferences, and specific needs, thereby delivering a tailored and personalized shopping experience (Bakar et al., 2023). In contrast, a purchasing agent refers to an individual, firm, or entity engaged in professional commercial activities on behalf of consumers, particularly in sourcing and acquiring products that may not be easily accessible to them (Hollander & Rassuli, 1999).

While personal shoppers are widely recognized—especially in Western countries and Southeast Asia—their roles are generally associated with luxury retail environments. For instance, in countries such as Malaysia and Singapore, personal shoppers often assist clients in purchasing high-end fashion items and luxury goods, including designer bags and apparel. By contrast, purchasing agents typically operate across broader product categories and geographical boundaries, reflecting a more transactional and cross-border dimension of social commerce.

Previous studies conceptualize purchasing agents as intermediaries who bridge the gap between buyers and sellers by facilitating procurement processes on behalf of consumers (Singh, 2000). They typically acquire customers through social networks and promote products via digital platforms. Furthermore, purchasing agents have been defined as intermediaries between foreign businesses and domestic consumers, responsible for managing communication, arranging product shipment, and conducting quality inspections. Through these roles, they enable consumers to access overseas goods without the need to travel abroad (Yeni et al., 2024).

Empirical insights from FeMaleRadio in 2017, as cited by Kurniasih (2019), further illustrate the operational practices of purchasing agents in Indonesia. Their activities include visiting shopping malls, photographing discounted or newly released products, and posting them on Instagram to engage followers. They also manage the entire transaction process, including order placement, payment collection, and delivery coordination. Interactions between purchasing agents and customers are primarily conducted through online platforms rather than face-to-face meetings, often incorporating mechanisms such as live purchase orders (POs). In addition to travel-related activities, individuals frequently engage in shopping abroad for purposes such as personal collection, purchasing souvenirs for relatives, or reselling products for profit (Yuliani, 2021). This study also indicates a high level of consumer awareness regarding purchasing agent services.

From an operational perspective, purchasing agents generally apply a standardized service fee per product, although in some cases this fee is embedded within the product price. Delivery charges vary depending on the customer's location. Many agents adopt a pre-order system, requiring advance payment to mitigate the risk of order cancellation. Once the products are secured, the agent confirms the order and proceeds with packaging and shipment. If a product is unavailable, the agent promptly notifies the customer, who may choose to cancel or substitute the item. In the event of cancellation, a full refund is typically provided (Gadjong, 2022).

2.2 Purchase Intention

Purchase intention is conceptualized as an outcome of cognitive learning and evaluative processes that shape an individual's perception toward a product or service (Astuti & Putri, 2018). Extending this perspective, Siripipatthanakul et al. (2021) define purchase intention as encompassing not only the likelihood of future repurchase but also the willingness to recommend a platform or service to others. As a central construct in marketing and consumer behavior research, purchase intention reflects an individual's planned behavior to engage in a transaction, influenced by factors such as personal preferences, attitudes, and external stimuli. Moreover, purchase intention represents a motivational state that evolves over time, strengthening from initial awareness into a deliberate desire, ultimately leading consumers to translate their mental evaluations and needs into actual purchasing behavior. Decision-making across the entire purchase process—encompassing pre-purchase, purchase, and post-purchase stages—is closely associated with individuals' purchase intentions (Sosanuy et al., 2021). As illustrated in Figure 2, the post-purchase stage involves consumers evaluating their overall experience, which subsequently influences their decisions regarding store revisit intentions and the likelihood of repurchasing products or services (Ratasuk, 2023).

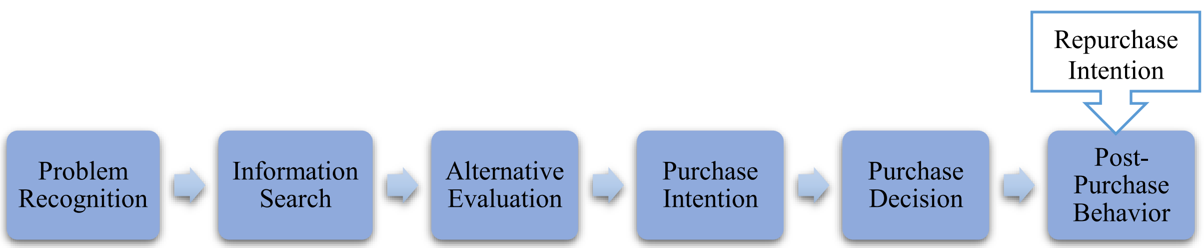

Figure 2: Buying Decision Process

Source: Kotler et al. (2012)

However, the realization of purchase intention is influenced by multiple factors, including the customer's interest and enthusiasm toward the product, social influences, and the overall perception of the offering (Nasution et al., 2025). In the context of social commerce, numerous factors have been identified in the literature as influencing purchase intention. These include technical factors such as information quality, service quality, and system quality; social factors such as relationship quality, social support, and social presence; and motivational factors, including hedonic and utilitarian motivations (Busalim, Masrom, & Zakaria, 2019).

Furthermore, prior studies emphasize that consumer demographics play a critical role in service marketing, as they significantly shape purchase intention (Chauhan et al., 2019; Kamboj et al., 2023; Olasina, 2015). In addition, Rai et al. (2022) found that demographic variables such as gender, age, education, and income significantly influence consumers' intentions to purchase smartphones.

Beyond demographic factors, Abdul and Mat (2017) argue that the number of followers serves as an important social signal, indicating sellers' credibility and trustworthiness in social media environments. Accounts with a large follower base are generally perceived as more reputable, which enhances engagement and strengthens consumers' purchase intentions. Consequently, when users observe a substantial following, they are more likely to trust the account's content and recommendations. Accordingly, this study investigates the factors influencing purchase intention among purchasing agents on Instagram in Indonesia. By positioning purchase intention as the key dependent variable (Shim et al., 2021), the study aims to provide insights into consumer behavior within the dynamic context of social commerce.

2.3 Trust

Trust refers to the trustor's confidence in the trustee or in a trusted third party (Yeon et al., 2019; Wang et al., 2026) and serves as a fundamental foundation of business relationships. Establishing trust and maintaining long-term relationships with customers are essential for fostering customer loyalty. According to Herzallah (2021), trust encompasses the beliefs, sentiments, expectations, and confidence associated with online interactions, intentions, and behaviors. In this regard, trust is directly linked to the purchasing process and indirectly influences consumers' attitudes.

Customers who trust a seller are more likely to make repeat purchases and share relevant information with others. Moreover, adopting transparent practices and providing accurate and comprehensive information can further strengthen consumer trust in e-commerce environments. Empirical studies consistently demonstrate that trust has a significant and positive effect on purchase intention in social commerce contexts (Dabbous, Aoun Barakat, & Merhej Sayegh, 2020), indicating that higher levels of trust lead to stronger purchasing intentions.

2.4 Perceived Service Quality (PSQ)

Perceived service quality (PSQ) refers to customers' subjective evaluation of the overall excellence or superiority of a service provided by a business. This evaluation is formed by comparing customers' expectations with their perceptions of both the inherent and external attributes of the product or service (Liao et al., 2022). In this sense, service quality reflects the extent to which a firm satisfies customer needs by delivering products and services that meet or exceed expectations.

Service quality is commonly conceptualized through five key dimensions. First, reliability refers to the ability to deliver promised services dependably and accurately. Second, assurance encompasses employees' knowledge, courtesy, and their ability to inspire trust and confidence. Third, tangibles (representation) relate to the quality of physical facilities, equipment, and personnel appearance. Fourth, empathy reflects the degree of care and individualized attention provided to customers. Finally, responsiveness refers to the willingness to assist customers and provide prompt service (Dapas et al., 2019). In the context of online commerce, high perceived service quality plays a critical role in building customer trust and fostering long-term relationships. As noted by Shafiee and Bazargan (2018), online selling platforms that deliver superior service quality are more likely to gain customer trust and sustain ongoing customer engagement.

2.5 Personalization

Personalization, defined as the tailoring of content and services to individual preferences, is a critical factor influencing consumer decision-making. Personalization involves delivering customized experiences based on insights into individuals' preferences and behaviors. Its increasing prominence in online environments (Thelwall et al., 2020) underscores its effectiveness in enhancing consumer engagement. By fostering direct and individualized interactions, personalization serves as a strategic tool for guiding customers through diverse content and purchasing options.

In the context of personal shopping, purchasing agents act as intermediaries of personalized information, leveraging their expertise to provide tailored recommendations and detailed product insights. This is particularly valuable for customers who are unfamiliar with the products. Empirical evidence suggests that the quality and benefits of personalization significantly enhance customer satisfaction (Chhabria & Yadav, 2023). Key advantages include improved time efficiency, enriched customer experience, strengthened customer loyalty, and increased satisfaction, all of which contribute to a higher likelihood of repeat purchases. Consistent with this, Afifah, Ainiyah, & Dehham (2024) argue that personalized interactions make consumers feel valued and recognized, thereby fostering loyalty and long-term satisfaction.

2.6 Customer Satisfaction

Customer satisfaction refers to an individual's sense of contentment or dissatisfaction resulting from the comparison between perceived online shopping performance and prior expectations (Santo & Marques, 2022). It is widely regarded as a key performance indicator that reflects the quality of the customer experience and the extent to which expectations are fulfilled (Manyanga, Makanyeza, & Muranda, 2022). This evaluative judgment significantly shapes customer attitudes and directly influences their intentions for future purchases.

Prior research highlights the behavioral consequences of satisfaction and dissatisfaction. Haralayya (2021) notes that dissatisfied customers tend to share negative experiences with approximately 9 to 10 others, whereas satisfied customers typically communicate positive experiences to four to six individuals. Moreover, highly satisfied customers are substantially more likely—up to six times—to engage in repeat purchases, demonstrate loyalty, and recommend products or services compared to those who are merely satisfied. These findings underscore the critical role of customer satisfaction in influencing both individual behavior and broader business outcomes, particularly in terms of customer retention, reputation, and long-term success.

2.7 Product Diversity

Product diversity, or product variety, refers to the range and assortment of different items that a purchasing agent can offer or source for customers. The perceived quality of products and services is influenced by several factors, including the breadth of available items, the types of products offered, and the reputation of established brands. These elements collectively shape the diversity of products and services available in online retail environments (Marlina & Vildayanti, 2025). A higher level of product diversity can enhance customers' purchasing tendencies by enabling them to satisfy their needs through a wider selection of options, thereby stimulating consumption (Hu, Ding, & Zeng, 2025). In short, key indicators of product diversity include brand variety, product comprehensiveness, variations in packaging, and product availability.

2.8 Price

Larano et al. (2023) highlight that price serves as a reliable indicator of value, particularly when it is associated with the perceived benefits of a product or service from the consumer's perspective. Prior to making a purchase, consumers typically evaluate product prices as part of their cost-saving considerations (Edwar et al., 2018). This evaluation plays a crucial role in shaping purchasing decisions. Jadhav & Khanna (2016) identify four key price-related factors influencing online shopping behavior: (1) preference for lower prices, (2) the buyer's ability to assess product pricing, (3) the perceived relationship between price and quality, and (4) the use of price as a basis for comparing similar products. Furthermore, online retailers often adopt price-oriented strategies due to the significant influence of pricing on consumer decision-making and the ease with which customers can compare prices across different sellers.

2.9 Electronic Word of Mouth (eWOM)

With the widespread adoption of social media, individuals can easily share their opinions and experiences regarding products and services within their networks. Electronic word-of-mouth (eWOM) has emerged as a digital extension of traditional word-of-mouth communication, driven by the rapid development of internet technologies. Social media platforms, in particular, serve as effective channels for the dissemination of eWOM due to their broad reach and interactive nature (Salmones, Herrero, & Martínez, 2021). As noted by Amin (2019), eWOM

encompasses various forms, including online reviews, ratings, feedback, comments, testimonials, and experience sharing. Consequently, users frequently seek and evaluate such information on social media before making purchasing decisions.
eWOM plays a critical role in reducing information asymmetry by providing consumers with valuable insights into products and brands (Krishnamurthy & Kumar, 2018). It supports decision-making by lowering perceived risk and enhancing confidence in purchase choices. Consumers often rely on the opinions and recommendations of others when evaluating alternatives (Nolan, Zhao, & Kamoche, 2024). Moreover, eWOM significantly influences consumer perceptions and product choices, with positive eWOM being particularly effective in building trust and strengthening purchase intentions. Early studies on eWOM valence primarily examined the differential impact of positive and negative reviews on the diffusion of online information (Brandes, Godes, & Mayzlin, 2022).

2.10 Hedonic Value

Hedonic value refers to the value customers derive from pleasurable and enjoyable experiences during consumption (Evelina, Kusumawati, & Nimran, 2020). It reflects the subjective and experiential benefits obtained from shopping activities, including emotional stimulation and sensory enjoyment associated with products or services. Hedonic consumption, therefore, emphasizes the multisensory, emotional, and imaginative aspects of the consumption experience. In the context of online shopping in Indonesia, Budiharseno, Handani, & Hwan (2020) highlight that factors such as practicality, enjoyment, and impulsiveness positively enhance the online shopping experience. These findings underscore the diverse motivations of consumers in digital environments, where both functional and experiential values shape purchasing behavior.

2.11 Development of Hypotheses

2.11.1 Perceived Service Quality and Customer Satisfaction

A purchasing agent plays a vital role in facilitating customers' purchasing decisions by delivering high-quality services, providing personalized recommendations, selecting suitable products, and offering guidance throughout the shopping process. By delivering a personalized and attentive experience, purchasing agents can significantly shape customers' perceptions of overall service quality. Perceived service quality is widely recognized as a key determinant of customer satisfaction, loyalty, and purchase intention. Prior research has consistently demonstrated the positive impact of service quality on customer satisfaction (Thaichon, 2017). Furthermore, the effective implementation of customer relationship management (CRM) enables firms to better understand customer segments, thereby increasing the likelihood of repeat purchases and supporting business growth (Nambiar et al., 2018).
In addition, existing studies suggest that trust plays a mediating role in the relationship between service quality and customer satisfaction. For instance, Kundu

& Datta (2015) identify customer trust as a key intervening variable linking service quality to satisfaction. Similarly, Shefira & Mangifera (2023), based on a study of 145 Shopee Food users in Indonesia, find that service quality enhances customer satisfaction through the mediation of trust. They further confirm that perceived service quality significantly influences customer satisfaction, with trust acting as an intermediary mechanism. Therefore, purchasing agents who provide high-quality services and foster trust are more likely to achieve higher levels of customer satisfaction and encourage repeat purchasing behavior. Based on the above discussion, this study proposes the following hypothesis:

H1: *Trust* positively *moderates the relationship between perceived service quality and customer satisfaction through a purchasing agent.*

2.11.2 Personalization and Customer Satisfaction

Personalization plays a significant role in influencing consumer behavior, as content tailored to individual preferences increases the likelihood of purchase (Tran & Pham, 2024). Supporting this view, Kazeminia, Kaedi, & Ganji (2019) find that personalization techniques positively affect purchase intention, particularly when consumers experience a high level of satisfaction. They further suggest that adapting elements of the purchasing process to align with an individual's decision-making style enhances the probability of purchase. In the context of purchasing agents, personalization involves providing recommendations that reflect customers' unique preferences, ensuring a better match between products and individual needs. Odzic & Bozkurt (2023) emphasize that enhancing personalization in online purchasing experiences can improve customer satisfaction and increase the efficiency of consumer interactions. Moreover, Kurniasih (2019) reports that some consumers prefer purchasing agents over official online stores due to the personalized services provided, which also influences satisfaction through customer testimonials. Accordingly, this study aims to examine how personalization efforts by purchasing agents affect customer satisfaction and, subsequently, influence purchase decisions.

H2: *There is a positive and significant relationship between personalization and customer satisfaction through a purchasing agent.*

2.11.3 Customer Satisfaction and Purchase Intention

Customer satisfaction is widely recognized as a key determinant of repurchase intention and long-term customer relationships (Miao et al., 2022). Supporting this view, Dash & Paul (2021) demonstrate a significant relationship among e-commerce service quality, customer satisfaction, and purchasing behavior. Furthermore, prior studies confirm a positive association between customer satisfaction and online purchase intention, with customer habits acting as a moderating factor in this relationship (Chu & Zhang, 2016). In the context of purchasing agents, Bere & Susanto (2022), based on respondents who purchased branded products through an Instagram purchasing agent (@Jastipbynunny), found that customer satisfaction has a positive and significant effect on purchase intention. Building on these findings, this study seeks to further examine the role of customer satisfaction in influencing consumers' intentions to make future purchases through purchasing agents.

H3: *There is a positive and significant relationship between customer satisfaction and purchase intention through a purchasing agent.*

2.11.4 Product Diversity and Purchase Intention

Rashaduzzaman (2020), based on 334 valid responses from a survey of MTurk participants in the United States, found that product variety significantly influences consumers' intention to purchase apparel from online shopping platforms. This finding is consistent with Istiqomah (2023), who also reported a significant relationship between product variety and purchase intention. Furthermore, Wang et al. (2020) suggest that online retailers can enhance customer attraction by expanding their product categories.

In the context of purchasing agents, product variety serves as a key differentiating factor by enabling them to meet diverse customer needs. By offering a wide range of products, purchasing agents position themselves as comprehensive solutions for consumers seeking convenience and variety. Sugiartana et al. (2025) found that the availability of multiple brands and the difficulty of obtaining certain products significantly influence consumers' preference for purchasing agent services. Despite its importance, limited research has examined how product diversification by purchasing agents affects consumer behavior. Therefore, it is expected that greater product diversity will provide customers with more choices, thereby increasing their likelihood of making a purchase. Accordingly, the following hypothesis is proposed:

H4: *There is a positive and significant relationship between product diversity and purchase intention through a purchasing agent.*

2.11.5 Price and Purchase Intention

Pricing is a critical factor that significantly influences consumer purchasing behavior and decision-making processes (Nolan, Zhao, & Kamoche, 2024). Consistent with prior research, Kelvin and Firdausy (2022) confirm that price has a significant effect on purchase intention. Furthermore, the establishment of appropriate and optimal pricing strategies can positively enhance consumers' buying interest in a product (Lionitan & Firdausy, 2023).

In the context of purchasing agents, where customers often expect personalized services, various pricing-related elements play an important role. These include early purchase order options, promotional discounts based on purchase volume, delivery fees, and service charges imposed by the purchasing agent. Wiraandryana & Ardani (2021) find that pricing significantly influences purchase intention in online purchasing agent settings. In addition, Hidayat, Harianto, & Taryana (2023) indicates that purchasing agents facilitate product selection and price comparison, thereby shaping consumers' perceptions of value. Therefore, purchasing agents should develop pricing strategies that are transparent, reasonable, and competitive in order to meet or exceed customer expectations. Accordingly, the following hypotheses are proposed:

H5: *There is a positive and significant relationship between price and purchase intention through a purchasing agent.*

2.11.6 eWOM and Purchase Intention

Prior studies provide important insights into the significant influence of electronic word-of-mouth (eWOM) on consumers' online purchase intentions. As consumers increasingly share their opinions on social media, eWOM has become a powerful mechanism shaping purchase decisions (Cham et al., 2021). In particular, the credibility and quality of eWOM information enhance its perceived usefulness and ease of use, which in turn influence information adoption and purchase intention (Rahaman et al., 2022).

Although existing research has examined the role of eWOM in influencing consumer behavior, a comprehensive understanding of its impact remains limited (Leong et al., 2021). Torres, Gerhart, & Negahban (2018) further suggest that the adoption of social media information positively affects purchase intention, highlighting the link between eWOM information adoption and consumer decision-making. Moreover, Tam, Hiep, & Lan (2025) finds that eWOM has a significant positive effect on purchase intention in the context of purchasing agents. Accordingly, eWOM enables consumers to share experiences and assist one another in identifying reliable purchasing agents, thereby influencing their purchase decisions. Therefore, the following hypothesis is proposed:

H6: *There is a positive and significant relationship between eWOM and purchase intention through a purchasing agent.*

2.11.7 Hedonic Value and Purchase Intention

Consumers are more likely to express purchase intentions when they perceive high hedonic value from a product or service. Hedonic value reflects the enjoyment, excitement, and experiential benefits derived from the consumption process. Recent research by Lee & Lee (2023), based on 283 respondents engaged in mobile live commerce, demonstrates that hedonic value has a stronger influence on purchase intention within experiential online environments. Similarly, Muslikhun, Harjanti, & Wahjoedi (2022) emphasize the importance of hedonic factors in shaping shopping behavior, highlighting that consumers derive enjoyment not only from the

products themselves but also from the overall shopping experience.
In the context of purchasing agents, customers are often motivated by hedonic considerations, such as the desire to explore new products, particularly from cross-border markets, or to obtain exclusive or limited-edition items from well-known brands. Supporting this, Gao et al. (2025), based on a sample of 238 consumers with overseas purchasing agent experience, finds that hedonic value has a positive and significant effect on purchase intention. Therefore, to further examine the relationship between hedonic value and purchase intention in this study, the following hypothesis is proposed:

H7: *There is a positive and significant relationship between hedonic value and purchase intention through a purchasing agent.*

3. Methodology

3.1 Research Design

This study focuses on consumers who have purchased through purchasing agents. Purchase intention is the dependent variable, trust serves as the *moderating* variable, and the independent variables include perceived service quality, personalization, customer satisfaction, product diversity, price, eWOM, and hedonic value. The proposed research framework is presented in Figure 3.

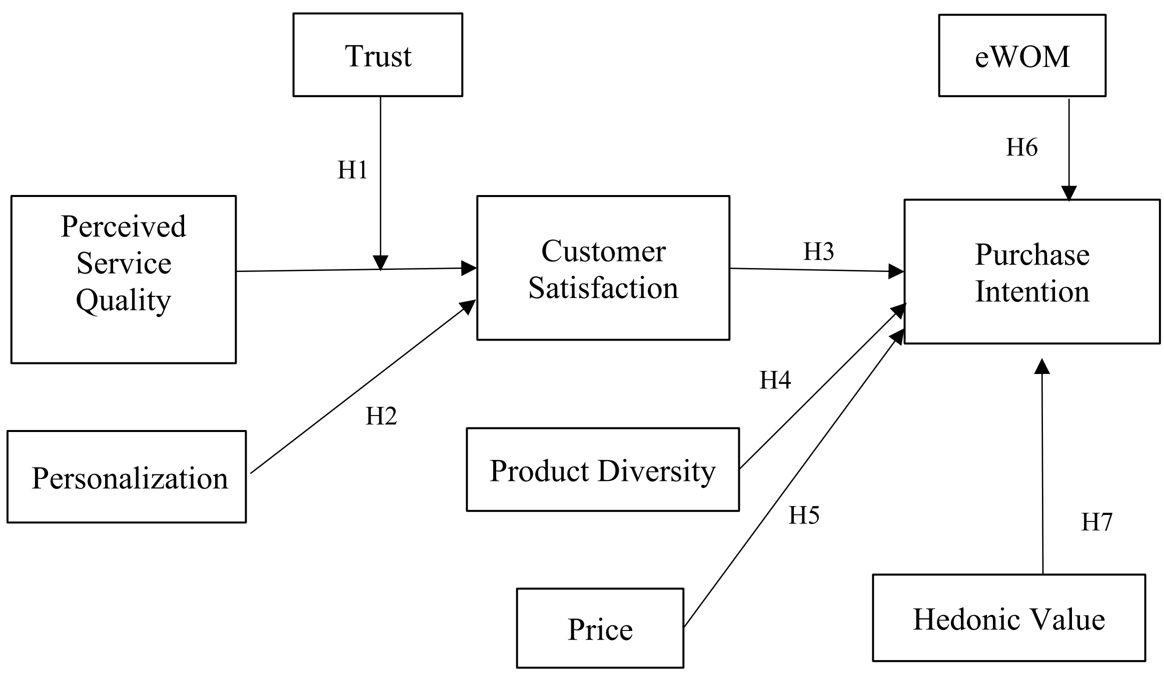

Figure 3: Research Framework

3.2 Sampling

Data for this study were collected through a structured questionnaire administered online via Google Forms. The questionnaire was distributed over a one-month period, from March 6, 2024, to April 6, 2024, through social media platforms including Instagram, WhatsApp, and LINE, targeting respondents in Indonesia. To ensure that participants met the study criteria, a screening (filter) question was included at the beginning of the questionnaire. Only responses from eligible participants were retained for further data analysis.

Sampling is a fundamental technique in research used to obtain information that represents a population. This study focuses on individuals in Indonesia who actively use Instagram as their primary social media platform and have engaged in at least one transaction through a purchasing agent. Based on sample size guidelines for structural equation modeling (SEM), a sample of 100 is considered small, 100–200 medium, and above 200 large (Kline, 2005). In addition, Comrey & Lee (2013) suggest that a sample size below 50 is poor, 100 is weak, 200 is adequate, 300 is good, 500 is very good, and 1000 is excellent. Accordingly, this study targets a sample size of at least 200 respondents to ensure sufficient statistical power and representativeness. The unit of analysis refers to the entity from which data are collected (Kumar, 2018). In this study, the unit of analysis is the individual. Specifically, the research focuses on the behaviors, perceptions, and attitudes of individuals who meet the predefined criteria, namely Indonesian consumers aged 17 years and above who have experience purchasing products through purchasing agent services.

3.3 Data Analysis Method

3.3.1 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) is a comprehensive statistical technique used to analyze complex relationships among variables by integrating multiple regression and factor analysis (Mohd Dzin & Lay, 2021). It is particularly suitable for examining causal relationships in cross-sectional data, as it enables the simultaneous estimation of multiple interrelated dependence relationships involving both latent and observed variables (Cohidon, Wild, & Senn, 2019).

One of the primary advantages of SEM is its ability to analyze multiple relationships concurrently while accounting for measurement error, thereby providing a more comprehensive and accurate representation of theoretical models (Hair et al., 2019). SEM consists of two main components: the measurement model, which specifies the relationships between latent constructs and their indicators, and the structural model, which examines the relationships among latent constructs. This dual structure allows for a confirmatory approach while maintaining flexibility in model evaluation and refinement (Dash & Paul, 2021).

SEM can be broadly categorized into two approaches: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). CB-SEM is primarily used for theory testing and confirmation, as it focuses on reproducing the covariance matrix of observed variables and assessing overall model fit (Hair et al., 2019). Originally developed by Karl Jöreskog (1973), CB-SEM is commonly implemented using software such as LISREL and AMOS.

In contrast, PLS-SEM is a variance-based approach that emphasizes prediction and the maximization of explained variance in endogenous constructs. It is particularly suitable for exploratory research, smaller sample sizes, and data that do not meet strict normality assumptions (Hair et al., 2019). Commonly used tools for PLS-SEM include PLS-Graph (Chin, 2009) and SmartPLS, which are widely recognized for their user-friendly interfaces and practical application in social science research.

3.3.2 Partial Least Squares - Structural Equation Modeling (PLS-SEM)

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a variance-based statistical technique that integrates causal analysis and predictive modeling within the broader framework of Structural Equation Modeling (SEM). Its primary objective is to explain the variance in endogenous (dependent) constructs. Unlike covariance-based SEM, PLS-SEM conceptualizes latent variables as composites formed by linearly combining their observed indicators (Hwang et al., 2020).

In PLS-SEM, the path model consists of two key components: the structural (inner) model and the measurement (outer) model (Hair et al., 2019). The structural model specifies the relationships among latent constructs, typically represented as circles or ovals, and reflects the hypothesized theoretical paths. In contrast, the measurement model defines the relationships between latent constructs and their observed indicators, which are commonly represented as rectangles. The development of the path model is grounded in two fundamental theoretical perspectives: measurement theory, which guides the selection and validation of indicators, and structural theory, which defines the relationships among constructs. The evaluation of PLS-SEM results involves several key considerations, including data characteristics (e.g., sample size and distribution), model complexity, estimation procedures, and assessment criteria (Hair et al., 2019). Notably, PLS-SEM is particularly suitable for studies with relatively small sample sizes, complex models, and a large number of variables (Fornell & Bookstein, 1982; Hair et al., 2019). Supporting this, Hoyle (1995) suggests that a sample size ranging from 100 to 200 is generally adequate for path modeling. Due to its flexibility and predictive capability, PLS-SEM has been widely applied across various disciplines, including behavioral sciences (Bass et al., 2003), marketing (Henseler, Ringle, & Sarstedt., 2015), organizational studies (Sosik, Kahai, & Piovoso, 2009), management information systems (Chin, 2009), and business strategy (Hulland, 1999).

4. Analysis and Result

4.1 Respondent Profile

This study collected data through an online questionnaire distributed via Google Forms, resulting in 235 responses obtained through personal networks, including family, friends, colleagues, and individuals with experience using purchasing agents. To ensure data validity, a screening question was applied to exclude respondents who had never used a purchasing agent via Instagram. Consequently, 32 responses were deemed invalid, leaving 203 valid responses for further analysis. The data collection process was conducted over approximately three weeks, from March 6 to March 27, 2024. The dataset was processed using Microsoft Excel and SmartPLS 4 for subsequent statistical analysis.

The demographic profile of respondents indicates that the majority are female (87.2%), reflecting a higher tendency among women to engage in online shopping, particularly through purchasing agents. Most respondents fall within the age range of 28–38 years (68.5%), hold an undergraduate degree (75.4%), and are employed (67.5%). In terms of income, 46.8% report a monthly income between IDR 4,000,000 and IDR 8,000,000 (approximately NT$8,000–16,000), which aligns with the average income level for undergraduate graduates in Indonesia.

Regarding purchasing behavior, many respondents consider the number of followers when selecting a purchasing agent, with 30% preferring agents with 500–5,000 followers. Overall, 77.8% of respondents indicate that a higher number of followers enhances their trust in a purchasing agent, consistent with prior findings that follower count serves as a signal of credibility and legitimacy (Abdul & Mat, 2017). Additionally, most respondents report purchasing through a purchasing agent two to five times (60.6%), with the majority spending between IDR 200,000 and IDR 600,000 (approximately NT$400–1,200) per transaction (58.6%).

4.2 Descriptive Statistics

This study employs descriptive statistics to summarize the data and assess its variability. Descriptive statistics provide a systematic way to organize and describe the key characteristics of a dataset. They include measures of central tendency and dispersion, such as the mean, median, minimum, maximum, and standard deviation.

Table 1: Descriptive Statistics

Variable	Indicator	N	Minimum	Maximum	Mean	Standart Deviation
Perceived of Service Quality (PSQ)	PSQ1	203	1.000	5.000	3.788	0.824
	PSQ2	203	1.000	5.000	4.084	0.835
	PSQ3	203	1.000	5.000	4.158	0.833
	PSQ4	203	1.000	5.000	4.246	0.793
Personalization (PRZ)	PRZ1	203	1.000	5.000	4.389	0.795
	PRZ2	203	1.000	5.000	4.094	0.880
	PRZ3	203	1.000	5.000	4.212	0.824
	PRZ4	203	1.000	5.000	4.404	0.803
Satisfaction (CST)	CST1	203	2.000	5.000	3.990	0.716
	CST2	203	2.000	5.000	3.897	0.765
	CST3	203	1.000	5.000	4.049	0.714
	CST4	203	1.000	5.000	3.852	0.909
Product Diversity (PDV)	PDV1	203	2.000	5.000	3.990	0.854
	PDV2	203	2.000	5.000	4.103	0.839
	PDV3	203	2.000	5.000	4.138	0.831
	PDV4	203	2.000	5.000	4.217	0.820
Price (PRC)	PRC1	203	1.000	5.000	4.527	0.751
	PRC2	203	1.000	5.000	4.438	0.781
	PRC3	203	1.000	5.000	4.118	0.960
	PRC4	203	1.000	5.000	4.103	0.995
eWOM (EWM)	EWM1	203	1.000	5.000	3.714	0.986
	EWM2	203	1.000	5.000	3.759	1.020
	EWM3	203	1.000	5.000	3.926	1.022
	EWM4	203	1.000	5.000	3.970	0.987
Hedonic Value (HDN)	HDN1	203	1.000	5.000	3.690	0.858
	HDN2	203	1.000	5.000	3.995	0.851
	HDN3	203	1.000	5.000	3.729	0.905
	HDN4	203	1.000	5.000	3.887	0.900
Purchase Intention (PIT)	PIT1	203	2.000	5.000	3.813	0.815
	PIT2	203	1.000	5.000	4.054	0.916
	PIT3	203	2.000	5.000	3.833	0.819
	PIT4	203	1.000	5.000	3.966	0.839

Given that this study utilizes interval-scale data, the mean and standard deviation are the primary statistics used for interpretation. The minimum and maximum values are derived from respondents' Likert-scale responses. The mean (average) is calculated by summing all response scores and dividing by the total number of respondents (N = 203). While the mean provides a measure of central tendency, it is sensitive to extreme values and the overall distribution of the data. The standard deviation reflects the extent to which the data are dispersed around the mean, indicating the level of variability within the dataset. It is calculated as the square root of the variance. Table 1 presents the descriptive statistics for the variables examined in this study.

4.3 Validity Testing

Convergent validity is a crucial aspect of measurement model assessment, ensuring that indicators adequately represent their underlying constructs (Zhou, 2019). According to Hair et al. (2019), the Average Variance Extracted (AVE) is a commonly used metric for evaluating convergent validity, with a recommended threshold of 0.50 or higher. As shown in Table 2, all constructs in this study exhibit AVE values exceeding the recommended threshold, ranging from 0.660 to 0.819. These results indicate that the constructs explain more than 50% of the variance of their respective indicators, thereby demonstrating strong convergent validity. Accordingly, all variables in this study meet the required criteria for convergent validity.

Table 2: The Average Variance Extracted (AVE)

Variable	Average variance extracted (AVE)	Decision
CST	0.732	Accepted
EWM	0.819	Accepted
HDN	0.684	Accepted
PDV	0.759	Accepted
PIT	0.672	Accepted
PRC	0.660	Accepted
PRZ	0.716	Accepted
PSQ	0.664	Accepted

4.4 Cross-Loading

Discriminant validity ensures that a construct is empirically distinct from other constructs in the model. According to Hair et al. (2019), indicator loadings for a given construct should be higher than their loadings on other constructs, with a recommended threshold of 0.70 or above. As shown in Table 3, all indicator loadings exceed the recommended cutoff, ranging from 0.751 to 0.943. These results indicate that each indicator has a stronger association with its respective construct than with other constructs. Therefore, the indicators demonstrate adequate discriminant validity, as each construct is clearly distinguished from the others (Suryani & Syafarudin, 2021).

Table 3: The Cross-Loading Test Result

Indicator	CST	EWM	HDN	PDV	PIT	PRC	PRZ	PSQ
CST1	0.892	0.161	0.543	0.445	0.564	0.454	0.462	0.543
CST2	0.887	0.230	0.451	0.435	0.530	0.404	0.392	0.544
CST3	0.861	0.220	0.451	0.443	0.511	0.455	0.452	0.566
CST4	0.778	0.253	0.513	0.445	0.506	0.399	0.377	0.486
EWM1	0.100	0.878	0.175	0.097	0.234	0.168	0.131	0.171
EWM2	0.190	0.898	0.193	0.138	0.285	0.230	0.150	0.199
EWM3	0.293	0.943	0.230	0.219	0.357	0.288	0.231	0.338
EWM4	0.283	0.899	0.199	0.207	0.318	0.292	0.204	0.305
HDN1	0.547	0.224	0.858	0.362	0.618	0.431	0.333	0.480
HDN2	0.484	0.223	0.822	0.357	0.618	0.381	0.281	0.371
HDN3	0.349	0.137	0.772	0.250	0.432	0.288	0.309	0.321
HDN4	0.481	0.137	0.853	0.355	0.575	0.361	0.315	0.368
PDV1	0.368	0.116	0.310	0.766	0.284	0.368	0.358	0.236
PDV2	0.465	0.159	0.364	0.889	0.425	0.488	0.448	0.385
PDV3	0.462	0.204	0.353	0.908	0.429	0.455	0.439	0.359
PDV4	0.489	0.172	0.384	0.913	0.416	0.492	0.457	0.383
PIT1	0.548	0.233	0.594	0.444	0.791	0.445	0.319	0.429
PIT2	0.527	0.335	0.537	0.351	0.808	0.496	0.375	0.436
PIT3	0.509	0.291	0.570	0.368	0.850	0.415	0.324	0.420
PIT4	0.432	0.240	0.551	0.317	0.831	0.421	0.338	0.420
PRC1	0.500	0.230	0.450	0.523	0.515	0.846	0.664	0.598
PRC2	0.452	0.174	0.373	0.470	0.471	0.869	0.656	0.572
PRC3	0.337	0.266	0.331	0.394	0.388	0.775	0.347	0.288
PRC4	0.303	0.247	0.275	0.267	0.366	0.753	0.389	0.343
PRZ1	0.514	0.178	0.366	0.472	0.410	0.609	0.890	0.594
PRZ2	0.262	0.113	0.198	0.296	0.183	0.459	0.751	0.470
PRZ3	0.284	0.177	0.260	0.347	0.276	0.488	0.818	0.417
PRZ4	0.499	0.205	0.375	0.484	0.439	0.612	0.916	0.643
PSQ1	0.546	0.225	0.409	0.287	0.436	0.421	0.490	0.851
PSQ2	0.485	0.319	0.352	0.330	0.444	0.477	0.534	0.820
PSQ3	0.508	0.218	0.390	0.321	0.412	0.486	0.569	0.822
PSQ4	0.495	0.187	0.379	0.366	0.404	0.490	0.515	0.763

4.5 Fornell-Larcker Criterion

The Fornell–Larcker criterion is commonly used to assess discriminant validity by comparing the square root of the Average Variance Extracted (AVE) for each construct with its correlations with other constructs (Fornell & Larcker, 1981). Specifically, the square root of the AVE—represented by the diagonal elements—should be greater than the corresponding inter-construct correlations in the same row and column. As presented in Table 4, the square root of the AVE for each construct exceeds its correlations with other constructs. This result indicates that each construct shares more variance with its own indicators than with other constructs, thereby confirming that the measurement model satisfies the criteria for discriminant validity.

Table 4: The Fornell-Larcker Criterion

Variable	CST	EWM	HDN	PDV	PIT	PRC	PRZ	PSQ
CST	0.856							
EWM	0.251	0.905						
HDN	0.572	0.223	0.827					
PDV	0.516	0.190	0.406	0.871				
PIT	0.617	0.336	0.688	0.453	0.820			
PRC	0.501	0.277	0.448	0.521	0.543	0.812		
PRZ	0.493	0.204	0.373	0.492	0.414	0.653	0.846	
PSQ	0.625	0.290	0.471	0.398	0.520	0.574	0.646	0.815

4.6 Heterotrait-Monotrait (HTMT)

The Heterotrait–Monotrait ratio (HTMT) is a widely used criterion for assessing discriminant validity, defined as the ratio of the average correlations between indicators of different constructs to the average correlations between indicators of the same construct (Russo & Stol, 2021). Although a threshold of 0.90 is generally acceptable, a more conservative cutoff of 0.85 is often recommended to ensure stricter discriminant validity (Henseler, Ringle, & Sarstedt., 2015). As shown in Table 5, all HTMT values are below the conservative threshold of 0.85. This result indicates that the constructs are empirically distinct from one another, thereby confirming strong discriminant validity among the variables examined in this study.

Table 5: The Heterotrait-Monotrait (HTMT)

Variable	CST	EWM	HDN	PDV	PIT	PRC	PRZ	PSQ
CST								
EWM	0.268							
HDN	0.654	0.244						
PDV	0.580	0.197	0.459					
PIT	0.718	0.373	0.803	0.514				
PRC	0.574	0.314	0.517	0.586	0.640			
PRZ	0.523	0.215	0.414	0.530	0.449	0.725		
PSQ	0.732	0.321	0.554	0.456	0.624	0.670	0.735	

4.7 Reliability Testing

Indicator reliability refers to the extent to which the variance of an observed indicator is explained by its underlying latent construct. In PLS-SEM, indicator reliability is primarily assessed through outer loadings, while internal consistency reliability is commonly evaluated using Cronbach's alpha and composite reliability (Ab Hamid et al., 2017).

As presented in Table 6, the outer loadings range from 0.751 to 0.943, exceeding the recommended threshold of 0.708 (Hair et al., 2014). This indicates that all indicators exhibit satisfactory reliability in representing their respective constructs (Mohd Dzin & Lay, 2021). Therefore, all reflective indicators are considered reliable for measuring the latent variables, including purchase intention as the dependent variable.

Furthermore, internal consistency reliability is confirmed through Cronbach's alpha values. According to Gliem & Gliem (2003), a value of 0.70 or higher indicates acceptable reliability. As shown in Table 6, all constructs exceed this threshold, with Cronbach's alpha values ranging from 0.829 to 0.894, demonstrating good internal consistency. Specifically, PRC (0.829), PSQ (0.830), PIT (0.837), HDN (0.847), CST (0.877), PRZ (0.873), and PDV (0.894) exhibit strong reliability. Additionally, EWM reports a Cronbach's alpha of 0.927, indicating very high internal consistency.

Table 6: The Outer Loading and Reliability Test Result

Indicator	Outer Loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
CST1	0.892	0.877	0.880	0.916
CST2	0.887			
CST3	0.861			
CST4	0.778			
EWM1	0.878	0.927	0.946	0.947
EWM2	0.898			
EWM3	0.943			
EWM4	0.899			
HDN1	0.858	0.847	0.859	0.896
HDN2	0.822			
HDN3	0.772			
HDN4	0.853			
PDV1	0.766	0.894	0.914	0.926
PDV2	0.889			
PDV3	0.908			
PDV4	0.913			
PIT1	0.791	0.837	0.838	0.891
PIT2	0.808			
PIT3	0.850			
PIT4	0.831			
PRC1	0.846	0.829	0.846	0.885
PRC2	0.869			
PRC3	0.775			
PRC4	0.753			
PRZ1	0.890	0.873	0.939	0.909
PRZ2	0.751			
PRZ3	0.818			
PRZ4	0.916			
PSQ1	0.851	0.830	0.833	0.887
PSQ2	0.820			
PSQ3	0.822			
PSQ4	0.763			

4.8 Structural Model

Bootstrapping is a resampling technique used in PLS-SEM to generate empirical sampling distributions and assess the significance of path coefficients (Magno, Cassia, & Ringle, 2024). It enables hypothesis testing without relying on strict normality assumptions. Prior research indicates that a 95% confidence level ($p < 0.05$), corresponding to a t-value of 1.96, is commonly adopted for hypothesis validation (Zeng et al., 2021). Figure 4 illustrates the structural model employed in this study. In addition, multicollinearity was assessed using the Variance Inflation Factor (VIF).

According to Hair et al. (2019), VIF values below 5 indicate that collinearity is not a critical concern. As presented in Table 7, all VIF values range from 1.108 to 1.828, well below the recommended threshold. Although some studies suggest that collinearity issues may arise at lower thresholds, such as VIF values above 3

(Becker et al., 2015), the results in this study indicate no evidence of multicollinearity among the indicators.

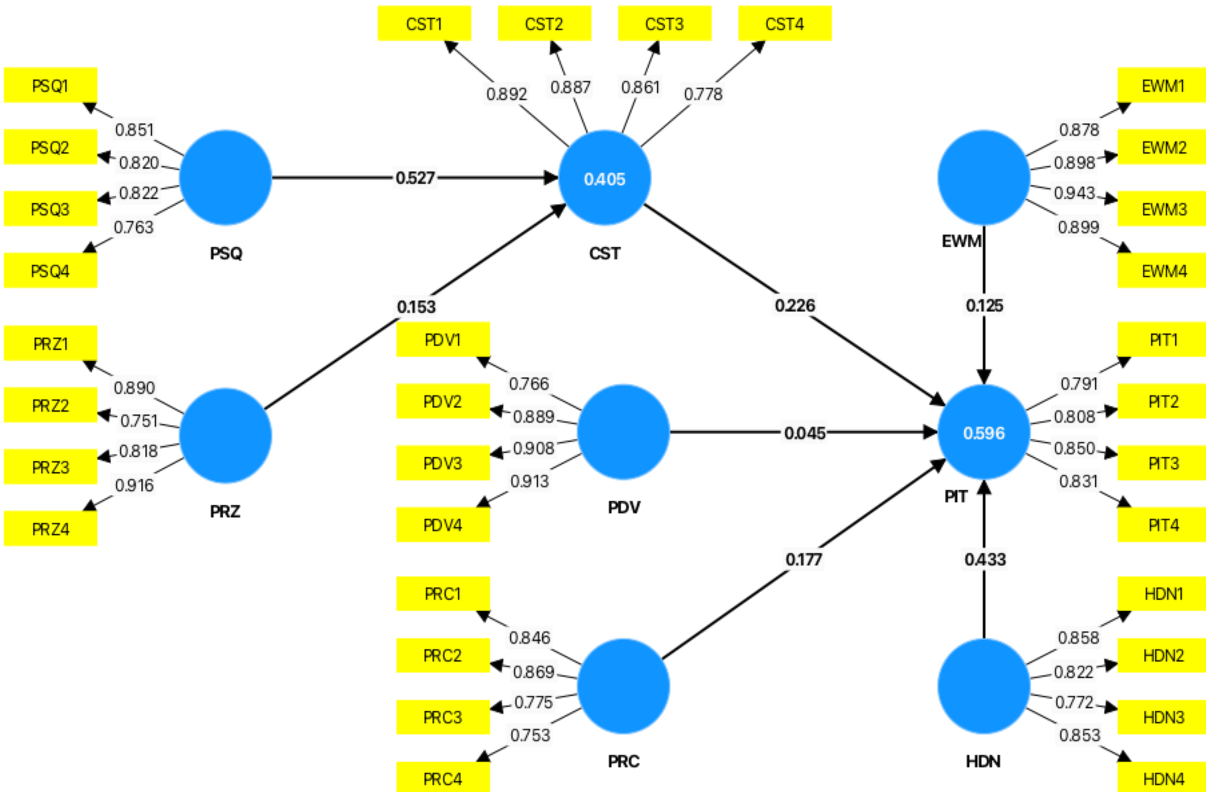

Figure 4: Structural Model Testing

Table 7: Inner Model VIF Result

Variable	VIF
CST -> PIT	1.828
EWM -> PIT	1.108
HDN -> PIT	1.584
PDV -> PIT	1.570
PRC -> PIT	1.619
PRZ -> CST	1.716
PSQ -> CST	1.716

The coefficient of determination (R^2) is used to assess the explanatory power of the structural model (Russo & Stol, 2021). As presented in Table 8, the R^2 value for customer satisfaction is 0.405, while the R^2 for purchase intention is 0.596. These results indicate that 40.5% of the variance in customer satisfaction and 59.6% of the variance in purchase intention are explained by the model's exogenous constructs. According to established guidelines, R^2 values above 0.25 are considered to indicate moderate explanatory power (Henseler, Ringle, & Sarstedt., 2015; Hair et al., 2019). Therefore, both constructs demonstrate acceptable and moderate levels of predictive accuracy, suggesting that the model provides a meaningful explanation of the endogenous variables.

Table 8: R-square (R^2) Result

Variable	R-square	Adjusted R-square
CST	0.405	0.399
PIT	0.596	0.586

The adjusted coefficient of determination (adjusted R^2) provides a more accurate estimate of the model's explanatory power by accounting for the number of predictors. As shown in Table 8, the adjusted R^2 for customer satisfaction is 0.399, indicating that 39.9% of its variance is explained by the independent variables, while the remaining variance is attributable to factors not included in the model. Similarly, the adjusted R^2 for purchase intention is 0.586, suggesting that 58.6% of its variance is explained by the model.
The effect size (f^2) assesses the relative impact of each exogenous construct on an endogenous construct (Russo & Stol, 2021). It measures the strength of the relationship between variables on a standardized scale. According to Cohen (1988), f^2 values of less than 0.02 indicate no effect, values between 0.02 and 0.15 indicate a small effect, and values between 0.15 and 0.35 indicate a medium effect.

Table 9: f-square (f^2) Result

Path	**f-square**	**Result**
CST -> PIT	0.069	small effect
EWM -> PIT	0.035	small effect
HDN -> PIT	0.293	medium-sized effect
PDV -> PIT	0.003	no effect
PRC -> PIT	0.048	small effect
PRZ -> CST	0.023	small effect
PSQ -> CST	0.272	medium-sized effect

Based on the results presented in Table 9, the constructs in this study exhibit varying levels of effect size. Customer satisfaction, electronic word-of-mouth (eWOM), and price demonstrate small effects on purchase intention. Product diversity shows no effect on purchase intention, which is consistent with its non-significant p-value. Personalization exhibits a small effect on customer satisfaction. In contrast, hedonic value has a medium effect on purchase intention, while perceived service quality shows a medium effect on customer satisfaction.

4.9 Prediction Model

The predictive relevance of the structural model is assessed using the Q^2 statistic, where values greater than zero indicate that the model has predictive relevance for a given endogenous construct. According to Hair et al. (2019), Q^2 values of 0.02, 0.15, and 0.35 can be interpreted as small, medium, and large predictive relevance, respectively.

As presented in Table 10, the Q^2 values for CST1, CST2, CST3, PIT1, PIT2, PIT3, and PIT4 range from 0.285 to 0.382, exceeding the threshold of 0.25 and indicating medium predictive relevance. In contrast, CST4 has a Q^2 value of 0.233, suggesting a small level of predictive relevance. Overall, these results demonstrate that the PLS path model exhibits acceptable predictive capability.

Furthermore, predictive performance was evaluated by comparing Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values between the PLS-SEM model and a linear model (LM) benchmark (Hair et al., 2019). As shown in Table 10, 7 out of 16 indicators have higher RMSE and MAE values in the PLS-SEM model compared to the LM benchmark. Since higher RMSE and MAE values indicate lower predictive accuracy, these findings suggest that the model demonstrates moderate predictive power overall.

Table 10: Prediction Model Test Result

Path model	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
CST1	0.302	0.601	0.486	0.585	0.453
CST2	0.285	0.650	0.540	0.660	0.537
CST3	0.320	0.592	0.457	0.598	0.450
CST4	0.233	0.801	0.639	0.756	0.567
PIT1	0.382	0.644	0.515	0.661	0.504
PIT2	0.371	0.730	0.547	0.733	0.548
PIT3	0.357	0.661	0.532	0.702	0.549
PIT4	0.324	0.693	0.540	0.733	0.566

4.10 Model Fit

Model fit in this study is assessed using the estimated model approach, as recommended by Magno, Cassia, & Ringle (2024) for reporting PLS-SEM results. The Standardized Root Mean Square Residual (SRMR) is defined as the difference between the observed correlation matrix and the model-implied correlation matrix. As presented in Table 11, the SRMR value is 0.085, while the Normed Fit Index (NFI) is 0.739. According to Hulland (1999), an SRMR value below 0.08 is generally considered indicative of a good fit. Although the SRMR value in this study slightly exceeds this threshold, it remains within an acceptable range for PLS-SEM applications. In addition, the NFI value of 0.739 suggests a moderate level of model fit, indicating that the model provides a reasonably adequate representation of the observed data. Taken together, these results suggest that the proposed model demonstrates an acceptable level of fit and is suitable for further interpretation of the structural relationships.

Table 11: Model Fit Test Result

Criteria	Saturated model	Estimated model
SRMR	0.070	0.085
d_ULS	2.556	3.832
d_G	1.061	1.114
Chi-square	1276.636	1301.517
NFI	0.744	0.739

Hypothesis testing was conducted using data from 203 Indonesian respondents, processed with Microsoft Excel and SmartPLS 4. Based on the analysis results, hypotheses H1, H2, H3, H5, H6, and H7 are supported, while H4 is not supported. The detailed results are presented in Table 12, and each hypothesis is further discussed in this subsection.

Table 12: Summary of the Hypotheses Result

Hypotheses	Standard Estimation	Conclusion
H1: Trust positively moderates the relationship between perceived service quality and customer satisfaction through a purchasing agent.	0.527 (0.000)	Supported
H2: There is a positive and significant relationship between personalization and customer satisfaction through a purchasing agent.	0.153 (0.024)	Supported
H3: There is a positive and significant relationship between customer satisfaction and purchase intention through a purchasing agent	0.226 (0.001)	Supported
H4: There is a positive and significant relationship between product diversity and purchase intention through a purchasing agent	0.045 (0.473)	Not supported
H5: There is a positive and significant relationship between price and purchase intention through a purchasing agent	0.177 (0.004)	Supported
H6: There is a positive and significant relationship between eWOM and purchase intention through a purchasing agent.	0.125 (0.037)	Supported
H7: There is a positive and significant relationship between hedonic value and purchase intention through a purchasing agent	0.433 (0.000)	Supported

The findings show that **H1** is supported, indicating that trust strengthens the relationship between perceived service quality and customer satisfaction, as reliable and high-quality service enhances customer confidence. **H2** is also supported, demonstrating that personalization significantly improves customer satisfaction by providing tailored recommendations and enhancing customer engagement. Furthermore, **H3** confirms that customer satisfaction positively influences purchase intention, as satisfied customers are more likely to repurchase and recommend the service. However, **H4** is not supported, revealing that product diversity does not significantly affect purchase intention, possibly due to decision fatigue and choice overload when too many options are available. In contrast, **H5** is supported, showing that price positively influences purchase intention, particularly when it aligns with customers' budgets and offers perceived value through promotions. Similarly, **H6** is supported, indicating that electronic word-of-mouth (eWOM) significantly enhances purchase intention by providing credible information through reviews and testimonials, thereby reducing perceived risk. Finally, **H7** is supported, confirming that hedonic value positively affects purchase intention, as emotional enjoyment, excitement, and the appeal of unique products encourage purchasing behavior. Overall, these results suggest that both functional factors (service quality, price, eWOM) and emotional drivers (trust, personalization, hedonic value) jointly shape customer satisfaction and purchase intention in the context of purchasing agents.

5. Conclusion

This study examined the determinants of purchase intention through purchasing agents in Indonesia using PLS-SEM with 203 respondents. The findings confirm that **t**rust and personalization significantly enhance customer satisfaction, while customer satisfaction, price, eWOM, and hedonic value positively influence purchase intention. Among these, hedonic value emerges as the strongest driver, highlighting the importance of emotional and experiential factors in online purchasing behavior. Conversely, product diversity shows no significant effect, suggesting that excessive choices may lead to decision fatigue and reduced purchase intention.

From a theoretical perspective, the results reinforce the role of trust as a moderating mechanism and confirm that customer satisfaction serves as a key mediator linking service-related factors to behavioral intention. The findings also extend prior research by demonstrating that emotional (hedonic) value can outweigh functional attributes in shaping purchase decisions in cross-border and agent-based commerce contexts.

Practically, purchasing agents should focus on delivering high service quality, building trust, and providing personalized interactions to enhance satisfaction and long-term relationships. Strategic emphasis on competitive pricing, promotional activities, and active management of eWOM (e.g., reviews and testimonials) is essential to strengthen purchase intention. Additionally, rather than offering excessive product variety, agents should adopt curated and targeted product selections to reduce consumer overload and facilitate decision-making. Overall, this study provides a comprehensive understanding of consumer behavior in the Indonesian purchasing agent market and offers actionable insights for improving customer satisfaction and purchase intention in increasingly competitive online environments.

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