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NAVIGATING DIGITAL DISRUPTION: CONSUMER BEHAVIOR-DRIVEN INNOVATION FOR SUSTAINABLE BUSINESS

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Abstract

This study aims to analyze the influence of Digital Innovation and Consumer Behavior on Customer Experience and Competitive Advantage in the context of retail product consumers in the Greater Jakarta area. Using a quantitative approach, data were collected from 200 respondents and analyzed using a structural model. The results showed that Digital Innovation has a significant positive effect on Customer Experience (path coefficient = 0.195; T = 2.538; P = 0.006) and Competitive Advantage (path coefficient = 0.140; T = 1.884; P = 0.030). Consumer Behavior also has a significant positive effect on Customer Experience (path coefficient = 0.381; T = 5.717; P = 0.000) and Competitive Advantage (path coefficient = 0.309; T = 4.179; P = 0.000). Customer Experience is proven to be a significant mediator in the relationship between the two on Competitive Advantage. These findings emphasize the importance of digital innovation, understanding consumer behavior, and customer experience in building sustainable competitive advantage. Therefore, the success of digital innovation must be measured by the extent to which a company creates value for stakeholders, including consumers, society, and the environment. Technology-based innovation, implemented ethically and sustainably, is a key foundation in the Marketing 6.0 era amid ongoing digital disruption.

Keywords: Digital innovation, consumer behavior, consumer experience, competitive advantage, digital disruption.

Introduction

The development of digital technology has brought about a paradigmatic shift in consumer behavior and the business strategies of companies worldwide. Digital transformation has not only expanded consumer access to products and services but also altered the way consumers interact with brands, influencing their purchasing decisions and expectations of the customer experience (Verhoef et al., 2021). Digital technologies, including e-commerce, social media, mobile applications, and artificial intelligence (AI), have eliminated geographical and temporal barriers, enabling consumers to make purchases quickly, easily, and personally (Huang & Rust, 2022). This situation encourages companies to adapt through continuous innovation to maintain competitiveness in an increasingly dynamic and competitive market.

Innovation in the digital landscape now extends beyond creating new products to include transforming internal processes, digital marketing, and customer-focused business models (Teece, 2018). An omnichannel strategy that combines various digital and physical channels has become essential for providing a seamless and consistent customer experience (Verhoef et al., 2021). Furthermore, utilizing consumer data from digital interactions allows companies to develop more targeted personalization through AI-driven recommendation algorithms and machine learning (ML) (Grewal et al., 2017). This more profound understanding of consumer preferences and behaviors not only enhances customer satisfaction but also fosters long-term loyalty and retention (Lemon & Verhoef, 2016).

Technological advancements also bring new challenges related to data ethics, sustainability, and inclusivity. Digital consumers are increasingly aware of the social and environmental impacts of the products they consume and demand transparency and social responsibility from companies (Sheth, 2020). Therefore, sustainable and inclusive innovation is key for companies to achieve not only economic profits but also create sustainable social value (Nidumolu et al., 2009). This approach aligns with the global trend toward a circular economy and the widespread adoption of environmentally friendly business practices (Geissdoerfer et al., 2017).

The Digital Innovation Revolution in Consumer Behavior and Business Strategy

The development of digital technology has brought significant changes to consumer behavior and the global business landscape. This transformation has not only affected how consumers search for and select products but has also compelled companies to adapt through ongoing innovation in their products, processes, marketing, and business models. Digital innovation now plays a crucial role in helping companies

stay competitive and relevant in this rapidly changing era (Verhoef et al., 2021).

The digital technologies supporting this innovation include advanced tools like big data, artificial intelligence (AI), machine learning (ML), and augmented and virtual reality (AR/VR). Utilizing these technologies enables companies to deliver more personalized and engaging experiences to consumers while enhancing operational efficiency and facilitating data-driven decision-making (Huang & Rust, 2022). Additionally, the omnichannel approach, which combines various sales and communication channels, has become essential in meeting the needs of modern consumers for convenience and consistent service across multiple platforms (Beck & Rygl, 2015; Lemon & Verhoef, 2016).

However, the progress of digital innovation must be considered in conjunction with ethics, sustainability, and inclusivity. Rapid technological advancements present new challenges related to data privacy, algorithm transparency, and the environmental consequences of digital technology use. Therefore, companies are expected to innovate not only to increase economic returns but also to integrate sustainability and ethical principles into their business strategies, thereby creating sustainable long-term value (Chatterjee et al., 2021; Kennedy & Bocken, 2020).

The theoretical framework underlying the study of digital innovation and consumer behavior involves theories of technological innovation, consumer behavior theory, and models of organizational adaptation to technological change (Ajzen, 1991; Botsman & Rogers, 2010). Innovation performance indicators frequently used in the literature include technology adoption rates, consumer satisfaction, process efficiency improvements, and long-term financial impact. A comprehensive assessment of these indicators helps gauge the effectiveness of digital innovation implemented by companies (OECD, 2018).

Recent articles and literature studies from various reputable international journals and local sources indicate that the success of digital innovation is significantly influenced by an organization's ability to manage big data, thoroughly understand consumer behavior, and integrate new technologies with adaptive marketing strategies (Chaffey et al., 2016; Kannan & Li, 2017). Furthermore, companies that successfully adopt an omnichannel business model can achieve a sustainable competitive advantage by providing seamless and personalized services to consumers (Lemon & Verhoef, 2016).

Looking ahead, the challenges of digital innovation are becoming increasingly complex, with rising consumer expectations and rapid technological advancements. Opportunities include the development of new technologies such as the Internet of Things (IoT), blockchain, and increasingly sophisticated artificial intelligence. Meanwhile, risks related to cybersecurity, algorithmic bias, and unequal access to technology must be seriously addressed to ensure innovation can deliver broad benefits without causing significant adverse impacts (Rabby et al., 2022).

Overall, digital innovation has become a key driver of changing consumer behavior and modern business strategies. A deep understanding of these dynamics, coupled with a holistic and ethical approach, is the foundation for companies seeking to survive and thrive in this digital era.

Theoretical Framework and Performance Indicators of Digital Innovation

Theoretical Framework of Digital Innovation

Digital innovation is a multidimensional concept that refers to the application of digital technology to create new products, services, processes, and business models that add value to consumers and companies. Understanding digital innovation can be enriched by referring to several key theories, including the diffusion of innovation theory, technology adoption theory, and the theory of complex adaptive systems.

(Rogers, 2014) The diffusion of Innovation Theory, as proposed, explains how innovations spread among individuals or organizations through the stages of awareness, interest, evaluation, trial, and adoption. In the context of digital innovation, this diffusion becomes more dynamic due to the rapid spread of digital technology and the influence of digital social networks. Meanwhile, technology adoption theory, specifically the Technology Acceptance Model (TAM), developed emphasizes two main factors influencing technology adoption: perceived ease of use and perceived usefulness. This model is highly relevant in explaining how consumers and organizations adopt new digital innovations (Davis, 1989).

Furthermore, the theory of complex adaptive systems (CADA) views organizations as open systems capable of dynamically adapting to environmental changes through interactions between internal and external elements (Holland, 2006). This theory offers a perspective that digital innovation is not merely the implementation of technology, but also a process of organizational evolution that necessitates flexibility, continuous learning, and collaboration among various stakeholders.

Digital innovation is a complex and multidimensional idea that involves applying digital technology to develop new products, services, processes, and business models that deliver value to both consumers and

organizations. A deeper understanding of digital innovation can be achieved by exploring several key, complementary theories, including the Diffusion of Innovation Theory, Technology Adoption Theory, and the Theory of Complex Adaptive Systems.

1. Diffusion of Innovation Theory (Rogers, 2014)

This theory explains how an innovation spreads and is adopted by individuals or organizations through five sequential stages: awareness, interest, evaluation, trial, and adoption. In the context of digital innovation, this spread becomes much faster and more dynamic due to the easily accessible and globally distributed characteristics of digital technology, as well as the influence of digital social networks that accelerate communication and information exchange. This allows digital innovation to spread not only linearly but also through complex social interactions and influences, thus forming a more adaptive and responsive innovation ecosystem.

2. Technology Adoption Theory (Davis, 1989)

One of the most well-known models is the Technology Acceptance Model (TAM), which emphasizes two key factors influencing technology adoption: perceived ease of use and perceived usefulness. This model is relevant for understanding how consumers and organizations decide to adopt digital innovations, as these decisions depend heavily on the extent to which the technology is perceived to help solve problems and how easy it is to use. TAM helps explain user resistance or acceptance of digital innovations and can guide the design of more user-friendly and value-added technologies.

3. Theory of Complex Adaptive Systems (Holland, 2006)

This approach views organizations as dynamic and complex open systems, capable of continuously adapting to environmental changes through interactions between internal and external elements. In the context of digital innovation, this theory presents the perspective that innovation is not simply the implementation of technology, but rather a process of organizational evolution that involves flexibility, continuous learning, and collaboration among various stakeholders, both within and outside the organization. This approach highlights the importance of interconnected and responsive systems in fostering sustainable innovation, as well as the need for organizations to adapt to the rapid changes of the digital era.

Digital Innovation Performance Indicators

Measuring the success of digital innovation requires comprehensive and multidimensional performance indicators. According to the OECD (2018), innovation performance indicators can be categorized into three main aspects: innovation input, process, and output.

Innovation Input

Innovation input encompasses resources allocated to innovation, including investments in digital technology, skilled human resources, and information technology infrastructure. Research by Zhang et al. (2018) emphasized that the quality and quantity of these inputs significantly determine the level of innovation an organization can achieve.

In an increasingly digitalized business environment, innovation input plays a crucial role in shaping the overall success of the innovation process. Innovation input refers to all resources allocated by an organization to support the creation, development, and implementation of new solutions. These inputs include investments in digital technology, human resource development, and access to adequate information technology infrastructure. The quality and quantity of these inputs are key factors that influence the intensity and effectiveness of the resulting innovation (Zhang et al., 2018).

First, investing in digital technology is a vital part of innovation input. Organizations that dedicate sufficient budgets to software, automation systems, artificial intelligence, and cloud-based technologies will gain a competitive edge in their innovative capabilities. These investments not only support the development of new products or services but also improve operational efficiency and enable quicker responses to market changes (Bharadwaj et al., 2013). The right technology enables companies to integrate data, accelerate decision-making, and test various prototypes more effectively.

Second, skilled human resources are an essential asset in the innovation process. Digital innovation requires a combination of technical skills and soft skills, including creativity, collaboration, and critical thinking. Organizations that invest in training, recruiting digital talent, and cultivating an innovative culture are better positioned to generate new ideas and implement them successfully (Barney, 1991).Additionally, the presence of interdisciplinary teams capable of working together enhances the quality of innovation by offering a broader perspective in problem-solving.

Third, information technology (IT) infrastructure serves as the foundation that supports the entire digital innovation ecosystem. A robust IT infrastructure comprises a reliable network system, a secure and integrated data platform, and digital collaboration tools that facilitate remote work and enable real-time synchronization. With a solid IT infrastructure, organizations can create an agile, connected, and data-driven work environment—three key characteristics that foster sustainable innovation (Chen et al., 2012).

Research by Zhang et al. (2018) confirms that the success of innovation depends not only on having a brilliant idea or the right market strategy, but is also greatly influenced by the extent to which the organization provides adequate input for innovation. Without sufficient and well-targeted resource support, innovation efforts are likely to fail to achieve their transformational goals.

Thus, innovation input should be viewed as a strategic investment, not simply an operational expense. Organizations that consistently allocate resources to technology, people, and infrastructure will be better prepared to face the challenges of digital disruption and create a sustainable competitive advantage.

Innovation Process

The innovation process includes the activities of developing, testing, and implementing new digital technologies. Cross-functional collaboration and agile methodology are important indicators in this process (Rigby et al., 2016). Additionally, the application of data analytics and artificial intelligence methods during the innovation process facilitates effective decision-making and accelerates innovation cycles (Davenport & Ronanki, 2018).

The innovation process is central to sustainable digital transformation in today's organizations. Innovation is no longer just about creating new ideas; it involves a series of activities that include developing, testing, and implementing technological solutions that can adaptively solve business challenges. In this context, the innovation process must be designed systematically yet flexibly to keep up with constantly changing market dynamics.

One crucial factor in the effectiveness of the innovation process is the implementation of agile methodology, a managerial approach focused on rapid iteration, continuous learning, and cross-functional collaboration. Agile enables innovation teams to work in short cycles (sprints) to produce prototypes that can be quickly tested and further developed based on user feedback. Rigby et al. (2016) note that organizations that successfully adopt agile broadly can increase organizational agility and accelerate the achievement of innovative results.

Cross-functional collaboration is essential for digital innovation. Innovation can't occur in isolated departments; it requires synergy among information technology, marketing, operations, finance, and human resources. Diverse perspectives from cross-functional teams enhance ideas and help create more comprehensive solutions. This collaboration also promotes broader participation in the change process and reduces resistance to adopting new innovations (Tushman et al., 1996).

In the digital age, decision-making during the innovation process increasingly depends on data analytics and artificial intelligence. Data is used not only to understand customer needs and market trends but also to validate innovation hypotheses, assess prototype performance, and identify areas for improvement (Davenport & Ronanki, 2018). Artificial intelligence enables organizations to automate evaluation and forecasting, thereby accelerating the innovation cycle and reducing the cost of mistakes.

Furthermore, integrating digital technologies like collaborative platforms, cloud computing, and modern software development tools boosts the efficiency of the innovation process. These technologies speed up team coordination, support experimentation, and improve the scalability of solutions. Innovation is no longer viewed just as a long-term activity but as an ongoing, iterative process that is constantly updated and refined.

Therefore, an effective innovation process requires a blend of an agile approach, cross-functional teamwork, and data-driven technologies. Organizations that can align these three components will be better positioned to navigate digital disruption and create new value sustainably. The innovation process is not just an operational task but a vital strategy for success in the complex and quickly changing digital era.

Innovation Output

Innovation output can be measured through several dimensions, such as:

- The rate at which consumers adopt new digital products or services.
- Financial impact of innovation, such as increased revenue or cost efficiencies (Kane et al., 2015)
- Consumer satisfaction and loyalty towards digital innovation (Lemon & Verhoef, 2016).
- Social and environmental impact, such as the innovation's contribution to sustainability (Kennedy & Bocken, 2020).

Innovation output refers to the tangible results of an organization's innovative efforts, including new products, services, or business methods, as well as the social and environmental impacts they generate. Measuring innovation output is essential for assessing the effectiveness of innovation strategies, ensuring business sustainability, and understanding the value created by innovative investments. Key factors for measuring innovation output include adoption rate, financial impact, customer satisfaction and loyalty, and contribution to sustainability.

One key indicator of innovation success is the rate at which consumers adopt a new product or service. Successful innovation is typically marked by high market acceptance, measured by the number of new users, usage frequency, and market reach. According to Rogers (2014), the adoption rate of an innovation depends on consumers' perceptions of the relative advantage, compatibility, complexity, trialability, and observability of its benefits. Innovative digital products or services, such as AI-based applications or the latest e-commerce platforms, are deemed successful if they achieve widespread and ongoing use.

Furthermore, the financial impact of innovation is a crucial dimension in a business context. Practical innovation will deliver economic value in the form of increased revenue, market growth, or operational cost efficiencies. Kane et al. (2015) demonstrated that companies that strategically invest in digital innovation achieve increased profit margins and efficiency across their value chain. Innovations in business processes, such as digital technology-based automation, have also been shown to reduce production costs and accelerate market response times.

Another equally important dimension is consumer satisfaction and loyalty towards digital innovation. Lemon & Verhoef (2016) emphasized that consumers' experiences with digital innovation significantly influence their perceived value and emotional attachment to a brand. Innovations that enhance convenience, personalization, and customer interaction will lead to increased customer loyalty and retention. Therefore, organizations need to continuously measure customer perceptions of new features, user experience, and the innovation's superiority over competitors.

Beyond commercial aspects, innovation output can also be viewed in terms of its social and environmental impact, particularly in the context of sustainable innovation. Innovations that contribute to reducing carbon emissions, achieving energy efficiency, or increasing social inclusion have long-term strategic value. Kennedy & Bocken (2020) stated that sustainable business models that combine circular economy principles with social objectives can create shared value for both business and society. Innovations in renewable energy, environmentally friendly products, or digital services for education and healthcare are concrete examples of innovation outputs with broad impact.

Overall, innovation output reflects an organization's success in transforming ideas and resources into tangible value. By measuring output across multiple dimensions, market adoption, financial impact, consumer loyalty, and social contribution organizations can comprehensively evaluate their innovation strategies and formulate more informed policies for long-term sustainability.

The Influence of the Omnichannel Paradigm on Digital Innovation

The omnichannel paradigm has become a crucial strategic framework for digital innovation in the retail and service sectors (Beck & Rygl, 2015). It is recognized that omnichannel requires seamless integration between various marketing and sales channels to create a consistent and personalized customer experience. (Lemon & Verhoef, 2016) Confirmed that companies that successfully adopt an omnichannel strategy demonstrate better performance in terms of customer retention and operational efficiency.

In the constantly changing digital age, the omnichannel approach has become an essential strategic framework for fostering digital innovation, especially in retail and service industries. Omnichannel refers to an integrated method that merges multiple interaction channels—both physical and digital—to provide a seamless, consistent, and personalized customer experience across all touchpoints. Unlike traditional multichannel strategies that handle channels separately, omnichannel focuses on synchronized and unified data flows to deliver quick, relevant, and contextual responses to customer needs (Beck & Rygl, 2015).

Implementing an omnichannel strategy encourages companies to innovate not only in product and service delivery but also in business models, operational processes, and digital marketing approaches. Modern consumers expect the flexibility to easily switch channels, such as browsing products on a mobile app, purchasing through a website, and picking up items at a physical store. Therefore, companies must leverage digital technologies like big data analytics, artificial intelligence (AI), the Internet of Things (IoT), and customer relationship management (CRM) systems to unify information from multiple channels and provide a consistent and responsive experience.

One of the main effects of adopting the omnichannel approach on digital innovation is a more personalized, dynamic, and improved customer experience. By combining data from various interaction points, companies can develop a deeper understanding of customer behavior, preferences, and transaction history. This allows for more accurate product recommendations, tailored promotions, and proactive customer service. According to Lemon & Verhoef (2016), companies that successfully implement an omnichannel strategy show higher customer retention rates and better operational efficiency due to reduced redundancy and increased responsiveness.

Furthermore, the omnichannel paradigm also requires organizations to alter their internal structures and collaboration patterns between departments, especially

between information technology, marketing, logistics, and customer service teams. To support omnichannel-focused digital innovation, companies need to develop integrated technology platforms and data architectures capable of enabling real-time information flow across channels. This shift represents a move from a siloed approach to a more flexible and collaborative system, aligning with the principles of a data- and customer-driven organization.

However, implementing an omnichannel strategy faces challenges, especially regarding technological complexity, brand consistency, and customer data security. Companies must ensure that channel integration does not lower the quality of the experience and that all channels keep a unified brand identity. Additionally, with the increasing amount of cross-channel data, managing data privacy and security becomes crucial, particularly as consumer awareness of data protection issues grows.

Overall, the omnichannel paradigm's impact on digital innovation is transformative. It prompts companies to adopt advanced technologies, redesign customer experiences, and create more agile and responsive business processes. Companies that can strategically implement these approaches will be better equipped to handle digital disruption and build long-term competitive advantages in an increasingly connected and customer-focused market ecosystem.

Challenges and Opportunities in Measuring Digital Innovation Performance

While performance indicators provide valuable measurement tools, measuring digital innovation still faces significant challenges, including:

- The complexity of measuring the long-term impact of disruptive digital innovations (Chesbrough, 2007).
- The lack of comprehensive, real-time data on the innovation process (Lobacz & Szanter, 2022).
- Expanding indicators to include aspects of ethics, inclusivity, and sustainability, which are increasingly demanded by the market and regulations (Geissdoerfer et al., 2017).

However, these challenges also open up opportunities for the development of new measurement methodologies that leverage digital technologies themselves, such as AI-based analytics and digital platforms for real-time monitoring of innovation performance.

The development of digital technology has brought about a fundamental transformation in human life, particularly in the way consumers behave and interact with products and services. Previously, consumers relied on physical stores, printed catalogs, or television advertisements to find information; however, now all their needs can be met with just a touch of a finger on a mobile screen (Kannan & Li, 2017). This change has led to a surge in consumer expectations, which no longer suffice with product quality alone, but relatively demand speed, convenience, and a personalized experience in their shopping process (Lemon & Verhoef, 2016).

Unlimited access to information and services through various digital platforms—such as e-commerce, social media, and mobile apps—puts consumers in a much more powerful position than ever before. Consumers can now compare prices between sellers, read reviews from other users, and even make purchasing decisions in seconds, anytime and anywhere (Grewal et al., 2017). This phenomenon has made speed and convenience the primary values sought by consumers. The omnichannel concept, which enables consumers to initiate a product search online and complete it offline, or vice versa, highlights the increasingly blurred boundaries between the physical and digital worlds (Verhoef et al., 2021).

Consumers want the freedom and flexibility to seamlessly switch between channels, forcing companies to undergo a complete transformation. This requires them to not only offer superior products but also create holistic, relevant, and personalized customer experiences (Lemon & Verhoef, 2016). This digital consumer pressure is fueling the urgency of innovation. In an era of rapid technological change and market trends, conventional, reactive approaches are no longer sufficient. Innovation is the key to survival and growth (Brynjolfsson et al., 2014).

However, the innovation required goes beyond new products to transforming how companies operate, interact with customers, and create an adaptive and integrated business ecosystem (Mikalef et al., 2020). Transformation encompasses new business models, improved customer service, and the adoption of technology to enhance the overall user experience (Davenport & Ronanki, 2018). One of the strategic pillars of this innovation is data.

Digital consumers unconsciously generate a rich digital footprint through their activities across various platforms. Savvy companies collect, analyze, and leverage this data to understand customer behavior patterns, preferences, and needs (Chen et al., 2012). Data forms the basis of personalization—an approach that allows products and services to be tailored to each individual. This approach has been shown to increase customer satisfaction, loyalty, and lifetime value (Chatterjee et al., 2021).

Real-world examples of this personalization can be seen on major e-commerce platforms, such as Tokopedia and Amazon, which utilize machine learning-

based algorithms to recommend products to users based on their search and purchase history (Huang & Rust, 2022) The use of artificial intelligence (AI) not only enhances the customer experience but also improves operational efficiency and boosts company competitiveness in an increasingly competitive digital marketplace (Brynjolfsson et al., 2014).

Thus, the development of digital technology has triggered fundamental changes in consumer behavior and how companies respond through data-driven innovation and intelligent technology. Speed, convenience, and personalization are key to success in facing the challenges of an ever-changing market (Kannan & Li, 2017; Verhoef et al., 2021)

Technological advancements, such as artificial intelligence (AI) and machine learning (ML), have brought about significant changes in the way companies interact with their customers. The implementation of AI-based chatbots enables companies to offer 24/7 customer service, provide rapid responses, and efficiently resolve various requests (Huang & Rust, 2022). Furthermore, augmented reality (AR) and virtual reality (VR) technologies are increasingly being adopted in the retail sector to create immersive shopping experiences. Consumers can virtually try products before purchasing, a practice previously only possible in-store, increasing convenience and building consumer trust in the product (Pantano et al., 2020).

Changes in consumer behavior, driven by increasing awareness of social and environmental issues, are also fueling innovation. Consumers now evaluate products not only based on price and quality, but also on their social and environmental impacts (Kotler & Armstrong, 2018). Brands that demonstrate transparency, ethics, and a commitment to sustainability are more likely to establish long-term relationships with consumers who value social responsibility and corporate responsibility. As a result, companies are encouraged to develop environmentally friendly innovations, such as utilizing recycled materials, reducing emissions in production processes, and implementing product recycling programs (Kane et al., 2015). Innovation is now not only about technology, but also about values and a commitment to a sustainable future (Geissdoerfer et al., 2017)

In the context of the sharing economy and the experience economy, consumption patterns are undergoing drastic changes. Consumers, especially younger generations, tend to opt for access over ownership, with a preference for subscription-based services or sharing platforms, such as Airbnb, Gojek, and Spotify, that offer flexibility and resource efficiency (Botsman & Rogers, 2010; Hamari et al., 2016) Consumers also place experiences as an essential part of consumption, rather than just physical products, opening up opportunities for companies to design customer experience-oriented business models (Pine & Gilmore, 1999).

In marketing, traditional approaches are increasingly being replaced by content and community strategies. Consumers now actively contribute to value creation through reviews, testimonials, social media discussions, and participation in digital campaigns (Kozinets et al., 2014). Therefore, companies need to develop innovative marketing strategies that involve influencers, build strong narratives through digital storytelling, and encourage community engagement. This strategy not only increases brand exposure but also creates an emotional bond between consumers and the company (Hanna et al., 2011).

While innovation does not always have to be revolutionary, consistent, small innovations based on consumer feedback often have significant long-term impacts. An agile and iterative approach to product and service development allows companies to quickly adapt to changing market needs (Rigby et al., 2016). Speed and agility are key in a dynamic business environment (Doz & Kosonen, 2010).

Digital transformation also opens up opportunities for cross-sector collaboration. Companies no longer exist in isolation; instead, they form a mutually supportive and interconnected ecosystem. For example, the integration of digital payment platforms, logistics companies, and e-commerce companies speeds up and simplifies transaction and product delivery processes (Adner, 2017). This collaboration creates added value not only for companies but also for consumers as end users.

More broadly, digitalization and innovation are expanding access for previously unreachable groups, such as residents in remote areas or individuals with disabilities. Through digital platforms, companies can offer inclusive and adaptable services, thereby expanding their market share while strengthening corporate social responsibility (Jaeger et al., 2012)

However, companies that fail to innovate risk losing relevance. Digital consumers are highly dynamic and easily switch to other brands if they feel their needs are not being met. Consumer loyalty now depends on a company's ability to understand their needs and respond with continuous innovation (Reinartz et al., 2009). In an era of seamless connectivity, consumer behavior is becoming a strategic compass for a company's innovation direction (Verhoef et al., 2021)

Therefore, companies need a long-term vision rooted in a deep understanding of digital consumers. A data-driven, sustainability-oriented, and change-oriented innovation culture must be established across the board, encompassing production processes, marketing

strategies, and customer relationships. In this way, companies are not only able to face current challenges but are also prepared to meet the increasingly complex and rapidly changing dynamics of the future (Teece et al., 2016).

Innovation Theory and Practice in a Digital Context

Innovation in an organizational and business context is not simply creating something new, but rather a complex and ongoing process involving various interacting elements (Crossan & Apaydin, 2010). In the dynamic digital economic landscape, innovation plays a role not only as a response to change but as a key driver for creating competitive advantage (Teece et al., 2016). Conceptually, innovation encompasses significant changes that increase value, whether through the creation of new products or services or improvements to processes, business models, and organizational approaches (OECD, 2018).

According to Schumpeter (1954), innovation is a manifestation of "creative destruction"—the process by which old products, processes, or structures are replaced by something better and more relevant. In the digital age, this change occurs very rapidly due to short technological cycles and high adaptation pressures (Bhardwaj et al., 2024). Therefore, innovation is no longer a strategic choice, but rather a systemic necessity (Chesbrough, 2007).

Innovation can occur in various dimensions. Product innovation, specifically the creation of new goods or services or significant improvements to existing ones, is crucial for building differentiation and fostering consumer loyalty (Utterback, 1994). Often, impactful product innovations are not the most complex, but rather the most relevant to consumer needs (Christensen et al., 2018).

Process innovation emphasizes how companies efficiently produce and distribute products or services. The use of automation, intelligent logistics systems, and digital integration speeds up response times, lowers costs, and enhances service consistency (T. Davenport et al., 2020). In the digital economy, slow and unintegrated processes are major barriers to customer experience (Brynjolfsson et al., 2014).

Organizational innovation involves changes in structure, culture, and human resource management. Bureaucratic organizations tend to be less responsive to rapid change, making agile structures and collaborative cultures that support continuous learning necessary (Birkinshaw et al., 2008). Transformational leadership is also essential for inspiring innovation across the organization (Bass & Riggio, 2006).

In marketing, innovation is essential because digital consumers buy not just products but also value and experiences (Nidumolu et al., 2009). Digital marketing strategies use social media, data-driven campaigns, and participatory approaches that involve customer communities, creating strong emotional bonds and building loyalty (Kotler & Keller, 2018).

Data is the foundation of digital innovation. With big data and predictive analytics, companies can gain a deeper understanding of consumer behavior and offer personalized services on a large scale (Manyika et al., 2011). Companies like Netflix and Shopee leverage data to improve retention and user experience (Gomez-Uribe & Hunt, 2015).

AI and machine learning allow systems to learn from data and keep improving services. AI in customer service, such as chatbots, can understand context and provide quick solutions that boost satisfaction while lowering operational costs (Huang & Rust, 2022). AR and VR technologies in retail create immersive experiences, allowing consumers to try products and reduce the uncertainty of online shopping virtually (Pantano et al., 2020), These innovations boost consumer trust.

Digital transformation also encourages companies to incorporate sustainability into their innovation processes. Consumers are increasingly aware of the environmental and social impacts of products, prompting the development of green innovations such as biodegradable packaging and low-emission production (Geissdoerfer et al., 2017). This strategyenables companies to successfully balance technological advancements with market trust.

The sharing and experience economy trends emphasize access and experiences over product ownership (Botsman & Rogers, 2010; Pine & Gilmore, 1999). Subscription-based and asset-sharing business models, such as those employed by Grab, Spotify, and Airbnb, are examples of innovations that are transforming the way value is delivered to consumers (Hamari et al., 2016).

Ultimately, innovation must be rooted in a deep understanding of people—their needs, expectations, and experiences interacting with products or services. A creative, adaptive, and sustainable approach to innovation is not just a business strategy, but a philosophy that must be embedded in the organizational culture (Teece et al., 2016).

Measuring Innovation Success and Building a Sustainable Innovation Ecosystem

Measuring innovation success is not a simple task, as its impacts are often long-term and multidimensional (Crossan & Apaydin, 2010). Therefore, companies need to combine quantitative and qualitative indicators to obtain a comprehensive picture (OECD, 2018).

1. Quantitative Indicators
- Number of New Products: Indicates how actively a company is exploring and developing (Utterback, 1994)
- Sales Performance and Market Adoption: Measures how well new products are received, including the proportion of revenue derived from them (Kane et al., 2015; D. Teece et al., 2016)
- Innovation Cycle Time: The length of time from idea to launch is important in evaluating a company's agility—the faster it is, the more competitive it is (Rigby et al., 2016)
- Number of Patents: Is an indicator of the intensity of innovation and market protection, especially in high-tech sectors (Mathras et al., 2016).

2. Qualitative Indicators
This aspect assesses the organizational culture—whether it supports experimentation, risk-taking, collaboration, and employee creativity (Birkinshaw, Hamel, & Mol, 2008). Transformational leadership is also important in providing space for initiative and resource support (Bass & Riggio, 2006).

3. Innovation Ecosystem
Modern companies are now building innovation ecosystems that involve various external actors such as academics, startups, and communities through open innovation (Chesbrough, 2007) . This collaboration enhances the speed of innovation and risk sharing, similar to Google's or Tesla's open innovation programs (Chesbrough & Rosenbloom, 2002). This approach is also popular in the public sector for creating complex solutions through cross-stakeholder collaboration (Mulgan & Albury, 2003)

4. Internal Innovation Management System
This system includes structural policies, incentives, and a digital platform for bottom-up idea management. Companies can monitor and screen ideas through pilot projects before implementing them fully (Van de Ven, 1986).A structured system helps make innovation part of the organization's DNA (Teece et al., 2016).

5. Incremental Innovation and Lean Innovation
This approach focuses on minor improvements through rapid testing and real-world customer data. Even minor, steady innovations can make a big difference when part of a long-term plan (Benner & Tushman, 2003).

6. Digital Technology Integration
The success of digital innovation also depends on how effectively technologies such as AI, IoT, blockchain, and cloud computing are integrated into business strategies and workflows (Bharadwaj et al., 2013). For example, AI-based chatbots provide faster and more accurate services, fundamentally changing human-machine interactions (Huang & Rust, 2022).

7. A Culture of Tolerance for Failure
Innovative companies cultivate a culture that encourages measured failure as part of the learning process (Edmondson, 2011). Without tolerance for failure, there is no room for innovation and transformation.

The Future of Innovation in the Digital Age and Changing Consumer Behavior

The rapid development of digital technology is a crucial foundation for future innovation in various organizations, whether small or large, local or global (Brynjolfsson et al., 2014). Changing consumer behavior, which seeks instant access, personalized experiences, and emotional connections with brands, has driven companies to adjust their strategies and operations to stay relevant continually (Verhoef et al., 2021). Adaptive and innovative organizations hold an advantage over those that depend only on size or legacy reputation when facing digital competition (Teece, 2018).

Going forward, innovation will not only be a means of survival but also a key instrument for creating new business models oriented not only toward financial gain but also toward creating social and environmental value. This approach, known as sustainable innovation, integrates sustainability principles into innovation strategies to address global challenges such as climate change, resource constraints, and social inequality (Schaltegger et al., 2012) Companies that implement sustainable innovation demonstrate excellence in maintaining a balance between economic growth and social responsibility.

The concept of sustainability in innovation also goes hand in hand with social inclusivity. In the digital age, innovations that fail to reach marginalized groups or remote areas risk missing out on significant market potential and social contributions. Digital technology opens up opportunities for broader social inclusion, enabling access to market services, education, finance, and employment for groups such as people with disabilities, remote communities, and traditional MSMEs. Companies that successfully implement inclusive digital innovation not only expand their markets but also strengthen their social role in creating a more just and equitable world (United Nation, 2020).

However, a major challenge for future innovation is the rapid pace of technological change. Technology life cycles are getting shorter, with innovations once seen as cutting-edge quickly becoming outdated (Botsman & Rogers, 2010). Artificial Intelligence (AI), for example, which was once mainly used in analytics and facial recognition, now extends into the creative, healthcare, education, and strategic decision-making sectors (Kaplan & Haenlein, 2019). This situation demands that companies not only adopt new technologies but also rethink the role of humans in an increasingly tech-driven work environment (Davenport & Ronanki, 2018).

As technology advances, investing in developing the digital skills of human resources becomes increasingly important. Merely acquiring advanced technology is no longer enough; companies must build internal capacity to understand, manage, and optimize it. Continuing education, reskilling, and fostering an innovative mindset are essential parts of a long-term innovation strategy. A culture of lifelong learning helps organizations stay resilient to technological disruptions and rapid market changes (OECD, 2018).

Furthermore, the ethical and regulatory challenges associated with technological innovation are becoming increasingly complex. AI, biometric data, and quantum computing are opening new opportunities while raising concerns about privacy, data security, and algorithm fairness (Floridi et al., 2018). Regulation, which often lags behind technological developments, creates a gray area that risks eroding public trust. Therefore, future innovation must be grounded in ethical and transparent governance, with principles of responsible innovation and stakeholder involvement in the design and evaluation of new products or services (OECD, 2018).

In an increasingly connected global ecosystem, cross-border collaboration is key to successful innovation. Different countries, sectors, and organizations now have significant opportunities to share knowledge, technology, and resources (Chesbrough, 2007). Open innovation models are becoming the new norm, where success is no longer determined by the number of discoveries made in-house, but rather by an organization's ability to absorb and apply external knowledge (Chesbrough & Bogers, 2013). Collaborations with startups, universities, research institutions, and governments accelerate the innovation process while broadening its impact (West & Bogers, 2013).

The future innovation paradigm will shift from simply creating "better products" to generating "deeper value." This value is not only assessed by product features or process efficiency, but also by contributions to quality of life, community well-being, and planetary sustainability (Hamel & Breen, 2007; Porter & Kramer, 2011).Therefore, the success of future innovation must be measured not only by Return on Investment (ROI), but also by the resulting social, ecological, and cultural impacts (Elkington, 1997).This holistic approach reflects a fundamental transformation in how organizations view innovation.

In conclusion, innovation is no longer just a short-term project or program. It is a system, a culture, and a long-term commitment that must be integrated into every aspect of the organization(Bessant & Tidd, 2013).

Companies that can cultivate an innovative ecosystem supported by data, technology, collaboration, and empathy for consumers and the environment will be able to survive and lead in the digital age. Organizations with a transformative vision and a sustained commitment to innovation will thrive and become future leaders (Kane et al., 2015). Thus, innovation has become the heart of organizational survival in the 21st century.

Research Methods

This study used a quantitative approach to analyze the influence of variables. Based on the literature study, the following research variables were obtained:

X_1: Digital Innovation
X_2: Consumer Behavior
Z: Consumer Experience
Y: Competitive Advantage

By using Structural Equation Modeling (SEM) based on Partial Least Squares (PLS) analysis. Quantitative data were collected through a questionnaire using a 1–5 Likert scale, where several indicators measured each latent variable. Variable validity was tested using Convergent Validity and Discriminant Validity, while reliability was tested using Cronbach's Alpha and Composite Reliability.

The sample size was determined according to the criteria required for SEM analysis. Due to the large population size, a minimum sample size of 5 to 10 times the number of indicator variables is recommended by Hair Jr (2014). This study included 18 indicators. The following is the sample calculation using Hair's formula:

N = 10 x 20 indicators
N = 200 Respondents

Based on the above calculation, the required sample size is 200 respondents. The sample was divided proportionally based on the percentage of retail product consumers in the Greater Jakarta area.

Reliability Tests

Cronbach's Alpha

Cronbach's Alpha is used to measure instrument reliability with a score that is not simply 1 or 0 ((Hair Jr, 2014). This method uses the following formula:

$$r_{11} = \left[\frac{k}{(k-1)}\right]\left[1 - \frac{\sum \sigma_b^2}{\sigma_t^2}\right]$$

Legend:

r_{11} = Instrument reliability coefficient
K = Number of valid items
$\sum \sigma_b^2$ = Total item variance
σ_t^2 = Total score variance

The calculation using the Cronbach's Alpha formula is acceptable if the calculated r is greater than the table r by 5%.

Cronbach's alpha is a method often used to measure the consistency of a measurement instrument. Cronbach's alpha values range from 0 to 1, with higher values indicating greater reliability. Alpha values of 0.70 and above are generally considered adequate for research purposes. Meanwhile, higher values, such as 0.80 or 0.90, reflect a higher level of reliability.

Composite Reliability

Composite reliability is an index that indicates the extent to which a measurement instrument is reliable. Data with a composite reliability value greater than 0.7 is considered to have a high level of reliability (Jöreskog et al., 2016). Composite reliability for a block of indicators measuring a construct can be evaluated using Cronbach's alpha.

The second stage of this research focuses on designing a measurement model, which aims to determine how each latent construct is measured through its representative indicators.

The Measurement Model

Table 1
Outer model equation

Construct Variables (*Laten Variables*)	*Observed Variables* (*Indicator Variables*)
X_1	$X_{11} + X_{12} + X_{13} + X_{14} + X_{15}$
X_2	$X_{21} + X_{22} + X_{23} + X_{24} + X_{25}$
Y	$Y_{11} + Y_{12} + Y_{13} + Y_{14} + Y_{15}$
Z	$Z_1 + Z_2 + Z_3 + Z_4 + Z_5$

This research applies a reflective measurement model approach, where indicators are considered direct reflections of the latent construct (Schumacker & Lomax, 2010). The mathematical equation form of the measurement model can be seen on Table 1.

The Structural Model (Inner Model)

The structural model, also known as the inner model, is a component in SEM that describes the relationships between variable constructs and explains hypotheses regarding the influence of independent variables on the dependent variable.

Model Estimation Using the PLS Algorithm

The model parameter estimation process uses the iterative Partial Least Squares (PLS) algorithm. The PLS algorithm optimizes three main parameters: path coefficients in the structural model, outer loadings in the reflective measurement model, and outer weights in the formative measurement model. The estimation process is carried out using an iterative procedure that combines principal component analysis and canonical correlation analysis to achieve optimal convergence.

Goodness of Fit Evaluation

For the structural model, evaluation is carried out by examining the R-square value, which describes the proportion of variance in the endogenous variables that can be explained by the predictor variables, and the Q-square (Stone-Geisser) value, which assesses the model's predictive relevance. Furthermore, the effect size (f-square) is used to identify the practical contribution of each predictor variable to the dependent variable. In the context of this study, the model demonstrated adequate explanatory power, explaining significant variance in the endogenous variables (Byrne, 2010).

Hypothesis Testing

The research hypothesis was tested using bootstrapping techniques to obtain accurate estimates of standard errors and confidence intervals. The bootstrapping procedure was performed with multiple resamples to ensure the stability of the estimates and produce a robust sampling distribution. Hypothesis testing was conducted using statistical criteria, namely a t-statistic value exceeding the critical limit and a p-value smaller than the specified significance level, in this case 5% for a one-tailed test. This was performed using SmartPLS software, which consists of two stages: the Outer Model and the Inner Model.

Validity Test

The test aims to determine whether the measurement instrument used, such as a questionnaire, is valid.

A questionnaire is considered valid if its questions adequately reveal the aspects intended to be measured.

Convergent Validity

The convergent validity of this measurement is considered sufficient if the outer loading is above 0.7 and the Average Variance Extracted (AVE) value is at least 0.5. Based on the test results, the indicators used met the following validity criteria:

Table 2
Outer loading factors of digital innovation

Indicator	Outer Loadings	AVE	
$X_{1.1}$	0.762	0.591	Valid
$X_{1.2}$	0.752		Valid
$X_{1.3}$	0.777		Valid
$X_{1.4}$	0.730		Valid
$X_{1.5}$	0.822		Valid

Source: Data Processing Results, 2025

The test results show that the five indicators have outer loadings values ranging from 0.730 to 0.822 with an AVE value of 0.591. Indicator X_{15} has the highest outer loading of 0.822, while indicator X_{14} has the lowest value, but it still meets the minimum criterion of 0.730. The AVE value of 0.592 is higher than the minimum limit of 0.50. Thus, all questions can be considered valid and capable of measuring the construct of the Competitive Advantage variable effectively.

Table 3
Outer loadings factors of consumer behavior indicators

Indicator	Outer Loadings	AVE	
$X_{2.1}$	0.741	0.651	Valid
$X_{2.2}$	0.880		Valid
$X_{2.3}$	0.827		Valid
$X_{2.4}$	0.846		Valid
$X_{2.5}$	0.731		Valid

Source: Data Processing Results, 2025

The Consumer Behavior variable test results showed excellent results, with outer loadings ranging from 0.731 to 0.880 and an AVE value of 0.651, the highest among all variables. All indicators were declared valid because their loading values exceeded the minimum threshold of 0.70. Indicator X_{22} had the highest outer loading value, at 0.880, indicating that it makes the most substantial contribution to consumer behavior.

Meanwhile, the indicator with the lowest outer loading value was $X_{2.5}$, with a score of 0.731. Although this value is still considered valid, its contribution to the consumer behavior variable is relatively minor compared to the other indicators. These findings can be used as evaluation material to strengthen respondents' perceptions of the institution's digital innovation.

Table 4
Outer loading factors of consumer experience indicators

Indicator	Outer Loadings	AVE	
Z_1	0.874	0.651	Valid
Z_2	0.841		Valid
Z_3	0.784		Valid
Z_4	0.815		Valid
Z_5	0.704		Valid

Source: Data Processing Results, 2025

The test results for the Customer Experience variable show Outer Loadings values ranging from 0.704 to 0.874 with an AVE value of 0.650. Indicator Z_1 has the highest Outer Loadings of 0.874, while indicator Z_5 has the lowest value of 0.704, but still meets the validity criteria. The AVE value of 0.651 exceeds the minimum limit of 0.50. Thus, all questions can be considered valid and capable of measuring the Customer Experience variable effectively.

Table 5
Outer loadings of competitive advantage

Indicator	Outer Loadings	AVE	
Y_1	0.734	0.625	Valid
Y_2	0.722		Valid
Y_3	0.884		Valid
Y_4	0.850		Valid
Y_5	0.748		Valid

Source: Data Processing Results, 2025

The test results for the Competitive Advantage (Y) variable showed outer loadings ranging from 0.722 to 0.884, with an AVE of 0.625. Indicator Y_3 provided the most significant contribution, with a loading of 0.885, followed by Y_4, which had a value of 0.850. The AVE value of 0.625 exceeds the minimum threshold of 0.50.

Meanwhile, indicator Y_2 had the lowest outer loading, at 0.722. Although still in the valid category, its contribution to the Competitive Advantage variable is relatively lower than the other indicators. Therefore, all questions can be declared valid and effectively measure the construct of the Competitive Advantage variable.

Discriminant Validity

Discriminant validity refers to the extent to which an indicator can differentiate when measuring an instrument variable. This test is conducted using three approaches: the Fornell-Larcker Criterion, Cross-Loading, and Heterotrait-Monotrait Ratio (HTMT).

Fornell-Larcker Criterion

Table 6
Fornell-Larcker Criterion Results

Var	X_2	Z	Y	X_1
X_1	0.730	0.716	0.754	0.769
Y	0.687	0.736	0.791	
Z	0.719	0.806		
X_2	0.807			

Source: Data Processing Results, 2025

The Fornell-Larcker Criterion test results indicate that all constructs have good discriminant validity. The square root of the AVE value for each variable is greater than the correlation between variables. The Digital Innovation variable has a square root of AVE of 0.769, the Innovation variable has a square root of AVE of 0.807, the Customer Experience variable has a square root of AVE of 0.806, and the Competitive Advantage variable has a square root of AVE of 0.791. These values are higher than the correlations with other variables, indicating that each variable is unique and can be clearly distinguished from the others.

Cross Loadings

Taible 7
Cross loading result

	(X_2)	(Z)	(Y)	(X1)
$X_{1.1}$	0.576	0.607	0.617	0.761
$X_{1.2}$	0.484	0.626	0.442	0.753
$X_{1.3}$	0.631	0.617	0.522	0.777
$X_{1.4}$	0.452	0.378	0.636	0.730
$X_{1.5}$	0.646	0.513	0.675	0.823
$X_{2.1}$	0.740	0.511	0.582	0.590
$X_{2.2}$	0.880	0.626	0.633	0.672
$X_{2.3}$	0.828	0.390	0.471	0.420
$X_{2.4}$	0.847	0.449	0.493	0.484
$X_{2.5}$	0.732	0.793	0.541	0.678
Y_1	0.433	0.489	0.735	0.479
Y_2	0.649	0.653	0.723	0.554
Y_3	0.565	0.606	0.885	0.688
Y_4	0.545	0.567	0.850	0.663
Y_5	0.502	0.582	0.749	0.571
Z_1	0.703	0.873	0.554	0.722
Z_2	0.628	0.841	0.659	0.590
Z_3	0.542	0.785	0.576	0.622
Z_4	0.528	0.816	0.667	0.515
Z_5	0.472	0.706	0.506	0.402

Source: Data Processing Results, 2025

Cross-loading analysis shows that each indicator has a higher loading factor on its intended variable compared to the other variables. For example, indicators X1.1 to X1.5 have the highest loading factors on the digital innovation construct, as do the different indicators. This indicates that each indicator accurately measures the variable it is intended to measure and does not overlap with other variables.

Heterotrait – Monotrait Ratio (HTMT)

Table 8
Heterotrait – Monotrait Ratio (HTMT)

Variable	(X2)	(Z)	(Y)	(X1)
(X_1)	0.826	0.835	0.892	
(Y)	0.781	0.857		
(Z)	0.788			
(X_2)				

Source: Data Processing Results, 2025

The HTMT test results show that all HTMT values are below the threshold of 0.90, with the highest value being 0.892 for the relationship between Digital Innovation and Competitive Advantage. An HTMT value below 0.90 indicates that all variables have adequate discriminant validity and can be clearly distinguished from one another.

Reliability Test

Reliability testing was conducted to evaluate the internal consistency of the research instrument. The results of the reliability testing indicated that all constructs in this study had excellent reliability, as indicated by Cronbach's Alpha and Composite Reliability values, all of which were above the minimum threshold of 0.7.

Table 9
Reliability result

Var	Cronbach's Alpha	Composite Reliability	Desc
(X1)	0.827	0.879	Reliable
(X2)	0.867	0.903	Reliable
(Z)	0.864	0.902	Reliable
(Y)	0.848	0.893	Reliable

Source: Data Processing Results, 2025

The Digital Innovation variable has the lowest reliability with a Cronbach's Alpha value of 0.827 and a Composite Reliability of 0.879. The Consumer Behavior variable has the highest reliability with a Cronbach's Alpha value of 0.867 and a Composite Reliability of 0.903, indicating that the indicators in this variable have excellent consistency in measuring the Innovation variable. The Customer Experience variable shows a Cronbach's Alpha value of 0.864 and a Composite Reliability of 0.902, indicating an outstanding level of reliability. The Competitive Advantage variable has a Cronbach's Alpha value of 0.848 and a Composite Reliability of 0.893, indicating very adequate reliability.

Outer Model Equation System

The outer model equation system in this study describes the structural relationship between latent variables and their measurement indicators using a reflective measurement model approach. In this approach, each indicator is viewed as a reflection or manifestation of the underlying latent construct, where the causal relationship flows from the latent variable to its indicators. The following system of outer model equations in this study can be written as follows:

a) Digital Innovation (X_1)
System of Equations:
$X_{1.1} = \lambda_{1.1} \times X_1 + \varepsilon_{1.1}$
$X_{1.2} = \lambda_{1.2} \times X_1 + \varepsilon_{1.2}$
$X_{1.3} = \lambda_{1.3} \times X_1 + \varepsilon_{1.3}$
$X_{1.4} = \lambda_{1.4} \times X_1 + \varepsilon_{1.4}$
$X_{1.5} = \lambda_{1.5} \times X_1 + \varepsilon_{1.5}$
Loading Factor Value:
$X_{1.1} = 0.761 \times X_1 + \varepsilon_{1.1}$
$X_{1.2} = 0.753 \times X_1 + \varepsilon_{1.2}$
$X_{1.3} = 0.777 \times X_1 + \varepsilon_{1.3}$
$X_{1.4} = 0.730 \times X_1 + \varepsilon_{1.4}$
$X_{1.5} = 0.823 \times X_1 + \varepsilon_{1.5}$

b) Consumer Behavior (X_2)
System of Equations:
$X_{2.1} = \lambda_{2.1} \times X_2 + \varepsilon_{2.1}$
$X_{2.2} = \lambda_{2.2} \times X_2 + \varepsilon_{2.2}$
$X_{2.3} = \lambda_{2.3} \times X_2 + \varepsilon_{2.3}$
$X_{2.4} = \lambda_{2.4} \times X_2 + \varepsilon_{2.4}$
$X_{2.5} = \lambda_{2.5} \times X_2 + \varepsilon_{2.5}$
Loading Factor Value:
$X_{2.1} = 0.740 \times X_2 + \varepsilon_{2.1}$
$X_{2.2} = 0.880 \times X_2 + \varepsilon_{2.2}$
$X_{2.3} = 0.828 \times X_2 + \varepsilon_{2.3}$
$X_{2.4} = 0.847 \times X_2 + \varepsilon_{2.4}$
$X_{2.5} = 0.732 \times X_2 + \varepsilon_{2.5}$

c) Consumer Experience (Z)
System of Equations:
$Z_1 = \lambda Z_1 \times Z + \varepsilon Z_1$
$Z_2 = \lambda Z_2 \times Z + \varepsilon Z_2$
$Z_3 = \lambda Z_3 \times Z + \varepsilon Z_3$
$Z_4 = \lambda Z_4 \times Z + \varepsilon Z_4$
$Z_5 = \lambda Z_5 \times Z + \varepsilon Z_5$
Loading Factor Value:
$Z_1 = 0.873 \times Z + \varepsilon Z_1$
$Z_2 = 0.841 \times Z + \varepsilon Z_2$
$Z_3 = 0.785 \times Z + \varepsilon Z_3$
$Z_4 = 0.816 \times Z + \varepsilon Z_4$
$Z_5 = 0.706 \times Z + \varepsilon Z_5$

d) Competitive Advantage (Y)
System of Equations:
$Y_1 = \lambda Y_1 \times Y + \varepsilon Y_1$
$Y_2 = \lambda Y_2 \times Y + \varepsilon Y_2$
$Y_3 = \lambda Y_3 \times Y + \varepsilon Y_3$
$Y_4 = \lambda Y_4 \times Y + \varepsilon Y_4$
$Y_5 = \lambda Y_5 \times Y + \varepsilon Y_5$
Loading Factor Value:
$Y_1 = 0.735 \times Y + \varepsilon Y_1$
$Y_2 = 0.723 \times Y + \varepsilon Y_2$
$Y_3 = 0.885 \times Y + \varepsilon Y_3$
$Y_4 = 0.850 \times Y + \varepsilon Y_4$
$Y_5 = 0.749 \times Y + \varepsilon Y_5$

Overall, all loading factor values in the outer model equation system are above 0.7, indicating that each indicator has good convergent validity and is able to adequately reflect the underlying latent variables. This high loading factor value also indicates that the measurement model used in this study has a level of reliability and validity that can be statistically accounted for. Meanwhile, the error term (ε) in each equation represents the variance in the indicator that cannot be explained by the latent variables, which is also an important component in understanding the limitations of the measurement model used.

Measurement Model (Inner Model)

After the measurement model (Outer Model) has been proven valid and reliable, the next step is to evaluate the structural model (Inner Model). The purpose of evaluating the Inner Model is to test the relationships between latent variables in the research model and evaluate the model's overall predictive ability.

Creating a Path Diagram

The path diagram in this study was created using SmartPLS software, depicting the structural relationships between the research variables, as shown in Figure 4.6. The resulting structural model illustrates the complex relationships between variables. The variables in this model consist of two exogenous variables: Digital Innovation (X_1) and Consumer Behavior (X_2), and two endogenous variables: Customer Experience (Z) and Competitive Advantage (Y).

Based on the output, path coefficients were obtained, indicating the magnitude of the direct influence between latent variables. Digital Innovation (X_1) has a direct relationship with Customer Experience (Z) of 0.195 and with Competitive Advantage (Y) of 0.140. Meanwhile, Consumer Behavior (X_2) shows a stronger

relationship with Customer Experience (Z) of 0.381 and with Competitive Advantage (Y) of 0.309. Furthermore, Customer Experience (Z) also contributes to Competitive Advantage (Y) with a path coefficient of 0.261.

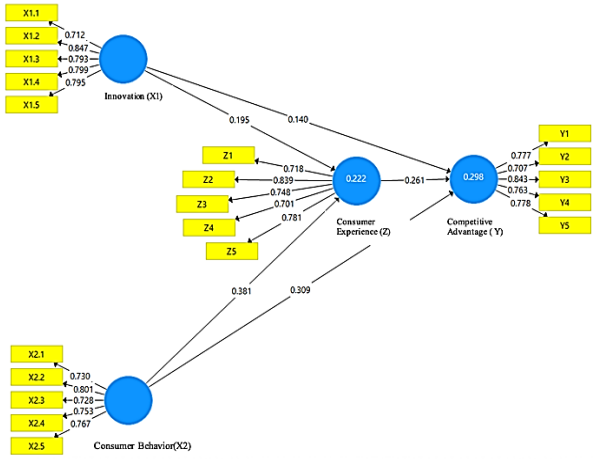

Figure 1. Structural model (path diagram)

The resulting R-square (R^2) value for the Customer Experience (Z) variable is 0.222, indicating that the variability in Customer Experience can be explained by the Digital Innovation and Consumer Behavior variables. Meanwhile, the R^2 value for the Competitive Advantage (Y) variable is 0.298, indicating that the variability in Competitive Advantage can be explained by Digital Innovation, Consumer Behavior, and Customer Experience.

Inner Model Equation System

Based on Figure 1 and the results of the analysis, the relationships between latent variables in the structural model can be expressed in the following system of equations:

$$Z = \gamma_1 X_1 + \gamma_2 X_2 + \varepsilon_1$$
$$Y = \beta Z + \gamma_3 X_1 + \gamma_4 X_2 + \varepsilon_2$$

Where:

X_1 = Digital Innovation
X_2 = Consumer Behavior
Z = Consumer Experience
Y = Competitive Advantage
γ = The coefficient of direct influence from exogenous to endogenous variables
β = Coefficients that have a direct influence between endogenous variables
ε = Error Term (residual)

Based on the analysis, the coefficient values in the system of equations above are as follows:

$$Z = 0.195X_1 + 0.381X_2 + \varepsilon_1$$
$$Y = 0.261Z + 0.140X_1 + 0.309X_2 + \varepsilon_2$$

Coefficient of Determination (R^2)

The Coefficient of Determination (R^2) is used to measure the degree to which exogenous variables can explain variation in endogenous variables in a structural model. The higher the R^2 value, the greater the proportion of variation explained by the model, indicating good predictive ability. According to Hair Jr (2014), an R^2 value of 0.75 is categorized as substantial, 0.50 as moderate, and 0.25 as weak. The following results were obtained:

Table 10
Value of determination coefficient (R^2 Test)

Dependent Variable	R^2
Consumer Experience (Z)	0.222
Competitive Advantage (Y)	0.298

Source: Data Processing Results, 2025

Based on the output, the R-squared (R^2) value for the customer experience (Z) variable was 0.222, indicating that 22.2% of the variability in customer experience can be explained by the Digital Innovation (X_1) and Consumer Behavior (X_2) variables.

The R^2 value for the competitive advantage (Y) variable was 0.298, indicating that 29.8% of the variation in Competitive Advantage can be explained by digital innovation (X_1), Consumer Behavior (X_2), and Customer Experience (Z).

The coefficient of determination obtained fell into the weak category, yet still indicated that the model had an adequate ability to explain the relationships between the studied variables.

Goodness of Fit Model

Goodness of Fit (GoF) is a comprehensive indicator used to evaluate the overall fit of a model, encompassing both the measurement model and the structural model. The GoF value is calculated by taking the square root of the product of the average communality (AVE) and the average coefficient of determination (R^2) of the endogenous variables in the model.

$$GoF = \sqrt{\overline{AVE} \; x \; \overline{R^2}}$$

$$AVE = \frac{0.592+0.652+0.650+0.626}{4} = \frac{2.520}{4} = 0.630$$

$$R2 = \frac{0.222+0.298}{2} = \frac{0.520}{2} = 0.260$$

$$GoF = \sqrt{0.630 \; x \; 0.260} = 0.404$$

The GoF value is 0.404, which exceeds the minimum limit for the high fit category, this model is able to represent the phenomenon studied comprehensively and consistently. The Goodness of Fit (GoF) value reflects the characteristics of a strong and reliable model. The average AVE value of 0.630 indicates that each construct in the model exhibits high convergent validity, where the related construct successfully explains more than 60% of the variance in the indicators. This suggests that the indicators used accurately represent the latent construct being measured. The average R^2 value of 0.260 indicates that the structural model has sufficient predictive ability, accounting for 26% of the variance in the endogenous variables.

Testing the Significance of Direct Relationships Between Variables

The criteria used to assess the significance of the relationship were T-statistic values > 1.96 and P-values < 0.05 for a 5% significance level. The results of the significance test for the relationship between variables are presented in the path coefficients table, which displays the five relationship paths examined in this research model.

Table 11
Path coefficients

Relationship between variables	Original Sample (O)	Mean (M)	Std. Deviation (STDEV)	T Stat	P Values
(X1) → (Y)	0.140	0.144	0.074	1.884	0.030
(X1) → (Z)	0.195	0.202	0.077	2.538	0.006
(Z) → (Y)	0.261	0.261	0.080	3.279	0.001
(X2) → (Y)	0.309	0.316	0.074	4.179	0.000
(X2) → (Z)	0.381	0.387	0.067	5.717	0.000

The analysis results indicate that all relationships between variables in this study were significant. Consumer behavior emerged as the variable with the most significant influence on both customer experience and competitive advantage. These results underscore that consumer behavior is a strategic factor that organizations must focus on to enhance competitiveness and customer satisfaction. This demonstrates that digital innovation remains a strategic element supporting organizations' efforts to achieve competitive advantage.

Hypothesis Testing

The relationship between variables was tested using T-statistics and P-values. The hypothesis is accepted if the T-statistic is >1.96 and the P-value is <0.05 at a 5% significance level. The following are the results of the hypothesis testing:

H_1: Digital Innovation has a positive effect on Customer Experience.

The test results indicate that Digital Innovation has a positive effect on Customer Experience, with a path coefficient of 0.195, a T-statistic of 2.538, and a P-value of 0.006. Because the T-statistic is >1.96 and the P-value is <0.05, H1 is accepted. This indicates that the implementation and utilization of digital innovation within a company can improve customer satisfaction. Effective Digital Innovation can help companies respond to customer needs more quickly and accurately, thus positively impacting customer perceptions and experiences.

H_2: Consumer Behavior has a positive effect on Customer Experience.

The second hypothesis test yielded a path coefficient of 0.381, a T-statistic of 5.717, and a P-value of 0.000. These values indicate a highly significant relationship ($p < 0.001$); thus, H2 is accepted. These results confirm that Consumer Behavior plays an essential role in driving Customer Experience. Each form of Consumer Behavior has been shown to influence customer perceptions, resulting in a superior experience.

H_3: Digital Innovation has a positive effect on Competitive Advantage.

The influence of Digital Innovation on Competitive Advantage is indicated by a path coefficient of 0.140, a T-statistic of 1.884, and a P-value of 0.030. Although the T-statistic is slightly below the conventional threshold (1.96), the P-value is less than 0.05, allowing this hypothesis to be accepted at the 5% significance level. This finding suggests that digital innovation continues to make a significant contribution to achieving a competitive advantage, although not as strongly as other variables. This suggests that strategic use of Digital Innovation is necessary to strengthen a company's competitive position.

H_4: Consumer Behavior has a positive effect on Competitive Advantage.

The analysis results indicate that Consumer Behavior has a positive and significant effect on Competitive Advantage, with a path coefficient value of 0.309, a T-statistic of 4.179, and a P-value of 0.000. Thus, H4

is accepted with a very high level of significance. These results strengthen the argument that understanding consumer behavior is a key source of competitive advantage. Adapting to Consumer Behavior enables organizations to produce products or services that are unique, more valuable, and difficult for competitors to imitate.

H_5: Customer Experience has a positive effect on Competitive Advantage.

The final hypothesis indicates that Customer Experience has a positive effect on Competitive Advantage, with a path coefficient of 0.261, a T-statistic of 3.279, and a P-value of 0.001. These results indicate a significant relationship at the 1% level of significance, thus H5 is accepted. This demonstrates that Customer Experience is not only an indicator of service success but also plays a strategic role in strengthening a company's competitive position in the market. The better the Customer Experience, the higher the loyalty and positive image, which reinforces competitiveness.

Direct and Indirect Influence Relationships

The following presents a summary of the direct and indirect influences of the variables Digital Innovation and Consumer Behavior on Customer Experience, which in turn influences Competitive Advantage.

Table 12
Summary of direct and indirect effects

Var	Original Sample (O)	Sample Mean (M)	Std. Dev.	T Stat	P Values
(X2) → (Z) → (Y)	0.099	0.102	0.037	2.695	0.004
(X1) → (Z) → (Y)	0.051	0.053	0.027	1.902	0.029

The test results indicate that the indirect effect of consumer behavior on Competitive Advantage through Customer Experience is statistically significant, with a T-statistic of 2.695 (> 1.96) and a P-value of 0.004 (< 0.05). This confirms the finding that customer experience plays a significant mediator in the relationship between behavior and competitive advantage.

Meanwhile, the indirect effect of digital innovation on Competitive Advantage through Customer Experience has a T-statistic of 1.902 and a P-value of 0.029. Although the T-statistic is slightly below the 1.96 threshold, P-values smaller than 0.05 indicate that this indirect effect can also be considered significant at the 5% significance level. Therefore, these results support the notion that customer experience mediates the relationship between digital innovation and customer behavior in terms of competitive advantage.

Conclusions and Implications

Based on the model and analysis obtained, meeting customer needs more effectively will create opportunities for a sustainable competitive advantage. Sustainable business requires companies to focus not only on new product development but also on internal process innovation, digital marketing strategies, and omnichannel distribution channel integration. An omnichannel approach delivers a consistent and seamless customer experience across all touchpoints, setting a new standard for meeting modern consumer expectations. The integration of physical and digital channels allows consumers to transition seamlessly between channels, thereby increasing customer loyalty and retention.

Theoretical frameworks addressing digital innovation, such as the diffusion of innovation theory (Rogers, 2014), technology adoption theory (Davis, 1989), and complex adaptive systems theory (Holland, 2006), provide a solid scientific foundation for understanding how innovations are accepted and adopted by organizations and individuals. These theories help explain that adopting digital innovation depends not only on technical factors but also on social dynamics, perceived benefits, ease of use, and the organization's capacity to adapt to external changes systematically.

Measuring digital innovation performance also requires a holistic approach, encompassing three main dimensions: innovation inputs, processes, and outputs. Innovation inputs include resource allocation, such as technology investment, human resource development, and IT infrastructure. The innovation process emphasizes the importance of cross-functional collaboration, agile methodologies, and the use of data-driven technologies to accelerate the innovation cycle. Meanwhile, innovation outputs reflect the tangible results of the innovation process, which can be observed through the level of market adoption, financial impact, customer satisfaction and loyalty, as well as contributions to social and environmental sustainability.

However, measuring the performance of digital innovation presents several challenges. The complexity of disruptive innovation, the limitations of real-time data, and the increasing market demands for ethics, inclusivity, and sustainability require a new approach to innovation evaluation. Therefore, companies need to develop more dynamic, data-driven measurement systems integrated with digital technologies, such as AI analytics and digital monitoring tools.

In the future, companies will be required to innovate not only technologically but also socially responsibly. Today's consumers are becoming increasingly aware of sustainability, data privacy, and corporate social responsibility issues. Therefore, the success of digital innovation must be measured by the extent to which

companies can create value not only for shareholders but also for consumers, society, and the environment.

Overall, digital innovation has transformed the way we understand consumers, design business strategies, and manage organizations. Technology-based innovation, reinforced by an understanding of consumer behavior and executed with ethical and sustainable principles, is a key foundation for companies seeking to survive and thrive in the ongoing era of digital disruption, ushering in Marketing 6.0.

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