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AI-Driven Omnichannel Integration and Online Customer Engagement Intention: Exploring the Mediating Role of Perceived Usefulness and Ease of Use through the TAM Lens

التكامل متعدد القنوات المدعوم بالذكاء الاصطناعي ونية تفاعل العملاء عبر الإنترنت: دراسة الدور الوسيط لكلٍّ من المنفعة المدركة وسهولة الاستخدام المدركة من خلال منظور نموذج قبول التكنولوجيا (TAM)

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Abstract:

Objectives: This study aims to investigate how AI-driven omnichannel integration influences online customer engagement intention, drawing on the Technology Acceptance Model (TAM). Specifically, it examines the mediating roles of perceived usefulness and perceived ease of use in shaping customers' engagement intentions across digital channels.

Methods: A quantitative research design was employed, using survey data collected from online consumers who interact with AI-enabled retail platforms. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships derived from TAM.

Results: The results indicate that AI-driven omnichannel integration positively affects both perceived usefulness and perceived ease of use, which in turn significantly enhance online customer engagement intention. Furthermore, perceived usefulness demonstrates a stronger mediating effect than perceived ease of use in explaining customer engagement behavior.

Conclusions: The study highlights the pivotal role of AI technologies in enhancing customer experience through seamless channel integration. It extends the TAM framework to the omnichannel context, providing managerial insights on how to leverage AI to enhance user perceptions and foster engagement in digital environments.

Keywords: *AI-driven omnichannel integration; Technology Acceptance Model (TAM); Perceived usefulness; Perceived ease of use; Online customer engagement intention.*

الملخص:

الأهداف: تهدف هذه الدراسة إلى تحليل كيفية تأثير التكامل متعدد القنوات المدعوم بالذكاء الاصطناعي على نية تفاعل العملاء عبر الإنترنت، بالاعتماد على نموذج قبول التكنولوجيا (TAM). كما تسعى إلى دراسة الدور الوسيط لكل من المنفعة المدركة وسهولة الاستخدام المدركة في تشكيل نية التفاعل لدى العملاء عبر القنوات الرقمية.

المنهجية: اعتمدت الدراسة على منهج كمي من خلال استبيان وُجِّه إلى مستهلكين يتفاعلون مع منصات تجزئة مدعومة بالذكاء الاصطناعي. وتم تحليل البيانات باستخدام نمذجة المعادلات البنائية بطريقة المربعات الصغرى الجزئية (PLS-SEM) لاختبار الفرضيات المستمدة من نموذج قبول التكنولوجيا.

النتائج: أظهرت النتائج أن التكامل متعدد القنوات المدعوم بالذكاء الاصطناعي يؤثر إيجابيًا على كل من المنفعة المدركة وسهولة الاستخدام المدركة، واللتين تسهمان بدورهما في تعزيز نية تفاعل العملاء عبر الإنترنت. كما تبين أن تأثير المنفعة المدركة كوسيط أقوى من تأثير سهولة الاستخدام المدركة في تفسير سلوك التفاعل عبر الإنترنت.

الخلاصة: تؤكد الدراسة على الدور المحوري لتقنيات الذكاء الاصطناعي في تحسين تجربة العملاء من خلال التكامل السلس بين القنوات. كما توسّع تطبيق نموذج قبول التكنولوجيا (TAM) في سياق القنوات المتعددة، مقدّمةً رؤى إدارية حول كيفية استثمار الذكاء الاصطناعي لتعزيز تصورات المستخدمين ودعم تفاعلهم في البيئات الرقمية.

الكلمات المفتاحية: *التكامل متعدد القنوات المدعوم بالذكاء الاصطناعي؛ نموذج قبول التكنولوجيا(TAM)؛ المنفعة المدركة؛ سهولة الاستخدام المدركة؛ نية تفاعل العملاء عبر الإنترنت.*

Citation

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1 Introduction

The retail sector is undergoing a radical transformation driven by the rapid growth of digital technologies and shifting consumer expectations. In this context, the omnichannel approach is recognized as a critical strategy with its primary objective of offering a shopping experience that is both seamless and coherent across all physical and digital touchpoints.

The key challenge for companies is not merely the number of channels available, but their qualitative integration, which involves maintaining brand consistency, using data in a synchronized way, and establishing continuity in the customer journey. Consequently, the degree of success of channel integration becomes one of the leading performance indicators as it is customers' perceptions of their overall experience that they directly influence.

Artificial intelligence is increasingly transforming the retail market by enabling smarter data analysis, personalized interactions, and real-time decision-making. Through AI-driven omnichannel integration, retailers can seamlessly connect online and offline channels, offering consistent and tailored customer experiences. This technological convergence plays a crucial role in shaping online customer engagement intention, as consumers are more likely to interact with retail platforms that are responsive, personalized, and efficient.

Figure 1 illustrates the projected growth of the artificial intelligence (AI) market in the retail sector by different regions over the period 2018-2030. The general trend depicts a very rapid rise in growth, with the market expected to reach almost USD 40.7 billion by 2030, compared to a tiny size in 2018. This trend mirrors the global penetration of the retail sector's AI applications.

Looking at the regional data, North America and the Asia-Pacific are the two leading markets. They will benefit most from technological advancements in North America and the pace of digitalization in the Asia-Pacific. Besides, Europe also plays a significant role in this enrichment. At the same time, the shares of both Latin America and the Middle East & Africa (MEA) are smaller, and the two markets show smooth and orderly growth over the entire forecast period.

One of the most striking aspects of this is the significant increase between 2024 (USD 11.6 billion) and 2030, when the market's worth more than triples. This surge highlights the transformative role of AI in retail areas like personalized marketing, inventory and demand forecasting, supply chain coordination, as well as customer experience. The ongoing upswing indicates that AI is evolving from a unique company feature to a fundamental necessity for competitiveness in the retail sector.

One of the most decisive factors in this transformation is the advent of AI, which is very helpful to the collection, analysis, and use of data coming from various touchpoints. AI facilitates a unified customer interaction across all channels without blurring their distinct purposes. Besides, AI not only enables higher operational efficiency through better inventory management and demand forecasting, but it also strengthens customer personalization by allowing customers to receive real-time recommendations and exclusive journeys. Therefore, omnichannel integration becomes AI-powered omnichannel integration, where the use of artificial intelligence and machine learning guarantees the same level, tempo, and appropriateness of the whole customer experience.

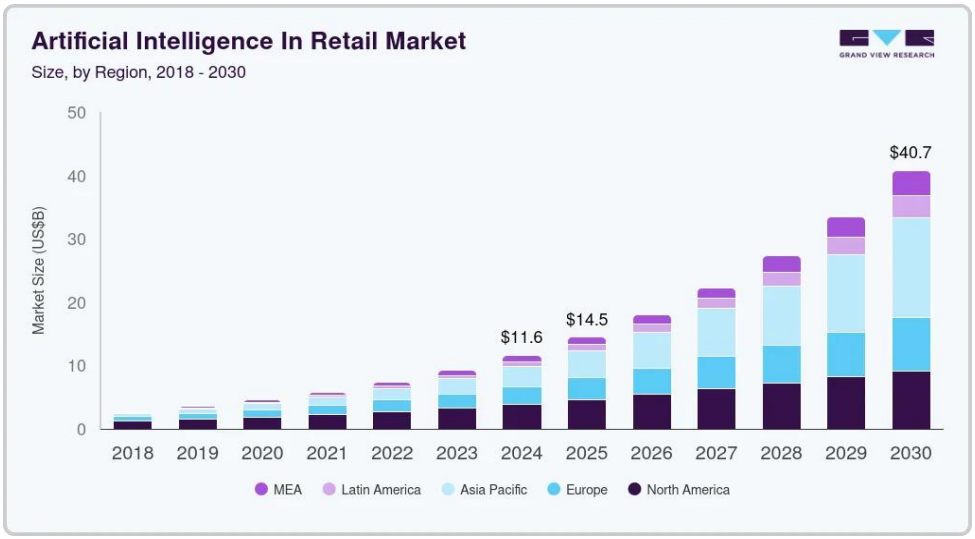


Figure 1: Artificial intelligence in retail Market (Artificial Intelligence in Retail Market Size, Share Report 2030)

The Technology Acceptance Model (TAM) provides a beneficial conceptual framework to outline this phenomenon. Per TAM, perceived usefulness and perceived ease of use are two essential features that have the most significant impact on consumers' recognition and adoption of new technology. When applied to AI-powered omnichannel integration, the mentioned features are crucial for understanding how shoppers evaluate the seamlessness, simplicity, and additional value of their shopping experiences. Thus, AI-driven integration can leverage a consumer's cross-channel behavior to influence their online engagement intention, that is, their propensity to actively and enduringly engage with the brand in the virtual space.

Consequently, this research aims to determine the role of AI in driving the omnichannel integration, along with an analysis of the mediating effect of perceived usefulness and ease of use as per TAM on online engagement intention. Drawing on these viewpoints, the present study makes a significant contribution by unpacking the processes that facilitate retailers' deployment of omnichannel strategies and consequent effectiveness in the digitalized retail landscape. The remainder of this paper is organized as follows. Section 2 presents a review of the relevant literature, focusing on three key aspects: artificial intelligence as a driver of seamless omnichannel integration, the two dimensions of AI-driven omnichannel integration, and online customer engagement intention. Section 3 introduces the proposed conceptual model, while Section 4 describes the research methodology adopted in this study. Section 5 reports the empirical results, and Section 6 discusses the findings. Finally, the paper concludes with a summary of the main contributions and implications.

2 Literature Review

Channel integration within a modern retail omnichannel framework is an organization's capability to effectively connect different customer touchpoints, thereby providing a seamless and uninterrupted consumer experience. Different from multichannel approaches, which generally isolate channels, omnichannel strategies strive for total harmony in terms of information, services, and communication. The measure of channel integration encompasses functionalities such as real-time data synchronization, brand image consistency, and customer journey continuity, enabling customers to transition between channels seamlessly. As previously noted in studies (Attaoui & Gaber, 2025; Bèzes, 2021a; Gao & Huang, 2021a; Sousa & Voss, 2006a), the central role of high-quality integration is in enhancing customer satisfaction, loyalty, and overall engagement, particularly in meeting the growing demands for instantaneity and personalization.

Today's customers want tailored, ongoing experiences that they can access via any channel, such as a website, mobile app, store, or even a social media interaction. Efficient omnichannel integration enables companies not only to raise their turnover and conversion rates, but also to increase their agility in reacting to the competitive challenges and the changing market trends. Thus, omnichannel strategies have become more than traditional distribution methods; they are a strategic lever for differentiation. Omnichannel integration is currently the top-of-the-list strategic priority of companies in both the retail and the service sectors. It means physically as well as digitally connecting, coordinating, and communicating sales channels to reach out to the customer with a friendly, straightforward, and uninterrupted experience.

The quality of channel integration is influenced by three main dimensions: the consistency of the brand message and identity, the synchronization of customer and transactional data in real time, and the smoothness of the purchasing journey across different touchpoints. A recent study lends support to the idea that these features are meeting the needs of the customers in terms of satisfaction and loyalty by delivering effective personalization, speed, and ease of use (Beck & Rygl, 2015; Verhoef et al., 2015a). Artificial intelligence (AI) has a key position in the process mentioned above. AI helps organizations to solve problems of both technical and organizational nature, such as channel integration, which involves managing large-scale data, synchronizing two different types of systems, and providing real-time personalization. Machine learning algorithms can identify consumption patterns, while chatbots and virtual aides simplify customer interactions. Therefore, AI-Driven omnichannel integration can be termed as the adoption of AI tools to achieve complete automation, personalization, and synchronization of all physical and digital channels, thereby resulting in a customer experience that is consistent, seamless, and driven by data (Pantano et al., 2020).

2.1 Artificial Intelligence as a Driver of Seamless Omnichannel Integration

Artificial intelligence facilitates seamless integration, enabling firms to mitigate the limitations associated with operating multiple channels. One of AI's strengths is its ability to collect, process, and analyze large amounts of real-time data, which enables firms to engage with their customers on a deeply personalized level, manage inventory and logistics in an optimized manner, and enhance the usability of the recommendation algorithms

they offer. By deploying AI, companies not only seek operational efficiency but also transform the very nature of their retail and e-commerce integration (Wamba et al., 2017). The omnichannel strategy, powered by AI, leverages technologies such as machine learning, predictive analytics, and natural language processing to consistently deliver personalized client experiences (S. Chatterjee & Chaudhuri, 2022). This strategy not only structures a customer journey, but also does it dynamically and adaptively. Every interaction feed knowledge model and enables real-time changes of offers and services (Verhoef et al., 2015a). The power of AI-driven integration is truly revealed in the context of customer relationships. As a result of an instantaneous switch from one channel to another, AI raises the level of perceived value and enhances customers' loyalty to the brand. Moreover, the shopping brand is not only more coherent but also engaging and personalized. Using AI, the user experience moves closer to a customer-centric journey as all the customer-specific interactions, corrected according to the preferences, habits, and needs of the individuals, are so tailored. Furthermore, this enables businesses to be proactive and agile, accurately estimating demand and quickly adapting to market trends (Pantano et al., 2020). Consequently, the employment of AI-driven omnichannel integration is the epitome of a well-thought-out design of staggered customer experiences. What differentiates it from mere technical channel integration is that it sets the model for an artificial intelligence-powered, unified, personalized, and evolving experience, capable of meeting the challenges of an increasingly volatile and complex digital environment.

Furthermore, AI is the key to the excellent data flow and management across channels, which is a central point of difference from the traditional methods of relying on the direct use of AI-driven technologies. Intelligent systems enable the real-time updating of information on customers, transactions, and stock levels, guaranteeing minimum discrepancies and thus higher operational efficiency (P. Chatterjee & Kumar, 2017; S. Chatterjee & Chaudhuri, 2022). Besides, they aid in data integration and cleansing, establishing a single trustworthy data store while distributing data to the recipients in the most efficient way. Fundamentally, AI is the one that discovers patterns during the continuous examination of cross-channel data, which, in turn, becomes a key source for new possibilities, as well as for fast and efficient reaction of store managers to both the trend-followers and the trend-setters (Kumar, V., Dixit, A., Javalgi, R. G., & Dass, 2021).

AI is another major factor in personalization and predictive analytics that should not be overlooked. Using complex algorithms, retailers can derive detailed customer segments down to individual levels based on purchase or browsing histories and offer product recommendations that fit each customer uniquely. Moreover, they can estimate demand to achieve the perfect balance of stock, thereby avoiding situations of either a lack of products or too many unsold goods(Prabu, 2023). With AI, there is also the opportunity to have a system of changing prices that will adjust according to the time at which it will be happening. Hence, one can find the price at that moment with the demand of the product, other competitors' pricing, and even the consumer's favorite price (Basal et al., 2024). Besides, customer journey anticipatory predictive modelling is the starting point of engagement maximization, where retailers predict and adapt purchasing steps at each touchpoint (S. Chatterjee & Chaudhuri, 2022).

Studies show that the infusion of AI into omnichannel strategies is not only a win with the customer but also a win with operational performance. The AI-driven retailers who take on such a strategy become more successful in retaining the competition, making more sales, and thus having loyal customers who, in return, promote the business, and they can even better invest the money received from marketing in their business (S. Chatterjee & Chaudhuri, 2022; Kumar, V., Dixit, A., Javalgi, R. G., & Dass, 2021). Access to Data and tools designed for AI decision-making and marketing broad-scaled strategies will be their next crucial stage, allowing their roles to morph from planning to implementation while also creating a more seamless interconnected retail space (Grewal et al., 2021). The next phase of retail instalments will be deeply grounded in their skills in integrating these technologies to bridge the gap between offline and online, thereby realizing the full potential of unified commerce, which is what the retail industry is betting on.

2.2 Dimensions of AI-Driven Omnichannel Integration

AI-Driven Omnichannel Integration (AI-DOI) is the capacity of omnichannel retailers to use AI to establish a seamless and uniform customer journey across all available channels (Sousa & Voss, 2006b). Traditional CIQ focuses mainly on the technical side of integrating touchpoints, such as email, mobile applications, social media, offline advertising, and search engine marketing. In contrast, AI-DOI emphasizes the role of all intelligent technologies that help in real-time personalization, behavioral prediction, and automated decision-making. AI through these channels has the capability not just to link the channels but to strategically coordinate them, resulting in a seamless and unified shopping experience as clients visit different outlets. To achieve AI-DOI, the planning, implementation, and evaluation stages must be fully supported by AI mobile analytics and adaptive

systems, ensuring complementarity between channels and alignment with broader marketing objectives. Different authors describe different features of AI-CIQ in various ways. As an illustration, (Shi et al., 2020) depicts the omnichannel experience as having the five dimensions (connectivity, consistency, flexibility, and personalization), which are the features that are significantly strengthened by the AI tools. Similarly, (Sousa & Voss, 2006b), (Lee et al., 2019) identify two main groups of integration dimensions: channel service configuration and integrated interactions. They also defined these categories as enriched by predictive algorithms and automated systems that enable personalization and adaptability within an AI-driven framework. While the channel service configuration elements mainly refer to the number of sub-dimensions, breadth of channel service choice, and transparency of channel service configuration, on the other hand, integrated interactions comprise content consistency and process consistency. We base this study on the Sousa and Voss method, which has been extensively identified and utilized in omnichannel literature.

2.2.1 AI-Driven Channel Service Configuration

The AI-driven configuration of channel services comprises the breadth of channel choice and the transparency of channel service design. The root of AI-driven channel choice breadth is the scope by which users can interact with the help of AI through various channels to meet their needs and likes(Gao & Huang, 2021b; Shen et al., 2018). For instance, retailers utilizing AI for managing customer relations and transactions across multiple touchpoints (e.g., phone, Instagram, online stores, mobile apps) are twice as effective in channel configurations as those with limited outlets. This widened breadth, facilitated by AI recommendation systems, gives customers power and personalization that, thus, encourages participation (Wu & Chang, 2016). As an instance, customers who are allowed to choose between online and offline purchases, supported by AI-generated suggestions, are more likely to experience satisfaction and feel less restricted than if they had only one channel to rely on (Bitner et al., 2002). Hence, the innovative organization of the different channels not only promotes easy conversions but also improves brand experience by activating the user-driven comparison with the adaptive purchase alternatives. The following aspect, AI-driven transparency of channel service configuration, refers to the extent of customers' awareness of channel options, services, and features, with AI providing customized guidance. The intelligent assistants and recommendation systems can guide consumers in the understanding of differences between various alternatives and in selecting the most appropriate (Kumar et al., 2019). For instance, the consumer may rely on AI-organized reviews on social media, experience the product in a store, and complete the purchase online with AI-personalized promotions. Thus, an end-to-end journey emerges, which is not only coherent but also flexible (Sousa & Voss, 2006b). Based on Social Exchange Theory, clients who feel freedom and support while choosing between AI-facilitated channels are more prone to reciprocity and form stronger bonds with omnichannel retailers (Calvo et al., 2023).

2.2.2 AI-Driven Integrated Interactions

Ensuring consistent and seamless interactions across channels is essential for customer engagement, and AI plays a central role in achieving this (Bèzes, 2021b). Integrated interactions are understood as the uniformity of experience across platforms, supported by two sub-dimensions: content consistency and process consistency.

Content consistency driven by AI enables a brand to maintain its identity, messaging, and tone consistently across all platforms, from bottom to top, thanks to intelligent automation. Language processing and generative AI enable companies to maintain a uniform voice while tailoring content to specific customer segments. For instance, consistency in communication between social media, websites, and AI-powered chatbots prevents confusion and strengthens customer trust. Setting up content governance with AI ensures that the tone, style, and messaging are consistent across all touchpoints, so People are talking about the same things (Elkhatat et al., 2023; Komara & Juhana, 2025).

Process consistency driven by AI highlights the element of uniformity of quality, speed, and overall perception of service by a customer across various channels, where the service is enhanced by automation and predictive systems. Innovative firms use AI to orchestrate the workflow, ensuring that tasks such as scheduling, content creation, and distribution are done systematically and transparently. This action not only fosters customer trust but also paves the way for personalization and reliability. When operations driven by AI are visible to the public, stakeholders comprehend the way decisions are made and the modality of service delivery, leading to a decrease in the levels of ambiguity and the number of mistakes. Consequently, process consistency facilitated by AI empowers reliability, raises productivity, and positively affects customer loyalty in the long run.

2.3 Online customer engagement intention

Online customer engagement (OCE) describes a multidimensional process where customers devote their mental, emotional, and behavioral resources to their interactions with a brand in the digital world. Contrary to passive consumption, OCE does not simply imply an active, two-way relationship whereby customers are only involved but also co-create with the brand, give feedback, and, through online platforms, reshape brand experiences(Attaoui & Gaber, 2024; ATTAOUI & GABER, 2025; Brodie & Hollebeek, 2011; van Doorn et al., 2010).

The concept of online engagement intention refers to a consumer's attitude and receptiveness to keeping the interaction alive or making it stronger through digital touchpoints. The intention here represents the motivational state that brings customers to give their attention, effort, and loyalty in virtual spaces. The sources of these intentions are, on the one hand, relational aspects such as trust, satisfaction, and commitment, and, on the other hand, contextual aspects such as the quality of channel integration and digital transparency (Harmeling et al., 2017; Kumar & Pansari, 2016a; Pansari & Kumar, 2017a). Typically, OCE is depicted as having two complementary psychological and behavioral dimensions. The psychological dimension accounts for the inner world of consumers, such as feelings of loyalty, cognitive involvement, perceptions of brand values, and trust, which all together make the consumers' loyalty and commitment grow (Brodie et al., 2013; Mollen & Wilson, 2010). On the other side, the behavioral dimension describes the performance of the consumers through visible actions such as repeat purchasing, word-of-mouth recommendations, online reviews, referrals, or participation in brand communities (Bijmolt et al., 2010; Jaakkola & Alexander, 2014). The two dimensions are very strongly linked as positive psychological experiences frequently lead to the realization of behavioral intentions, and in turn, they become long-term brand relationships. In this regard, OCE should not be viewed as isolated events, but rather as a continuous and dynamic process that integrates the customer’s intentions, perceptions, and behaviors. Through this process, customers actively participate in value creation while also demonstrating loyalty to the company (Attaoui & Gaber, 2024; Bijmolt et al., 2010; Brodie et al., 2013; Brodie & Hollebeek, 2011; Harmeling et al., 2017; Hoang et al., 2023; Jaakkola & Alexander, 2014; Kumar & Pansari, 2016a; Mollen & Wilson, 2010; Pansari & Kumar, 2017a; van Doorn et al., 2010).

3 Conceptual Model

The main concepts of our study's framework include the relationship between AI-driven omnichannel integration and online customer engagement intention, where perceived usefulness and perceived ease of use constitute the mediating variables. AI-driven omnichannel integration is a place where AI technologies are used to bring all the customer interactions, both offline and online, to the same level by synchronizing, automating, and personalizing them, thus ensuring a seamless, coherent, and customer-centric experience (Verhoef et al., 2015a; Wamba et al., 2017). Several studies confirm that AI-based integration leads to a significant upgrade of the quality of customer journeys, strengthens satisfaction and loyalty, and keeps attracting more active digital engagement of the users (Beck & Rygl, 2015; Pantano et al., 2020). The Technology Acceptance Model (TAM) is the theoretical background that clearly explains relationships by positioning perceived usefulness and perceived ease of use as key causes of technology adoption (Davis, 1989). In the case of AI-supported omnichannel integration, perceived usefulness means users’ evaluation of the additional benefits and the applicability of the provided experience, whereas perceived ease of use indicates that the level of communication between different channels is intuitive and effortless. Using TAM could help to reveal the deeper mechanisms that AI integration opens up about engagement. Positive AI effects can become real only if customers repeatedly bring up the good points of AI, making it easy for them to interact, enhancing their experience, and feeling comfortable navigating it. These perceptions play the role of mediators and have a direct influence on the degree to which online integration affects the intentions for involvement. AI, by assisting with smooth navigation, providing targeted recommendations, and allowing uninterrupted transitions between channels, creates a feeling in customers that not only do they trust the brand but also are ready to maintain a relationship, whether through loyalty programs, promotions, or brand communities. Therefore, literature agrees with the argument that AI-powered unification, by facilitating usefulness and ease of use, is at the centre of digital engagement implementation.

The conceptual model suggests that the AI-driven omnichannel integration is a primary factor in online engagement intention. Additionally, perceived usefulness and ease of use serve as mediators, influencing the user's perception and thereby the relationship between the two variables. This concept serves as a theoretical

foundation for a survey of 415 customers, utilizing PLS-SEM to assess the predictive relationships and mediating effects (Pantano et al., 2020).

The conceptual model of this paper is composed of the primary constructs. AI-driven omnichannel integration enables companies to utilize artificial intelligence technologies across both digital and brick-and-mortar channels, syncing, automating, and personalizing customer interactions. It involves such technologies as machine learning, predictive analytics, natural language processing, and computer vision. The main aim is to enable a seamless, consistent, and personalized customer experience, to facilitate the company's productive activities, and to provide each customer with the right suggestions at the right time (Verhoef et al., 2015a; Wamba et al., 2017).

Perceived usefulness (PU), one of the components of the Technology Acceptance Model (TAM), is the degree to which customers view AI-driven omnichannel integration as the main reason for the shopping experience. The goal is to assess whether the new technology can bring added value in various ways, such as facilitating product search, accelerating decision-making, or providing relevant recommendations. It can be achieved through a customer engagement strategy whereby customers with positive perceptions of the particular treatment are thus motivated to commit more to the channel (Davis, 1989a).

Perceived ease of use (PEOU), which originates from TAM, evaluates how intuitive and straightforward users find a communication channel that uses AI. It describes the degree to which customers see their interactions via mobile apps, websites, or physical stores as effortless and straightforward. The more the user is convinced that the service is easy to use, the more they will be willing to accept it, which will in turn remove any obstacle in the customer's journey and will allow a higher engagement rate with the online platform(Davis, 1989a).

Customer online engagement intention reflects the willingness of customers to actively involve themselves with the brand using digital means such as channel browsing, content interacting, buying, product recommending, or information sharing. The quality of the AI-powered omnichannel integration and the customers' perceptions of usefulness and ease of use are the primary influencers of this variable.

The inputs of perceived usefulness and perceived ease of use within this model are key mediators in nature. Although AI-driven omnichannel integration is the leading cause of online engagement intention, the effect's weight is higher when customers perceive the technology as valuable and easy to use. These perceptions disclose the mechanisms through which AI-enabled omnichannel consumer adoption and engagement occur.

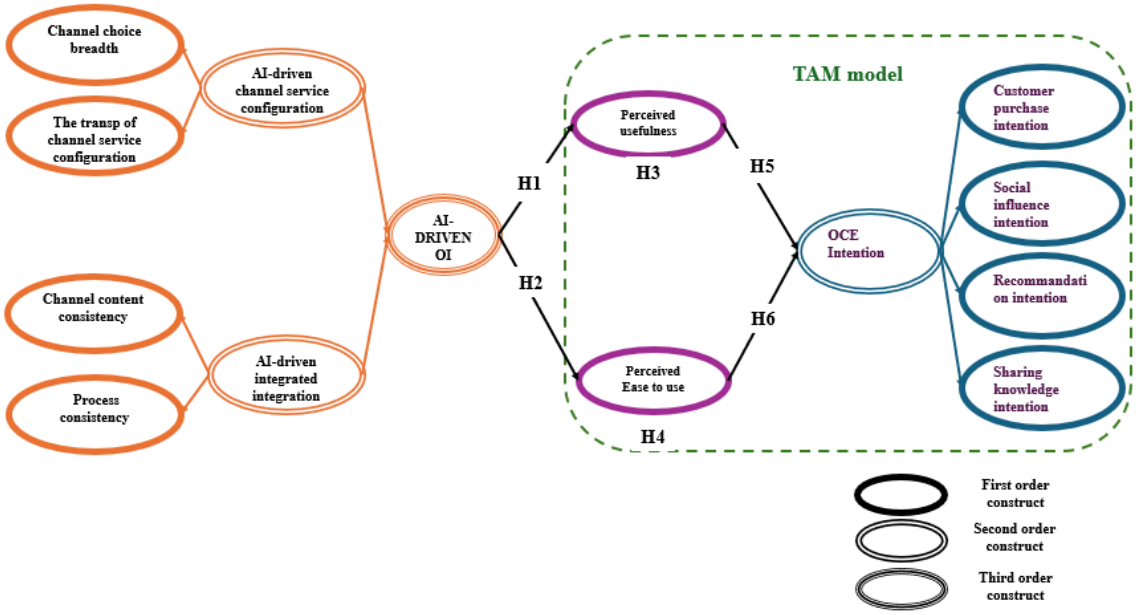


Figure 2: Conceptual model based on TAM model (Made by authors)

The conceptual framework (Figure.2) of this study is grounded in the Technology Acceptance Model (TAM), which highlights two central determinants of adoption of technology: perceived usefulness and perceived ease of use (Davis, 1989a). Drawing on this theoretical foundation, our model posits that AI-driven omnichannel integration directly influences customers' perceptions of usefulness and ease of use, which in turn shape their intention to engage online. Accordingly, the hypotheses are formulated as follows:

AI-driven omnichannel integration enables seamless coordination and consistency across multiple customer touchpoints through data integration, automation, and intelligent decision-making. By providing personalized, timely, and context-aware services, such integration enhances system performance and task efficiency. According to the Technology Acceptance Model (TAM), perceived usefulness reflects the degree to which a user believes that a system improves task performance (Davis, 1989b). When artificial intelligence is embedded in omnichannel systems, it strengthens information quality, service responsiveness, and decision support, thereby increasing users' perceptions of usefulness (Venkatesh & Davis, 2000; Verhoef et al., 2015b). Consequently, AI-driven omnichannel integration is expected to have a positive effect on perceived usefulness.

H1. AI-driven omnichannel integration has a positive effect on perceived usefulness.

AI-driven omnichannel integration improves system usability by ensuring consistency, automation, and intelligent coordination across channels. Through artificial intelligence, processes such as navigation, information retrieval, and service interactions become more intuitive, personalized, and less cognitively demanding for users. According to TAM, perceived ease of use refers to the degree to which a person believes that using a system requires minimal effort (Davis, 1989b). AI capabilities such as recommendation systems, chatbots, and predictive analytics simplify user interactions and reduce complexity, thereby enhancing perceived ease of use (Huang & Rust, 2021; Venkatesh & Davis, 2000). Consequently, AI-driven omnichannel integration is expected to positively influence the perceived ease of use.

H2. AI-driven omnichannel integration has a positive effect on perceived ease of use.

AI-driven omnichannel integration indirectly influences online customer engagement intention through perceived usefulness. By enhancing system performance, information relevance, and interaction efficiency across multiple channels, artificial intelligence strengthens users' perceptions of the usefulness of omnichannel systems. According to TAM, perceived usefulness is a key determinant of behavioral intentions (Davis, 1989b; Venkatesh & Davis, 2000). When customers perceive AI-enabled omnichannel systems as useful for achieving their goals efficiently, they are more likely to engage online through interaction, participation, and value co-creation. Therefore, perceived usefulness is expected to play a mediating role in the relationship between AI-driven omnichannel integration and online customer engagement intention (Hollebeek et al., 2014; Verhoef et al., 2015b).

H3. Perceived usefulness mediates the relationship between AI-driven omnichannel integration and online customer engagement intention.

AI-driven omnichannel integration can indirectly influence online customer engagement intention through perceived ease of use. By simplifying navigation, automating interactions, and providing intelligent support (e.g., chatbots, recommendations), AI reduces user effort and cognitive load, making the system more intuitive. According to TAM, perceived ease of use is a significant determinant of user behavioral intentions (Davis, 1989b; Venkatesh & Davis, 2000). When customers perceive AI-enabled omnichannel systems as easy to use, they are more likely to engage actively online, including interacting with content, participating in discussions, or co-creating value. Therefore, perceived ease of use is expected to mediate the relationship between AI-driven omnichannel integration and online customer engagement intention (Hollebeek et al., 2014; Verhoef et al., 2015b).

H4. Perceived ease of use mediates the relationship between AI-driven omnichannel integration and online customer engagement intention.

Perceived usefulness reflects the degree to which a user believes that using a system enhances their task performance (Davis, 1989). In the context of AI-driven omnichannel systems, when customers perceive the system as useful, they are more likely to engage actively online, including interacting with content, participating in discussions, or co-creating value. Prior research in technology acceptance and digital engagement highlights that higher perceived usefulness strengthens behavioral intentions and encourages online engagement (Hollebeek et al., 2014; Venkatesh & Davis, 2000). Therefore, perceived usefulness is expected to have a positive effect on online customer engagement intention.

H5. Perceived usefulness positively influences online customer engagement intention.

Perceived ease of use refers to the degree to which a user believes that using a system is free of effort (Davis, 1989). In AI-driven omnichannel environments, systems that are intuitive, user-friendly, and require minimal effort encourage customers to engage actively online, including browsing, interacting, or co-creating content. According to the Technology Acceptance Model (TAM), ease of use not only directly impacts behavioral intentions but also enhances engagement by reducing cognitive barriers (Venkatesh, 2000; Hollebeek et al.,

2014). Therefore, perceived ease of use is expected to have a positive effect on online customer engagement intention.

H6. Perceived ease of use positively influences online customer engagement intention.

The main objective of this work is to propose a research model aimed at exploring the effects of AI-driven omnichannel integration on OCE intention.

4 Methodology

4.1 Data Collection

This study applies to a quantitative methodology and gathers primary data to depict the consumers' perceptions within the retail context. It was carried out through an online questionnaire, which was available on social media and retail-related networks for 5 months (March – July 20, 2025). There were 415 valid responses in total that were used for the research. The emphasis on primary data was instrumental in capturing fresh insights into consumers' evaluation of AI-driven omnichannel practices. To test hypothetical relationships, the PLS-SEM method was used along with SmartPLS 4.0 software. This method allowed for the examination of the direct effects between the following latent variables: AI-driven omnichannel integration, perceived usefulness, perceived ease of use, and online customer engagement intention.

4.2 Development of the Instrument

The questionnaire consisted of two major parts. The first section was concerned with demographic variables, whereas the second contained study variables. As far as the measurement part is concerned, the scales were taken from existing and well-known research (Sousa & Voss, 2006c), to ensure the validity and reliability of the results. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) items have been taken by (Davis, 1989c). Moreover, technological integration, which is the main factor for AI-driven omnichannel integration, has been described through the items due to the technology as well as the channel consistency between the physical and the digital part. Finally, the Online Customer Engagement Intention was measured by the items that referred to the studies of consumer intention and digital engagement (Kumar & Pansari, 2016b; Pansari & Kumar, 2017b). A five-point Likert scale ("strongly disagree" = 1, "strongly agree" = 5) was used to collect responses for all statements.

4.3 Multivariate Normality

The dataset was checked for multivariate normality employing the Web Power method (Peng & Lai, 2012). Results of Mardia's tests for skewness and kurtosis (Kankainen et al., 2004) signified the presence of multivariate normality, as illustrated by p-values less than the 0.05 threshold.

4.4 Data Analysis

Once the data checks for normality were confirmed, given the complexity of the model that includes several reflective latent variables and a formative variable, we decided to use structural equation modeling, based on SEM-PLS least squares, using the Smart PLS 4 software. The analysis progressed through three main steps, starting with the measurement model assessment, then the structural model assessment, and finally, the mediation and moderation network assessment. PLS modeling was identified as an appropriate tool for our research, as it allows us to measure the relationships between the indicators and their respective latent constructs (reflective and formative variable measurement model), the relationships between constructs (structural model) at the same time, as well as the predictive capacity of the endogenous latent variable (Hair, Risher, et al., 2019; Henseler, 2018).

5 Results

5.1 The Sample characterization

Data collection took five months, from March to July 2025. A convenience sampling approach was adopted to facilitate access to respondents with relevant experience and familiarity with digital and AI-enabled omnichannel environments. Our sample is composed of women (54.7%) and men (45.3%), with a relatively balanced gender distribution. Respondents are of various ages, with the most common age range being 35 to 44 (67.7%). Senior managers are the most common socio-professional category in the sample (34.2%), with the remainder shared between the various CSPs, which are common. Finally, most respondents have a 5-year

higher education qualification (71.3%). A detailed overview of the socio-demographic characteristics of the respondents is presented in Table 1.

These sample characteristics are consistent with the research context, as AI-driven omnichannel systems primarily involve users who interact regularly with digital platforms and technology-enabled services. Moreover, respondents with higher managerial responsibilities and advanced educational backgrounds are more likely to evaluate the perceived usefulness and ease of use of AI-based omnichannel solutions, which aligns with the Technology Acceptance Model framework.

Table 1: Characteristics of the sample (n = 415)

Variable	Category	Percentage (%)	Number
Gender	Female	54,7%	227
	Male	45,3%	188
Age	Under 18	0%	0
	18–24	3,6%	15
	25–34	18,7%	78
	35–44	67,7%	281
	45–54	9.5%	39
	55–64	0.5%	2
	Over 65	0%	0
Socio-professional category (SPC)	Student	2.9%	12
	Employee	10.4%	43
	Civil servant	14.3%	59
	Manager	23.7%	98
	Senior manager	34,2%	142
	Entrepreneur	6.3%	26
	Retired	0%	0
Education level	Secondary education	0%	0
	Two-year university degree (DEUG or equivalent)	2.6%	11
	Bachelor's degree or equivalent	26,1%	108
	Master's degree or equivalent	60 %	249
	Doctorate or equivalent	11,3%	47

5.2 Assessment of measurement models

At this stage, the evaluation of the measurement model or the external model is given, which identifies the relationships between the items and the latent variables by checking the inbounds and outbounds validity, to estimate the measurement model for our research. An assessment report of reliability and convergent validity is proposed to establish the convergent validity of constructs; the reliability of individual items should first be checked by outer loading, which looks for the strongest connection between the indicators and the constructs. After that, composite reliability will be verified by assessing the internal consistency reliability (Cronbach's alpha and rho a), which is the degree to which different parts of a measurement scale interact to present the construct consistently. Finally, the average variance extracted (AVE) will be verified.

5.3 Assessing validity and reliability

The evidence presented in Tables 2, 3, and 4 strongly indicates that the measurement model is both consistent and valid. From Table 2, all first-order constructs are well-defined in terms of their internal consistency and convergent validity, as they exhibit both Cronbach's Alpha and composite reliability values greater than the recommended 0.70 threshold, and AVE values above 0.50 (Hair, Ringle, et al., 2019). In addition, Table 3 shows that the reliability and validity of the second-order constructs (CSC, II, and OCEI) are at the same level as those of the first-order ones, thus providing support for their measurement soundness. Table 4 focuses on the third-order formative construct, AI-Driven Omnichannel Integration, and its indicators are found to have statistically significant path coefficients ($p < 0.001$) in conjunction with acceptable VIF values (< 5), indicating that there are no multicollinearity issues and that this construct is robust to formative measurement. Collectively, this outcome is a good indication of the measurement model's sufficiency and, therefore, a solid basis for further structural analyses.

Table 2: Reliability and validity of (First-order reflexive construct)

	Cronbach's Alpha	Rho_a	Composite Reliability	Average Variance Extracted (AVE)
Channel choice breadth	0.812	0.824	0.882	0.653
Transparency of channel service configuration	0.836	0.847	0.894	0.679
Channel content consistency	0.801	0.818	0.876	0.641
Process consistency	0.827	0.841	0.885	0.662
Perceived usefulness (PU)	0.932	0.935	0.942	0.831
Perceived ease of use (PEOU)	0.851	0.857	0.910	0.772
Social influence intention	0.846	0.853	0.902	0.699
Customer purchase intention	0.872	0.878	0.918	0.738
Recommendation intention	0.854	0.861	0.909	0.714
Sharing value intention	0.868	0.872	0.91	0.726

Table 3: Reliability and validity of (Second-order reflexive construct)

	Cronbach's Alpha (Above 0.7)	Composite reliability (Above 0,7)	AVE (Above 0,5)
Formulas	$\frac{M.\ \bar{r}}{(1+(M-1).\ \bar{r})}$	$\frac{(\sum_{i=1}^{M} Li)^2}{(\sum_{i=1}^{M} Li)^2 + \sum_{i=1}^{M} var\ (ei)}$	$\frac{(\sum_{i=1}^{M} Li^2)}{M}$
Second-order constructs of the model	**Cronbach's Alpha**	**Composite reliability**	**AVE**
AI-driven Channel Service Configuration (CSC)	0.865	0.936	0.879
AI-driven Integrated Interaction (II)	0.809	0.957	0.919
OCEI (Online Customer Engagement Intention)	0.913	0.940	0.751

Table 4: Reliability and validity of (third-order formative construct)

Third order formative construct	Item Weights	2nd order dimensions	VIF	β	t-value	p-value
AI-Driven Omnichannel integration (AI-Driven OI)	Entre 0.670 et 0.875	**→ AI-driven Channel Service Configuration (AI-CSC)**	3.014	0.513	41.872	0.000
		→ AI-driven Integrated Interaction (AI-II)	3.027	0.535	44.286	0.000

5.3.1. Assessing the discriminant validity

Discriminant validity was verified using the Fornell-Larcker criterion, a method that assesses whether each construct is empirically distinct from the others. Table 5 shows that the square root of the average variance extracted (AVE) for each construct (values on the diagonal) is more than the correlation of that construct with all other constructs (off-diagonal values). For instance, the square root of the AVE for AI-Driven Omnichannel Integration (0.898) is larger than the correlations with OCEI (0.798), Perceived Ease of Use (0.657), and Perceived Usefulness (0.714), respectively. The AVE square root for OCEI (0.919) is above all the correlations with other constructs as well. Moreover, Perceived Ease of Use (0.879) and Perceived Usefulness (0.912) show the same pattern as well. This indicates that each construct shares a greater proportion of variance with its own indicators than with other constructs, thereby satisfying the Fornell–Larcker criterion and confirming discriminant validity in this study.

Table 5 also substantiates discriminant validity by displaying the Fornell-Larcker matrix (Fornell & Larcker, 1981) of all constructs. The diagonal values, denoting the square root of AVE for each construct, are always higher than the corresponding off-diagonal correlations, which provides the strongest indication that the constructs are not identical with each other. Together, these tests give a solid confirmation of the measurement model's discriminant validity.

Table 5: Fornell-Lacker criterion for discriminant validity

Construct	CCB	TCSC	CCC	PC	PU	PEOU	SII	CPI	RI	SVI
CCB	0.808									
TCSC	0.521	0.824								
CCC	0.498	0.544	0.801							
PC	0.507	0.533	0.511	0.814						
PU	0.552	0.561	0.546	0.559	0.911					
PEOU	0.498	0.529	0.512	0.524	0.642	0.879				
SII	0.466	0.491	0.478	0.489	0.611	0.537	0.836			
CPI	0.514	0.537	0.522	0.534	0.675	0.621	0.658	0.859		
RI	0.482	0.505	0.494	0.508	0.648	0.593	0.628	0.671	0.845	
SVI	0.495	0.523	0.507	0.519	0.661	0.607	0.641	0.684	0.663	0.852

Table 6: HTMT (Heterotrait–Monotrait Ratio) criterion for discriminant validity

Construct CCB	CCB	TCSC	CCC	PC	PU	PEOU	SII	CPI	RI	SVI
TCSC	0.61									
CCC	0.58	0.63								
PC	0.59	0.61	0.60							
PU	0.66	0.68	0.65	0.67						
PEOU	0.57	0.60	0.58	0.59	0.74					
SII	0.53	0.55	0.54	0.56	0.69	0.62				
CPI	0.60	0.62	0.61	0.63	0.76	0.70	0.72			
RI	0.56	0.58	0.57	0.59	0.73	0.68	0.69	0.74		
SVI	0.58	0.60	0.59	0.61	0.75	0.69	0.71	0.76	0.73	

CCB (Channel choice breadth), TCSC (Transparency of channel service configuration), CCC (Channel content consistency), PC (Process consistency), PU (Perceived usefulness), PEOU (Perceived ease of use), SII (Social influence intention), CPI (Customer purchase intention), RI (Recommendation intention, SVI (Sharing value intention).

To confirm the results obtained using the Fornell–Larcker criterion, discriminant validity was re-examined using the HTMT (Heterotrait–Monotrait Ratio) criterion (see table 6). All the obtained HTMT values are below the recommended threshold of 0.85, confirming satisfactory discriminant validity among the different constructs of the model. Consequently, the HTMT results reinforce and validate those derived from the Fornell–Larcker criterion.

5.4 Structural Model Assessment and Hypothesis Testing

After confirming the measurement model, we moved on to the structural model assessment. The test was based on various indicators of predictive quality and overall model fit. The first point is that the determination coefficients (R^2) for the four endogenous constructs are all relatively high, which means that these constructs can explain a large part of the variance in Perceived Usefulness, Perceived Ease of Use, and Online Customer Engagement Intention. The second point is that the predictive relevance (Q^2) according to Stone-Geisser is more than 0.35 for all the endogenous constructs, which implies that the model has a strong predictive capacity. The last point is that the Goodness of Fit (GoF) index is 0.675, which is significantly higher than the recommended threshold of 0.36 and, therefore, indicates the overall adequacy of the structural model.

Table 7 shows that all the hypotheses regarding the direct relationships between variables were corroborated, with p-values equal to 0.000 and t-statistics greater than 1.96, showing that AI-driven omnichannel integration had a significant impact on Perceived Usefulness (H1) and Perceived Ease of Use (H2) as well as the influence of Perceived Usefulness (H5) and Perceived Ease of Use (H6) on Online Customer Engagement Intention (OCEI) (see Table 7).

On the other hand, AI-driven omnichannel integration was found to have a non-significant direct effect on OCEI ($\beta = 0.045$, $t = 0.732$, $p = 0.464$); thus, the relationship is fully mediated by Perceived Usefulness and Perceived Ease of Use. Namely, the report shows that the AI-driven integration impact on customer engagement unfolds mostly through the users' perception of the usefulness and ease of use of the integration rather than through a direct route.

Besides that, the significance of the indirect paths (H3 and H4) is also evident in the sense that the constructs of the TAM model play the leading role in the explanation of users' online engagement behavior. The lack of a direct influence suggests the presence of specific sector-related factors that may be at play here, such as personalized experiences, brand reputation, or digital trust mechanisms that could be shaping consumers' engagement behaviors.

Table 7: Result of Structural Model Assessment and Hypothesis Testing

Direct links Analysis						
Hypothesis	**Path**	**β**	**t-value**	**p-value**	**Signification**	
H1	AI-DOI → PU	0.714	8.512	0.000	Significant	
H2	AI-DOI → PEOU	0.657	7.843	0.000	Significant	
H5	PU → OCEI	0.664	7.245	0.000	Significant	
H6	PEOU → OCEI	0.654	6.812	0.000	Significant	
Mediation Analysis						
Hypothesis	**Path**	**β**	**t-value**	**IC 95% (bootstrap)**	**p-value**	**Significance**
Direct link	AI-DOI → OCEI (direct)	0.045	0.732	[-0.052, 0.051]	0.464	Non-significant
H3	AI-DOI → PU → OCEI	0.466	6.123	[0.352, 0.574]	0.000	Significant
H4	AI-DOI → PEOU → OCEI	0.429	5.843	[0.318, 0.539]	0.000	Significant

Source: Smartpls 4.

6 Discussion

This section presents the results from Table 7, which are based on a 5% significance level. According to the literature, studies on how customers perceive AI-based omnichannel integration are still at the nascent stage, and there are not much empirical research works that explore its impact on such variables as Perceived Usefulness, Perceived Ease of Use, and Online Customer Engagement Intention (OCEI). The analysis backs up the statements in hypotheses H1 and H2. In particular, the AI-powered omnichannel integration has a statistically valid positive effect on the Perceived Usefulness ($\beta = 0.714$, $p = 0.000<0.05$, $t = 8.512>1.96$), thus indicating that the users acknowledge the real advantages of combined AI solutions. Correspondingly, integration considerably improves Perceived Ease of Use ($\beta = 0.657$, $p = 0.000<0.05$, $t = 7.843$), indicating that hassle-free AI-driven web services become more user-friendly. These outcomes strengthen the argument for the inclusion of the TAM variables when it comes to explaining online engagement behavior. Unexpectedly, the direct correlation between AI-driven omnichannel integration and OCEI was not substantial ($\beta = 0.045$, $p = 0.464>0.05$, $t = 0.732<1.96$), thus implying that the engagement impact was not direct. The structural model results indicate that the direct relationship between AI-Driven Omnichannel Integration (AI-DOI) and Online Customer Engagement Intention (OCEI) is non-significant ($\beta = 0.045$; $p = 0.464$), whereas the indirect effects through Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are highly significant. This pattern suggests the presence of full mediation, which can be justified at both theoretical and empirical levels.

Primacy of technological beliefs in the TAM: According to the Technology Acceptance Model (TAM) (Davis, 1989), the influence of advanced technologies on behavioral intentions does not occur directly, but rather through key cognitive beliefs, namely perceived usefulness and perceived ease of use.

Within this framework, AI-driven omnichannel integration represents a background technological infrastructure that customers do not evaluate in itself but instead assess through its functional and experiential benefits. Consequently, without an explicit perception of usefulness or ease of use, AI-DOI alone is insufficient to trigger online engagement intention.

AI-driven omnichannel integration often operates in a transparent and seamless manner for end users, through processes such as automation, channel synchronization, and algorithmic recommendations. As a result, customers do not directly attribute their engagement intention to the technology itself, but rather to the perceived value-in-use and the smoothness of the interaction experience. This technological invisibility helps explain why the direct AI-DOI → OCEI relationship is weak and non-significant, whereas the mediated paths through PU and PEOU remain robust and statistically significant.

The mediation research proves that both Perceived Usefulness (H3; $\beta = 0.466$, $p = 0.000<0.05$, $t = 6.123>1.96$) and Perceived Ease of Use (H4; $\beta = 0.429$, $p = 0.000 <0.05$, $t = 5.843>1.96$) completely dominate this association. The central issue of these findings is that initial consumer involvement is more likely the result of the way it is presented by helping them see that AI-integrated platforms are user-friendly and engaging.

Furthermore, the mediators themselves have a significant impact on OCEI. The higher the Perceived Usefulness, the more probable is engagement ($\beta = 0.664$, $p = 0.000 < 0.05$, $t = 7.245$), and this is equally true for

Perceived Ease of Use ($\beta = 0.654$, $p = 0.000 < 0.05$, $t = 6.812$), thereby confirming the importance of these TAM-related determinants in the promotion of the customer activity in online stores.

Overall, the findings suggest that the sole use of AI-driven omnichannel integration is insufficient to provoke customer engagement. The positive impact can only be realized via the perceptions of usefulness and ease of use; thus, the importance of a customer-centric product and experience is highlighted in online engagement strategies. There is also the possibility that these results could be due to certain contextual factors such as sector-specific user behaviors, platform trustworthiness, or personalized service features, which deserve to be explored in more detail.

These findings represent solid empirical evidence in favor of the theoretical framework in question, demonstrating that Perceived Usefulness and Perceived Ease of Use are crucial pathways through which AI-driven integration leads to online customer engagement.

Several theoretical and managerial implications might be identified based on the study findings. These implications help to understand not only the theoretical knowledge of AI-driven omnichannel integration but also the practical application of its use to improve customer engagement in digital retail environments.

Theoretical Implications: One of the contributions of this piece of research to theory is the expansion of the Technology Acceptance Model (TAM) (Davis, 1989a) application range from the general context to the specific case of AI-driven omnichannel integration in digital retail. The study reveals that Perceived Usefulness and Perceived Ease of Use act as full mediators between AI-driven integration and Online Customer Engagement Intention (OCEI). The result thereby underscores that adopting technology is not only a technical issue; instead, the individuals' cognitive perceptions play an instrumental role in deciding the engagement behavior. The empirical grounding in this study for the deployment of TAM latent variables in multi-channel retail environments helps to corroborate the model's theoretical contribution to digital service scenarios of various kinds (Venkatesh et al., 2003).

Moreover, this study reveals the theoretical framework for the relationship between technology and marketing theories. Seamless customer interactions across different channels are enabled by AI-driven integration; however, the impact on engagement is felt only through users' perceptions of usefulness and ease. The importance of psychological mechanisms becomes evident owing to complete mediation when the outcomes of digital innovations are evaluated, thus complementing previous works on cognitive and affective mediators for technology adoption (Hassanein & Head, 2007; Verhoef et al., 2015a). These findings constitute the theoretical foundation for understanding digital tools' success in specific contexts while, at the same time, being unable to engage users in other contexts, which leads to the development of more sophisticated customer engagement models in omnichannel ecosystems.

Managerial Implications: The findings from a managerial perspective have multiple major practical applications. In the first place, companies must understand that merely having AI-supported omnichannel systems does not, by itself, guarantee higher customer engagement. To turn technological potentials into real engagement, organizations need to create platforms that reach the highest level of Perceived Usefulness and Perceived Ease of Use. This can be done with services like easy-to-use interfaces, tailored product suggestions, uninterrupted flow between online and offline touchpoints, and instant customer support (Lemon & Verhoef, 2016).

Another observation in this article is the importance of the existence of teaching programs and support for both employees and customers. Users' training on how to take advantage of the AI-enabled services effectively can enhance their ease and utility perceptions, thus setting engagement intentions higher(Grewal & Roggeveen, 2020). Managers can not only check the behavioral side of things (e.g., clicks, time spent, repeat interactions) but also the cognitive side, as they can be leading indicators of engagement outcomes and service adoption (Kumar & Pansari, 2016b).

Moreover, many research findings indicate that the customer-centric approach is the best way to introduce AI-driven integration. By persistently collecting and analyzing feedback concerning usability and perceived benefits, organizations can change t

Their systems in small increments to boost engagement. Furthermore, the total mediation effect implies that managers should concentrate on elevating the user experience rather than just counting on the surprise or the technological cleverness of AI gadgets. These insights can influence financing decisions, platform creation, and customer experience management in AI-powered omnichannel environments.

7 Conclusion

This research enhances the comprehension of online customer engagement by AI-driven omnichannel integration, leading customers to perceive usefulness and ease of use, and improving their engagement. In contrast to previous studies that are usually concentrated on one channel or engagement dimension, our research covers both entirely digital and brick-and-mortar retail, checking how the integration of AI-powered technology impacts engagement through cognitive mediators.

From a theoretical standpoint, this study contributes to literature by extending the Technology Acceptance Model (TAM) to the context of AI-driven omnichannel integration. Rather than proposing a new theoretical framework, the findings empirically confirm that perceived usefulness and perceived ease of use fully mediate the relationship between AI-enabled omnichannel integration and online customer engagement intention. This result reinforces the central role of cognitive evaluations in technology-enabled service environments and suggests that the impact of advanced AI-driven integration mechanisms is indirect, operating through customers' perceptions rather than through direct effects on engagement.

The inclusion of AI in omnichannel retail is an overhaul of the department, which has a supply of limitless possibilities to improve customer experience, optimize operations, and spur business growth. Seamless integration powered by AI allows retailers to create a single customer profile, manage inventory live, deliver marketing on a one-to-one basis, and make decisions based on data across all channels. As a result, well-structured digital platforms not only extend the consistency and efficiency of customer interactions but also allow firms to identify high-traffic touchpoints, allocate resources effectively, and reduce operational redundancies.

The evidence of full mediation also carries important managerial implications. The results indicate that investments in AI-driven omnichannel technologies do not automatically translate into higher customer engagement. Instead, their effectiveness depends on the extent to which such technologies enhance customers' perceptions of usefulness and ease of use. This finding suggests that retailers should prioritize AI-enabled functionalities that simplify customer journeys, reduce cognitive effort, and deliver tangible functional value across channels, rather than focusing solely on the multiplication of touchpoints or technological sophistication.

While the findings of our study are broadly consistent with integration quality theories emphasizing online engagement through perceived usefulness and ease of use, we also draw attention to several practical and methodological constraints. Challenges related to data privacy, the effective deployment of technology, and staff preparedness remain critical areas requiring further consideration. In addition, difficulties encountered during questionnaire administration, particularly in respondent recruitment and survey length, required the implementation of a pre-test to refine the measurement instrument. Based on these observations, several promising directions for future research can be identified:

- Identifying both internal and external barriers to effective AI-driven channel integration and adoption of transparent practices.
- Testing the proposed model across various cultural and industry contexts, such as B2B environments, retail sectors, or public services.
- Incorporating actual behavioral data (e.g., web analytics, navigation patterns, conversion rates) to complement self-reported perceptions and strengthen validity.
- Exploring potential moderating influences of individual factors (e.g., digital literacy, age, expectations) or organizational factors (e.g., digital maturity, technology readiness).

Altogether, this research unveils the fact that AI-driven omnichannel integration should not simply be seen as a technical upgrade but rather as a strategic measure for developing one-to-one, uninterrupted user experiences, which, in turn, results in higher user engagement and being ahead of the competition. As the IoT, AR/VR, and 5G innovations merge with customer expectations that keep changing, retail will be an AI-driven affair where the combination of physical and digital experiences will be utilized to offer fully integrated and personalized shopping journeys. The retailers that fully exploit AI for omnichannel integration will not only be able to satisfy the needs of highly digital consumers but also will be able to keep a competitive edge that is sustainable in a fast-changing market environment.

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