Li, Y., Tsang, Y. P., Ho, D. C. K., Ozden, M., Lee, C. K. M., & Hu, H. (2025). Unraveling consumer resistance to innovative marketing in web 3.0: empirical findings and large language model insights. Enterprise Information Systems, 19(1–2), 183-210. DOI:10.1080/17517575.2025.2462069

Unraveling Consumer Resistance to Innovative Marketing in Web 3.0: Empirical Findings and Large Language Model Insights

Abstract: The rise of blockchain technology has enabled the emergence of Non-Fungible Tokens (NFTs) within Web 3.0, positioning them as innovative tools in digital marketing. However, consumer resistance poses significant challenges to their widespread adoption, with existing research lacking comprehensive analysis of the barriers driving this resistance. This study addresses this gap by applying innovation resistance theory to examine the functional and psychological barriers to NFT marketing adoption and the moderating role of consumer knowledge. Employing a dual-method analytical framework, the research integrates Covariance-Based Structural Equation Modeling (CB-SEM) of survey data from 610 respondents with insights from eight large language models (LLMs). The findings identify perceived risk as the most significant barrier, with its negative impact amplified by higher levels of consumer knowledge. Notably, 75% of the LLMs corroborate this result, emphasizing the central role of risk perception in NFT marketing resistance. As the first study to examine consumer resistance to NFT marketing innovations using both empirical investigation and generative artificial intelligence analysis, this research advances the understanding of consumer behavior in the context of innovative digital marketing. It also demonstrates the potential of LLMs as complementary tools in empirical research. The findings provide actionable insights for businesses and policymakers aiming to mitigate resistance and foster the adoption of blockchain-based digital marketing solutions.

Keywords: NFT Marketing; Non-Fungible Tokens; Innovation Resistance Theory; Large Language Models

1. Introduction

The advent of Web 3.0 marks a paradigmatic shift in global business operations, redefining the digital ecosystem through decentralized technological architectures and enhanced user autonomy. This transformation fundamentally reshapes business-consumer interactions in the contemporary digital economy, offering new paradigms for organizational strategy and market engagement (Murtas et al., 2023). Central to Web 3.0 is blockchain technology, which underpins the emergence of non-fungible tokens (NFTs)—unique digital assets authenticated through decentralized ledgers (Xie et al., 2024). NFTs represent a groundbreaking innovation within the Web 3.0 framework, providing marketers with novel tools to engage consumers in dynamic and personalized ways (Chohan and Paschen, 2023). By enabling the creation, trade, and ownership tracking of digital assets, NFTs empower users with greater control over their digital interactions while simultaneously expanding opportunities for organizations to participate in the evolving digital economy (Hofstetter et al., 2022; Ante, 2021).

Recent studies (e.g., Dan, 2021; Kaczynski and Duke Kominers, 2021; Chohan and Paschen, 2023; Xie et al., 2023; Xie et al., 2024) have emphasized the significant potential of NFTs in enterprise marketing strategies. NFTs enable businesses to create unique value propositions that not only open entirely new revenue streams but also cultivate long-term brand loyalty among consumers. In the Web 3.0 era, NFTs are more than just a marketing innovation. They represent a transformative opportunity for enterprises to advance information systems, enhance customer relationship management, and drive innovation across supply chain processes (Upadhyay et al., 2024; Xie et al., 2024). Recognizing this potential, leading global brands such as Gucci, Louis Vuitton, and Starbucks have actively incorporated NFTs into their enterprise systems and marketing strategies. These early adopters are not simply experimenting with the technology. Instead, they are actively reshaping the dynamics of consumer-brand interactions within the Web 3.0 ecosystem. The benefits of Web 3.0 technologies, however, are not confined to large enterprises. Potluri and Vajjhala (2018) noted that small and medium-sized enterprises (SMEs) can also leverage Web 3.0 technologies to enhance efficiency and performance. From an e-commerce perspective, Web 3.0 technologies provide organizations of all sizes with advanced tools to analyze consumer habits. This enables businesses to gain deeper insights into consumer interests, facilitating the delivery of highly personalized e-commerce shopping experiences (Murtas et al., 2023).

Despite the promising benefits of NFT marketing, its success largely depends on consumers' willingness to embrace this innovative approach. Skepticism toward emerging technologies often results in resistance, which can disrupt the entire value chain, including supply chain management and customer relationship management (Sestino et al., 2022; Xie et al., 2024). According to the innovation resistance theory proposed by Ram and Sheth (1989), consumers may resist innovations that challenge established enterprise-customer interactions, social norms, or perceived value systems. This resistance is particularly relevant in the context of NFTs, where adoption requires a significant shift from traditional enterprise information systems and consumer behaviors. Joseph (2010) emphasized the importance of examining consumer adoption from a rejection-based perspective, especially when dealing with highly innovative enterprise information technologies. Similarly, Sestino et al. (2022) argued that understanding the factors contributing to consumer resistance is critical for marketers seeking to develop and implement effective NFT-based marketing strategies.

The existing literature on NFT implementation has primarily focused on the technical architecture of NFTs (e.g., Arcenegui et al., 2021), their attributes and potential for value creation (e.g., Alexander and Bellandi, 2021; Stallone et al., 2021; Chohan and

Paschen, 2023), and the factors influencing consumers' purchase intentions (e.g., Xie et al., 2023; Xie et al., 2024). However, research examining the barriers that may lead to consumer resistance within the context of NFT marketing strategies remains limited. Addressing this gap is essential for developing a comprehensive understanding of the factors that hinder consumer adoption of NFTs and for identifying strategies to mitigate resistance. This is particularly important for innovative technologies like NFTs, which require consumers to navigate unfamiliar digital ecosystems and adopt new behavioral patterns (Xie et al., 2023). Unlike traditional products or services, NFTs frequently involve complex processes, such as setting up digital wallets, understanding blockchain mechanics, and assessing the intangible value of digital assets (Ali et al., 2023). These complexities can present significant psychological and practical barriers to adoption, deterring potential users and impeding the broader integration of NFTs into mainstream consumer markets.

Drawing upon these theoretical and practical imperatives, this study examines the barriers to NFT marketing from the perspective of consumer rejection. The theoretical foundation of this research is grounded in innovation resistance theory (Ram and Sheth, 1989), which has been extensively validated in studies exploring consumer resistance to technological and marketing innovations (Khalil et al., 2023). This study proposes a conceptual model that identifies and categorizes the barriers contributing to consumers' resistance intentions toward NFT marketing purchases. These barriers are organized into five distinct dimensions: usage, value, and risk within the framework of functional barriers, and tradition and image as components of psychological barriers. Furthermore, building upon prior research highlighting the pivotal role of consumer knowledge in shaping perceptions and behaviors towards emerging technologies (e.g., Teng and Wang, 2015; Shan et al., 2020), this study examines the moderating effect of consumer knowledge on the relationships between individual barriers and resistance intentions.

Methodologically, this study adopts an innovative dual-analytical approach that combines traditional empirical analysis with artificial intelligence-driven insights. Covariance-based structural equation modeling (CB-SEM) is employed as the primary analytical framework due to its robust capability to simultaneously evaluate complex theoretical relationships and assess measurement validity and reliability (Hair et al., 2022). While CB-SEM offers statistical rigor for quantifying relationships and testing theoretical models, its structured nature may fall short in capturing the dynamic and evolving aspects of NFT marketing, where consumer attitudes and behaviors are subject to constant change. Furthermore, the novelty of NFT marketing presents unique challenges for traditional survey-based methodologies. Respondents may have limited familiarity or exposure to the technology, and the validity of the study is contingent upon the accuracy and honesty of their self-reported responses. To overcome these methodological limitations, this study leverages insights from eight state-of-the-art large language models (LLMs), including GPT-4, LLaMA 3, Gemini-1.5, Chinchilla, Claude-3.5, Gemma, Qwen2, and RekaCore. Recent evidence highlights the ability of LLMs to extract nuanced relationships and generate theoretically grounded insights, making them particularly valuable for empirical research in emerging fields (Liu et al., 2024; Chen et al., 2025). The deliberate use of multiple LLMs mitigates model-specific biases and capitalizes on their advanced natural language processing capabilities, which are crucial for analyzing complex, multi-dimensional constructs (Liu et al., 2023). These models, trained on expansive repositories of academic literature and market data, can provide complementary perspectives to the empirical findings in consumer resistance behavior.

The present study contributes to extant literature and practice in three significant ways. First, it advances the theoretical understanding of consumer resistance intention within the context of enterprise NFT marketing adoption, addressing a critical knowledge gap in the emerging Web 3.0 marketing literature. Second, this research extends innovation resistance theory by examining the moderating role of consumer knowledge, thereby enhancing scholarly understanding of how knowledge mediates the resistance of consumers to enterprises' digital marketing innovations and technological implementations. Finally, by employing a novel dual-analytical approach, this study not only enhances the validity and depth of its findings but also contributes to methodological innovation in the study of consumer behavior within rapidly evolving technological domains. The research also offers significant theoretical, practical, and managerial implications for enterprise stakeholders and policymakers.

The remainder of the paper is structured as follows: Section 2 reviews the theoretical background related to NFT marketing, innovation resistance theory, and empirical research involving LLMs. Section 3 develops the model and hypotheses. Methodology and data analysis are presented in Sections 4 and 5, respectively. Section 6 discusses the findings and implications. The final section concludes the study, outlines limitations, and suggests future research directions.

2. Theoretical Background

In this section, we examine three critical areas of relevance: NFT marketing, the theoretical framework of innovation resistance theory, and empirical studies involving LLMs. Collectively, these sections establish a comprehensive theoretical foundation to contextualize and guide the research focus.

2.1 NFT Marketing

NFTs offer brands innovative opportunities to engage their audiences by leveraging blockchain technology to enable digital ownership of unique assets. From a marketing perspective, NFTs possess several desirable attributes, including scarcity, authenticity, proof of ownership, non-fungibility, royalties, and direct distribution infrastructure (Chohan and Paschen, 2023). These characteristics enable brands to devise novel marketing strategies, such as limited-edition NFT offerings tied to exclusive content or virtual experiences (Nadini et al., 2021). From an enterprise information systems perspective, NFTs can complement existing customer relationship management systems by enabling personalized loyalty programs that are transparent, verifiable, and secure. Blockchain technology ensures that NFT-based loyalty programs provide traceability and authenticity, thereby fostering trust in customer-brand relationships (Murtas et al., 2023). Furthermore, NFTs' ability to integrate with enterprise systems allows businesses to track consumer preferences in real-time, offering actionable insights for future marketing campaigns (Potluri and Vajjhala, 2018).

To capitalize on these opportunities, early adopters in industries such as fashion, retail, and hospitality have begun experimenting with NFT-based campaigns. For instance, Adidas collaborated with NFT collectibles like Bored Ape Yacht Club and Punks COMIC to enhance its marketing efforts by offering collaborative physical merchandise and ongoing digital applications to NFT owners. Such initiatives not only generate excitement but also foster customer loyalty and engagement by providing unique benefits to NFT holders (Hofstetter et al., 2022). Similarly, Starbucks' NFT rewards program, *Starbucks Odyssey*, integrates NFTs into its Starbucks Rewards app, offering interactive games and activities to incentivize customer engagement and drive repeat purchases.

Given the vast potential of NFTs in marketing, recent academic research has started to explore consumer behavior and motivations related to NFT adoption. For example, Albayati et al. (2023) used the theory of planned behavior to identify key factors influencing consumer adoption of NFTs, including social influence, technical criteria, NFT regulations, market impact, and trust. These findings suggest that social and technical factors significantly shape consumers' intentions and behaviors. Additionally, from a consumer value perspective, Alexander and Bellandi (2022) found that the willingness to purchase NFTs is driven by price value (e.g., brand reputation, exclusivity, scarcity, and past experiences) and social value (e.g., enhancing one's digital reputation). Empirical research further highlights the role of perceived attributes in influencing consumer adoption. Xie et al. (2023) demonstrated that factors such as perceived usefulness, playfulness, and scarcity of NFTs, along with the perception of NFTs as low-risk purchases, significantly strengthen consumers' purchase intentions for branded NFTs.

However, while these studies provide valuable insights into the factors driving consumer interest in NFTs and their potential marketing applications, they often overlook the barriers that may hinder broader adoption. Xie et al. (2024) noted that despite strong behavioral intentions, practical obstacles such as technical complexity and consumer skepticism frequently prevent actual adoption. Moreover, NFTs are currently positioned within Gartner's hype cycle beyond the "peak of inflated expectations" and into the "trough of disillusionment" (Gartner, 2022). This phase indicates that the initial excitement surrounding NFTs has subsided, with speculative behavior and inflated prices contributing to market volatility and consumer disillusionment. According to Gartner's framework, technologies in this phase face skepticism and require time to mature before they reach the "slope of enlightenment" or the "plateau of productivity" (Gartner, 2018). Additionally, many consumers lack a clear understanding of how NFTs function, the value they offer, and how to engage with them (Chohan and Paschen, 2023). This knowledge gap, combined with concerns over security, fraud, and regulatory uncertainty, often creates resistance to adoption (Nadini et al., 2021; Xie et al., 2024). For enterprises, this means that while NFT marketing holds significant long-term potential, navigating short-term market instability and consumer hesitancy is crucial.

Despite the growing body of research on NFTs, significant gaps remain in understanding the barriers that influence consumers' purchase intentions in NFT marketing. While Gartner's hype cycle offers insights into the lifecycle of emerging technologies, little is known about how enterprises can effectively navigate the transition from the "trough of disillusionment" to the "slope of enlightenment". Successfully managing this transition requires addressing both technical challenges and consumer-facing issues. Therefore, further empirical research into the factors driving consumer resistance would address a critical gap in the literature and provide actionable insights for leveraging NFTs to enhance marketing strategies.

2.2 Innovation Resistance Theory

The innovation resistance theory plays a significant role among the frameworks used to explore consumer resistance towards technology innovation (Khalil et al., 2023). Hew et al. (2019) defined innovation resistance as a rational thought process and decision-making process concerning the adoption and use of an innovation, driven by concerns about the potential changes it may bring to the existing status quo and deviations from established belief systems. According to Ram and Sheth (1989), consumers face various obstacles that hinder their willingness to embrace innovations, which can be classified into functional barriers and psychological barriers. Functional barriers encompass components such as value, risk, and usage. These barriers are more likely to manifest when consumers perceive that adopting an innovation would entail significant changes. On the other hand, psychological barriers stem from conflicts with consumers' preexisting beliefs and can be attributed to tradition and image-related concerns. Heidenreich and Handrich (2014) categorized customer resistance behaviors as either active or passive, with passive resistance arising from conflicts with established beliefs and studied through the lens of psychological barriers. In contrast, active resistance refers to resistance behaviors arising from the characteristics of the innovation itself and can be examined through the functional barriers proposed by the innovation resistance theory.

As the NFT market continues to witness ongoing innovations, applying the innovation resistance theory to understand consumer resistance towards NFT marketing becomes increasingly pertinent. While the innovation resistance theory has been applied to various domains such as drone food delivery services (Khalil et al., 2023), innovative mobile services (Chen et al., 2022), mobile payment solutions (Kaur, 2020), and the eco-friendly cosmetics industry (Sadiq et al., 2021), its application in the context of NFT marketing has been largely overlooked. The present study, therefore, seeks to leverage the innovation resistance theory to examine the underlying factors contributing to customer resistance in the NFT marketing domain. In doing so, it aims to provide timely insights to businesses on effective NFT marketing strategies that can mitigate consumer resistance and facilitate the successful adoption of this emerging technology.

2.3 Empirical Research involving LLMs

The growing capabilities of LLMs have opened new avenues for their application in empirical research (Kim et al., 2023; Liu et al., 2024; Chen et al., 2025). According to the categorization suggested by Wagner et al. (2024), these roles of LLMs can be categorized into three key types, namely annotators, judges, and subjects. Each category highlights the distinct ways in which LLMs contribute to the research process.

Regarding LLMs as annotators, they have been increasingly utilized in empirical research (Kim et al., 2023; Liu et al., 2024; Wagner et al., 2024). In specific, their ability to process and understand natural language enables them to label datasets, extract information, and identify patterns at scale. For instance, researchers can employ LLMs to annotate large text corpora with sentiment labels, topic classifications, or named entities, significantly reducing the time and cost associated with manual annotation (Alizadeh et al., 2025).

Another notable role of LLMs is serving as evaluators or judges in empirical research. Zheng et al. (2023) pointed out that LLM-as-a-judge is a scalable and explainable way to approximate human preferences. LLM-as-a-judge offers two key benefits: scalability and explainability. It reduces the need for human involvement, enabling scalable benchmarks and fast iterations. Additionally, LLM judges provide not only scores but also explanations, making their outputs interpretable (Liu et al., 2024). Existing studies in educational and psychological research have leveraged LLMs to grade essays, analyze arguments, or provide feedback on creative writing (Escalante et al., 2023).

Recent studies have demonstrated the potential of using LLMs as subjects to simulate human-like responses in behavior studies (Cui et al., 2024; Sadlier-Brown et al., 2024; Chen et al., 2025). In this context, LLMs are treated as participants, generating responses or insights that can be analyzed alongside, or as alternatives to, traditional human data. This approach enables researchers to explore the distinct perspectives and decision-making processes of artificial intelligence systems compared to human participants (Sadlier-Brown et al., 2024). The use of LLMs as subjects has several advantages. First, these models are capable of synthesizing vast amounts of knowledge from their training data, enabling them to provide well-informed and consistent responses to structured questions (Wagner et al., 2024). Additionally, LLMs can simulate responses in situations where collecting human data may be impractical, resource-intensive, or constrained by ethical considerations (Sadlier-Brown et al., 2024).

However, unlike human participants, LLMs lack personal experiences, emotions, and cultural contexts. Their outputs are entirely shaped by the training data and underlying algorithms, which may embed biases or fail to capture the nuanced complexities essential for understanding human behavior (De Nicola et al., 2024; Cui et al., 2024). Moreover, while LLMs are capable of generating human-like responses, these outputs are ultimately probabilistic predictions rather than genuine reflections of human thought processes (Wagner et al., 2024; Sadlier-Brown et al., 2024). In this regard, the experimental findings of Cui et al. (2024) highlight the significant potential of LLMs to complement human-based studies; however, they cannot yet fully replicate the depth and richness of insights provided by human participants.

As such, this study integrates LLM-generated insights with traditional human-generated data to develop a more comprehensive understanding of complex consumer behavior. Our research contributes to the emerging literature on the applications of LLMs in empirical studies within the marketing domain.

3. Conceptual Model and Hypotheses

To identify major barriers associated with NFT marketing from a consumer perspective, this study develops a conceptual model based on the innovation resistance theory framework. This model includes usage, value, and risk barriers as functional barriers, and tradition and image barriers as psychological barriers (refer to Figure 1). In this study, NFT marketing purchase resistance intention is defined as the inclination of consumers to refrain from engaging in NFT marketing-based purchases due to perceived obstacles. For instance, consumers who perceive significant usage barriers, such as difficulty in understanding how to purchase or use NFTs, are likely to exhibit higher resistance intentions. Similarly, those who perceive high value or risk barriers may hesitate to invest in NFTs, fearing a lack of return or potential loss. Furthermore, consumers who feel that NFTs conflict with their traditional values or who are concerned about the social perception of NFT ownership may exhibit stronger resistance. In addition, existing literature suggests that consumers with varying levels of knowledge concern may exhibit differences in their perceptions of these barriers and their intentions to make purchases (Ullah et al., 2021). Consumers who are more informed may perceive NFT marketing as immature or lacking meaningful value, prompting them to resist participating in purchases. Therefore, the study also considers the moderating effect of knowledge concern on the relationship between barriers and consumer resistance intention.

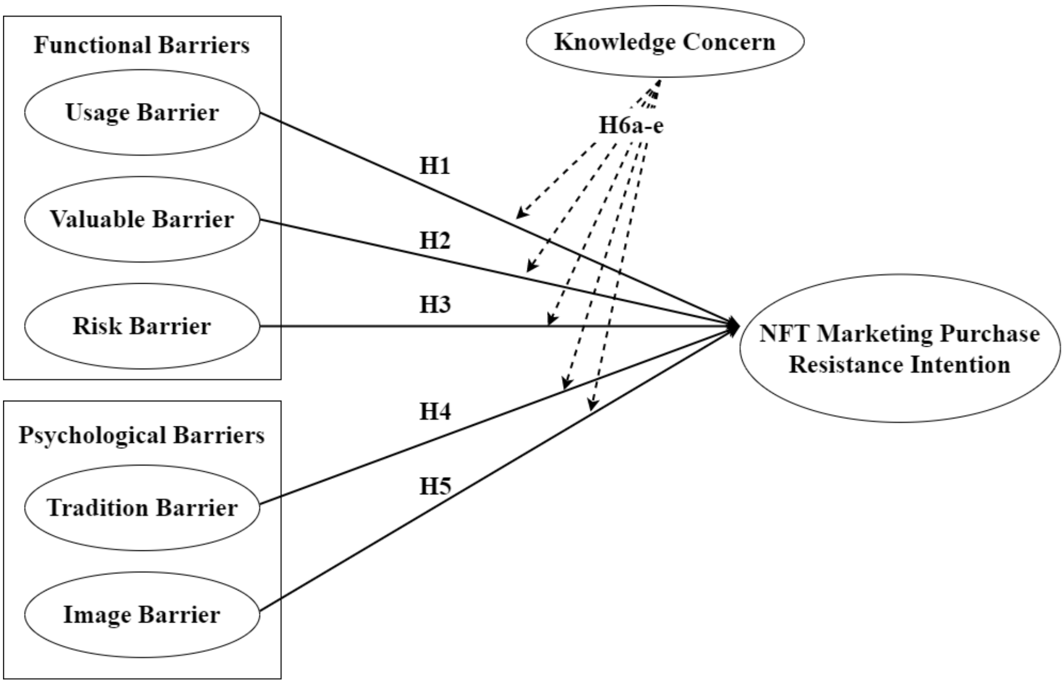

Figure 1. Conceptual model of barriers affecting NFT marketing purchase resistance intention.

3.1 The Usage Barrier and NFT Marketing Purchase Resistance Intention

The innovation resistance theory posits that a usage barrier arises when a product requires consumers to significantly alter their existing workflows, practices, or habits (Ram and Sheth, 1989). In the context of NFT-based products and services, recent research has revealed that many consumers possess a limited understanding of how these novel offerings function (Alexander and Bellandi, 2022). Consumers may also feel unfamiliar or uncertain about the process of interacting with NFTs and integrating them into their digital lives (Alexander and Bellandi, 2022). When innovative products are introduced to the general public, the usage barrier can discourage consumers from making a purchase (Lian and Yen, 2013). Accordingly, we argue that the usage barrier associated with NFTs would reduce their acceptability among consumers, leading to a reluctance to engage with NFT-based marketing strategies implemented by businesses. Consequently, this results in a higher resistance intention to purchase NFT marketing-based offerings. Thus, we propose the following hypothesis:

H1: The usage barrier significantly increases NFT marketing purchase resistance intention.

3.2 The Value Barrier and NFT Marketing Purchase Resistance Intention

The innovation resistance theory also suggests that a value barrier can arise when there is a perceived disconnect between a product's value and its expected performance (Ram and Sheth, 1989). Customers are typically reluctant to switch unless an innovative product offers significantly greater value for money compared to existing alternatives. Previous research has indicated that customers tend to be satisfied with the products already available to them and may believe that innovative offerings cannot provide higher value or meet their expectations (Kushwah et al., 2019). Additionally, customers may perceive that purchasing other products from the company is sufficient to demonstrate their support, and they may not see the need to invest in unfamiliar NFT collectibles that may not offer a clear return on investment or effectively showcase their loyalty to the brand (Sutcliffe, 2022). Furthermore, the literature has highlighted that investing in NFTs is often viewed as a risky endeavor, as they are commonly perceived as more of a liability than an asset (Sutcliffe, 2022). This perspective can contribute to consumer intention to avoid or boycott NFT-based offerings. Considering these factors, we propose the following hypothesis:

H2: The value barrier significantly increases NFT marketing purchase resistance intention.

3.3 The Risk Barrier and NFT Marketing Purchase Resistance Intention

Ram and Sheth (1989) have identified physical, economic, uncertainty, and social factors as the primary influencers of how consumers perceive risk. NFTs represent a burgeoning trend in transactional practices within the comprehensive sales market environment. The risks associated with owning, trading, or investing in NFTs may encompass factors such as market volatility, counterfeit or fraudulent NFTs, lack of regulation, technological risk, and legal and copyright issues (Kong and Lin, 2021). For instance, the NFT market is relatively new and lacks comprehensive regulation, which can expose individuals to risks like scams, misleading claims, or inadequate consumer protections. The risks of cyberattacks and asset theft are also inevitable. Consequently, customers approach NFTs with caution due to increased psychological and personal financial risks, as well as concerns related to trust. These factors collectively contribute to a lower adoption rate of NFTs in sales and marketing. Based on these observations, we propose the following hypothesis:

H3: The risk barrier significantly increases NFT marketing purchase resistance intention.

3.4 The Tradition Barrier and NFT Marketing Purchase Resistance Intention

The tradition barrier often exerts a significant influence on consumer behavior and can impact the success of a product or service (Khalil et al., 2023). According to Ram and Sheth (1989), resistance may arise when an innovation requires users to deviate from societal norms or established customs. Additionally, Chen et al. (2018) discovered that consumers tend to have a strong attachment to trust and habitual use of existing technologies, making them reluctant to embrace new methods. In the context of using NFTs as marketing strategies, consumers may find the process of purchasing NFTs complex, as they are accustomed to the convenience of using mobile devices for product purchases and accessing relevant information through official company websites. Gutierrez (2021) suggested that consumer hesitancy towards NFTs can be attributed to concerns about fraud, environmental costs, and the affordability of acquiring cryptocurrencies. Consequently, consumers perceive traditional marketing techniques as more convenient and persuasive in comparison to NFTs in B2C marketing. The tradition barrier is influenced by consumers' psychological states, leading them to resist NFTs by favoring the acceptance of current marketing techniques. Based on this analysis, we propose the following hypothesis:

H4: The tradition barrier significantly increases NFT marketing purchase resistance intention.

3.5 The Image Barrier and NFT Marketing Purchase Resistance Intention

The image barrier, as defined by Ram and Sheth (1989), pertains to the associations that consumers form with innovations, including the product category, industry, or place of manufacture. Negative associations in any of these aspects can result in an unfavorable perception of the product and create obstacles to its adoption. Consumer reviews, personal innovation stereotypes, word of mouth, and news stories all contribute to the way a product is perceived. NFTs represent a novel marketing strategy, and consumers often lack awareness and understanding of NFTs, as well as the potential outcomes and benefits associated with them (Nadini et al., 2021). Moreover, companies selling NFTs have not effectively communicated what NFTs are, leading to a negative impression and resistance among consumers (Ali et al., 2023). Additionally, Palaniyapan (2022) highlighted that NFTs are generally perceived as a low-trust environment across multiple industries. Consumers feel uncertain and skeptical about the NFT market, finding it complicated. Despite the increasing participation in NFTs, trust has not improved, and some consumers hold preconceived notions that businesses using NFTs as a marketing strategy will face negative consequences (Reinmoeller et al., 2022). Based on these observations, we propose the following hypothesis:

H5: The image barrier significantly increases NFT marketing purchase resistance intention.

3.6 Knowledge Concern as Moderator

Individual attitudes and beliefs are significantly shaped by the level of knowledge possessed by the individual (Ajzen, 1991; Borzekowski et al., 2021). In the context of NFT marketing, knowledge concern refers to consumers' apprehensions or focus on understanding the complexities and implications of non-fungible tokens. The NFT market has witnessed substantial growth and popularity in recent years, attracting a significant number of participants. However, the development and implementation of NFTs are complex processes that require expertise, extensive industry knowledge, and a thorough understanding of the target market. Roh et al. (2022) emphasized the impact of cognitive knowledge on consumers' purchase decisions, synthesizing the theories of consumption value and rational behavior. Compared to traditional marketing strategies, NFTs are more intricate as they involve transactions that are not limited to simple one-buy-one-sell processes. Hence, the level of knowledge concern plays a pivotal role in understanding consumer behavior and their inclination to engage with NFTs in a B2C marketing context. Furthermore, in the realm of NFT marketing, customers may show resistance intention if they anticipate experiencing negative emotions due to perceived barriers. Thus, we contend that the association between purchase intention and consumption barriers (usage, value, risk, tradition, and image) is moderated by the level of knowledge concern. Consumers with a higher level of knowledge concern are more likely to be attuned to the complexities and potential pitfalls associated with NFTs, which could exacerbate the negative influence of these barriers on their intention to engage with NFT-based marketing strategies. Based on this theoretical foundation, we propose the following hypotheses:

H6a-e: Knowledge concern moderates the association of NFT marketing purchase resistance intention with the usage barrier, value barrier, risk barrier, tradition barrier, and image barrier, respectively, such that a high level of knowledge concern exacerbates the impact of these barriers on NFT marketing purchase resistance intention.

4. Research Methodology

4.1 Covariance-based Structural Equation Modeling (CB-SEM)

Structural equation modelling (SEM) is a powerful statistical technique that facilitates the simultaneous modeling of relationships among multiple independent and dependent constructs (Gefen et al., 2000). As a second-generation statistical tool, SEM encompasses two primary approaches for parameter estimation: covariance-based SEM (CB-SEM) and variance-based Partial Least Squares SEM (PLS-SEM) (Haenlein and Kaplan, 2004). Table 1 presents a comparison of the selection criteria for CB-SEM and PLS-SEM, based on the existing studies (Haenlein and Kaplan, 2004; Hair et al., 2011). For many social science researchers, the term SEM is often used interchangeably with CB-SEM due to its prominence in the field.

The selection between CB-SEM and PLS-SEM is primarily dictated by the specific objectives of the research. CB-SEM is particularly well-suited for causal modeling scenarios where a robust theoretical foundation exists, and the goals involve testing and confirming established theories (Hair et al., 2011). This approach allows for the evaluation of complex interrelationships while adhering to stringent statistical assumptions regarding normality and measurement error. Moreover, global goodness-of-fit indices, which are integral to assessing the adequacy of the model, enable researchers to evaluate the model's performance in terms of theoretical alignment (Anderson and Gerbing, 1988).

PLS-SEM, on the other hand, is particularly well-suited for exploratory research and situations where the primary focus is on prediction and theory development (Hair et al., 2011). PLS-SEM allows researchers to analyze complex models with smaller sample sizes and without stringent requirements regarding data distribution. This approach is beneficial when the theoretical framework is still evolving (Gefen et al., 2000), as it emphasizes the identification of relationships rather than strict confirmation of existing theories.

Building on this foundation, CB-SEM is employed in this study, which is based on the established framework of innovation resistance theory. This theory provides a solid foundation for hypothesizing relationships between constructs, allowing for a comprehensive examination of the factors that influence consumer resistance to innovations. By utilizing CB-SEM, this study aims to analyze the collected questionnaire data holistically, thereby enhancing the validity and reliability of the findings.

Table 1. Comparison of criteria for selecting CB-SEM or PLS-SEM.

Criteria	CB-SEM	PLS-SEM
Research Goals	Theory testing, confirmation, or comparison of alternative theories	Exploratory research, focus on prediction, theory development
Measurement Model	Mainly reflective constructs	Reflective and formative constructs
Complexity	Suitable for small to moderately complex models	Supports highly complex models

Data Assumptions	Assumes normal distribution	No specific distribution assumptions
Minimum Sample Size	Typically 200	Range from 30 to 100
Parametric Estimated Value	Standardized or non-standardized	Standardized
Goodness of Fit Metrics	Multiple metrics available	One metric (Goodness of Fit)

4.2 Sample and Data Collection for the Empirical Investigation

Regarding the empirical investigation, this study adopts a quantitative approach, utilizing an online survey method for data collection. Respondents were recruited through the widely recognized online platform, Amazon Mechanical Turk, on May 9, 2024. As NFTs are accessible to the general public, individuals aged eighteen or older were eligible to participate in the study and complete the survey. A total of 650 respondents provided data, including participants recruited from personal networks and those obtained through Mturk. To ensure data quality, several criteria were applied during the data screening process, following the recommendations of DeSimone et al. (2014). Responses that were excessively rapid or exhibited uniform response patterns were excluded. Data accuracy and reliability analyses were conducted using SPSS software. Descriptive analyses were performed, including assessments of missing values, data normality, and outliers. The normal distribution of the collected data was assessed by examining skewness and kurtosis, with values within the range of +3 and –3 considered acceptable.

Finally, 610 responses remained for subsequent analysis. Based on the available data, the gender distribution of the respondents is as follows: 273 women (55.1%), 336 men (44.8%), and 1 participant who chose not to disclose their gender (0.01%). Regarding age ranges, the majority of the sample falls between 25 and 34 years old (43.6%) and 35 and 44 years old (22.3%), while the remaining participants are distributed across the age groups of 18–24 (17.4%), 45–54 (10.7%), 55–64 (5.6%), and 65 or older (0.5%). In terms of occupation, 88.5% of the respondents are employed, with 25.5% being self-employed, and 63% primarily working in white-collar positions, including fields such as information technology, management, academia and education, art, and design, among others. Additionally, 11.5% of the respondents are full-time students. Regarding income, 18.2% reported a monthly income of $5,000 to $10,000, 16.4% reported $5,000 or below, 15.7% reported $50,000 or above, and 15.2% reported $40,001 to $50,000. Furthermore, 12.6% reported a monthly income of $10,000 to $20,000, 11.8% reported $10,000 to $40,000, and 10% reported $20,000 to $30,000, respectively.

4.3 Measures for the Empirical Investigation

Given the limited availability of validated questionnaires dedicated to the investigation of NFT marketing, the current study adapted frequently utilized instruments from prior research to construct a multi-item survey instrument suitable for the research topic. Specifically, the measurement items for the research constructs were adapted from the usage barrier (4 items), value barrier (3 items), risk barrier (3 items), tradition barrier (3 items), image barrier (2 items), knowledge concern (3 items), and resistance intention (3 items) scales developed by Ram and Sheth (1989) and previously employed by Shankar and Nigam (2021) and Chen et al. (2022). To ensure simplicity and obtain accurate responses from participants, all items were presented using a 5-point Likert scale, which allowed respondents to express their level of agreement or disagreement with each statement, anchored by 1 (“Strongly Disagree”) and 5 (“Strongly Agree”).

4.4 Prompt for the Large Language Model Analysis

In addition to the survey-based empirical investigation, this study incorporated the advanced text processing capabilities and broad knowledge bases of LLMs as research subjects to gain complementary insights into the key barriers impacting consumer resistance intention towards NFT marketing.

To ensure the reliability and relevance of LLM-generated insights, a structured prompt engineering framework was implemented, designed to simulate a consumer perspective and extract meaningful responses. This methodology employed a combination of advanced prompting techniques, including role-play, chain-of-thought reasoning, self-consistency validation, and iterative prompting. Role-play was a foundational aspect of this approach, requiring the LLMs to adopt the mindset of a consumer engaging with NFT marketing. By framing the prompts within this simulated context, the LLMs were encouraged to generate responses that reflected plausible consumer thought processes and decision-making behaviors, enhancing the contextual relevance of the findings. Chain-of-thought reasoning further encouraged the LLMs to provide step-by-step analyses, enabling a transparent exploration of how specific barriers shape consumer resistance intentions. Self-consistency validation further enhanced the reliability of the findings by presenting similar questions with slight variations to assess the consistency of the responses, while iterative prompting allowed refinement of the questions to clarify ambiguities and probe deeper into the reasoning provided.

The study engaged eight prominent LLMs as research subjects within this structured framework. The analysis was primarily conducted using two sequential prompts. The first prompt established a consumer perspective and requested detailed reasoning: "*As a consumer considering NFT marketing purchases, analyze how usage barriers, value barriers, risk barriers, tradition barriers, and image barriers might affect your resistance intentions. Please explain your reasoning for each barrier's influence on your decision-making process*." Following the initial responses, a second prompt served both as a validation step and an opportunity for iterative refinement to confirm and expand upon the insights: "*Usage barriers, value barriers, risk barriers, tradition barriers, and image barriers. Which one(s) do you think will cause consumers' resistance intentions toward*

Non-Fungible Tokens (NFTs) marketing purchases? Please provide specific examples of how each barrier might manifest in consumer experiences." This follow-up prompt was iteratively refined based on the LLMs' initial outputs, ensuring that ambiguities were addressed and key points were explored in greater depth.

By utilizing LLMs as research subjects, this study uncovered an additional layer of analytical perspectives that enriched and complemented human participant data. Although LLMs cannot fully replicate the depth or authenticity of human experiences, their capacity to produce structured reasoning serves as a valuable supplement to traditional methods. The integration of these approaches enabled this research to achieve a more nuanced understanding of the barriers influencing consumer resistance intentions toward NFT marketing, contributing both theoretically and practically to the field.

5. Results and Analyses

5.1 Reliability and Validity of the Measurement Model

Previous studies have suggested varying threshold values for fit indices, such as $X^2/df<3.0$, $CFI\geq 0.92$, $RMSEA\leq 0.08$, and $TLI\geq 0.92$ (Hair et al., 2013). In this study, we conducted a confirmatory factor analysis (CFA) using AMOS 28.0 to evaluate the reliability and validity of the measurement items employed in the survey questionnaire. The results of the measurement model assessment indicate a strong fit, demonstrating its appropriateness for further modelling, with the following fit indices: $X^2/df=1.409$, $CFI=0.976$, $RMSEA=0.026$, and $TLI=0.983$. To assess the reliability and validity of the variables, we measured Cronbach's alpha, composite reliability (CR), and average variance extraction (AVE) for each variable. The results are presented in Tables 2 and 3. First, in Table 2, the Cronbach's alpha values in our model ranged from 0.70 to 0.79, indicating that the scales exhibit high reliability. According to the standards set by Fornell and Larcker (1981), CR should exceed 0.6, and AVE should exceed 0.5 under ideal conditions, while values between 0.36 and 0.5 are considered acceptable (Zhang and Zheng, 2020). Both Huang et al. (2013) and Lam (2012) have noted that if AVE is less than 0.5 but CR is greater than 0.6, the construct's convergent validity is still sufficient. In this study, CR values exceeded 0.60 (ranging from 0.67 to 0.82), and AVE values exceeded 0.36 (ranging from 0.41 to 0.61) in all cases, indicating that the criteria for convergent validity were met. To evaluate discriminant validity, this study used the Fornell-Larcker criterion. As shown in Table 3, the diagonal values, which represent the square root of AVE, are higher than the coefficients of the correlations between variables, indicating good discriminant validity (Fornell and Larcker, 1981). Moreover, to examine multicollinearity, we calculated the variance inflation factors (VIF) in this research. As outlined by Snee (1981), VIF serves as a measure of the degree of multicollinearity in regression analysis. Multicollinearity occurs when there is a significant linear relationship or correlation between one or more independent variables or inputs. This can negatively impact the results of a regression analysis by increasing the variance of the regression coefficients. The VIF values for this study, computed using SPSS 22.0, ranged between 1.000 and 1.032. According to the guidelines provided by Kock and Lynn (2012), the model is not significantly affected as long as the VIF values remain below the threshold value of 3. When the VIF equals 1, it signifies that the variables are not correlated, indicating the absence of multicollinearity in the regression model. Consequently, this study did not exhibit multicollinearity.

Table 2. Results of the reliability and convergent validity.

Construct	Measurement items	λ	CR	AVE	α
Usage Barrier	UB1	0.62	0.73	0.41	0.70
	UB2	0.61			
	UB3	0.67			
	UB4	0.64			
Value Barrier	VB1	0.72	0.81	0.59	0.72
	VB2	0.86			

	VB3	0.72			
Risk Barrier	RB1	0.71	0.74	0.48	0.70
	RB2	0.69			
	RB3	0.69			
Tradition Barrier	TB1	0.75	0.72	0.46	0.72
	TB2	0.59			
	TB3	0.70			
Image Barrier	IB1	0.73	0.67	0.51	0.79
	IB2	0.70			
Knowledge Concern	KC1	0.82	0.82	0.61	0.71
	KC2	0.79			
	KC3	0.73			
Resistance Intention	RI1	0.74	0.71	0.45	0.77
	RI2	0.67			
	RI3	0.60			

Note: λ refers to standardized loadings; CR refers to the composite reliability; AVE refers to average variance extracted; α refers to Cronbach's alpha

Table 3. Results of the discriminant validity.

	UB	VB	RB	TB	IB	KC	RI
UB	**0.64**						
VB	0.07	**0.77**					
RB	0.04	0.58	**0.69**				
TB	0.63	0.06	0.05	**0.68**			
IB	0.52	0.03	0.08	0.57	**0.71**		
KC	–0.02	0.12	0.18	–0.05	–0.05	**0.78**	
RI	0.05	0.51	0.60	0.02	0.07	0.27	**0.67**

Note: Bold numbers are square root of AVE values; UB: Usage barrier; VB: Value barrier; RB: Risk barrier; TB: Tradition barrier; IB: Image barrier; KC: Knowledge concern; RI: Resistance intention

5.2 Common Method Bias

We examined the presence of common method bias (CMB) in the variables included in this study, as suggested by Podsakoff and Organ (1986) and Podsakoff et al. (2003). CMB occurs when the relationships between multiple constructs are biased because all data are measured and obtained in a similar manner, whether they are independent or dependent variables. To assess the presence of CMB, we used non-statistical techniques. We noticed that some respondents completed the questionnaire very quickly, which prompted us to employ reserve codes and data screening before conducting statistical analysis. This step ensured a more balanced representation of attitudes and opinions and helped reduce the potential impact of CMB. Additionally, we followed the suggestions of Sonderen et al. (2013) by using reverse-phrased items to minimize response bias. Furthermore, we used SPSS 22.0 to perform Harman's single-factor analysis to examine data bias, as recommended by Podsakoff et al. (2012). The results showed that the total variance explained by this single factor was 20.593%, which is below the critical threshold of 50%. This demonstrates that the data is not significantly affected by CMB and confirms the absence of significant CMB issues or risks in the dataset.

5.3 Structural Model

Similar to the measurement model, we evaluated the structural model, which demonstrated a good fit ($X^2/df=1.619$, $CFI=0.966$, $RMSEA=0.032$, and $TLI=0.971$). The results presented in Table 4 of the structural model reveal that only the risk barrier ($\beta=0.747$, $p<0.001$) has a significantly positive impact on the resistance intention towards NFTs in B2C marketing. However, other barriers, such as the usage barrier ($\beta=0.169, p>0.1$), value barrier ($\beta=0.065, p>0.5$), tradition barrier ($\beta=-0.215, p>0.1$), and image barrier ($\beta=0.040, p>0.5$), were found to have a non-significant influence on NFT marketing purchase intention.

Table 4. Results of the path analysis.

Hypothesis	Path	β	SE	p
H1	UB→NFT marketing purchase RI	0.169	0.274	0.260
H2	VB→NFT marketing purchase RI	0.065	0.207	0.678
H3	RB→NFT marketing purchase RI	0.747	0.225	<0.001
H4	TB→NFT marketing purchase RI	-0.215	0.211	0.184
H5	IB→NFT marketing purchase RI	0.040	0.086	0.646

Note: UB: Usage barrier; VB: Value barrier; RB: Risk barrier; TB: Tradition barrier; IB: Image barrier; RI: Resistance intention; β: Standardized regression coefficient for comparing relationship strengths; SE: Standard Error; p: p-value

5.4 Moderation Analysis

To explore the moderating influence of knowledge concern, we employed Process Macro Version 4.2 within SPSS 22.0 (model 1). The results, presented in Table 5, reveal that knowledge concern does not moderate the relationship between NFT marketing and purchase resistance intentions regarding usage barriers (H6a: $B = 0.068$, $p = 0.811$, $LLCI = -0.027$, $ULCI = 0.127$), value barriers (H6b: $B = 0.608$, $p = 0.543$, $LLCI = 0.419$, $ULCI = 0.553$), tradition barriers (H6d: $B = 0.039$, $p = 0.857$, $LLCI = -0.045$, $ULCI = 0.109$), and image barriers (H6e: $B = 0.071$, $p = 0.388$, $LLCI = 0.100$, $ULCI = 0.163$). However, the findings indicate that knowledge concern does have a moderating effect on the relationship between risk barrier and purchase resistance intention (H6c). To gain a deeper understanding of this moderating role, Figure 2 illustrates the relationships between the risk barrier and purchase resistance intention, highlighting the moderating effect of knowledge concern. The results suggest that a higher level of knowledge concern exacerbates the negative impact of the risk barrier on NFT marketing purchase intentions.

Table 5. Results of the moderation analysis.

Knowledge Concern						
Hypothesis		*B*	*T*	*p*	*LLCL*	*ULCI*
H6a	UB→NFT marketing purchase RI	0.068	–0.024	0.811	–0.027	0.127
H6b	VB→NFT marketing purchase RI	0.608	0.606	0.543	0.419	0.553
H6c	RB→NFT marketing purchase RI	0.654	4.014	<0.001	0.509	0.636
H6d	TB→NFT marketing purchase RI	0.039	–0.857	0.388	–0.045	0.109
H6e	IB→NFT marketing purchase RI	0.071	0.867	0.388	0.100	0.163

Note: UB: Usage barrier; VB: Value barrier; RB: Risk barrier; TB: Tradition barrier; IB: Image barrier; RI: Resistance intention; *LLCL*: Lower limit of confidence interval; *ULCI*: Upper limit of confidence interval; *B*: Unstandardized regression coefficient for actual changes in the dependent variable; *T*: T-value which is the coefficient (*B*) divided by its standard error; *p*: p-value

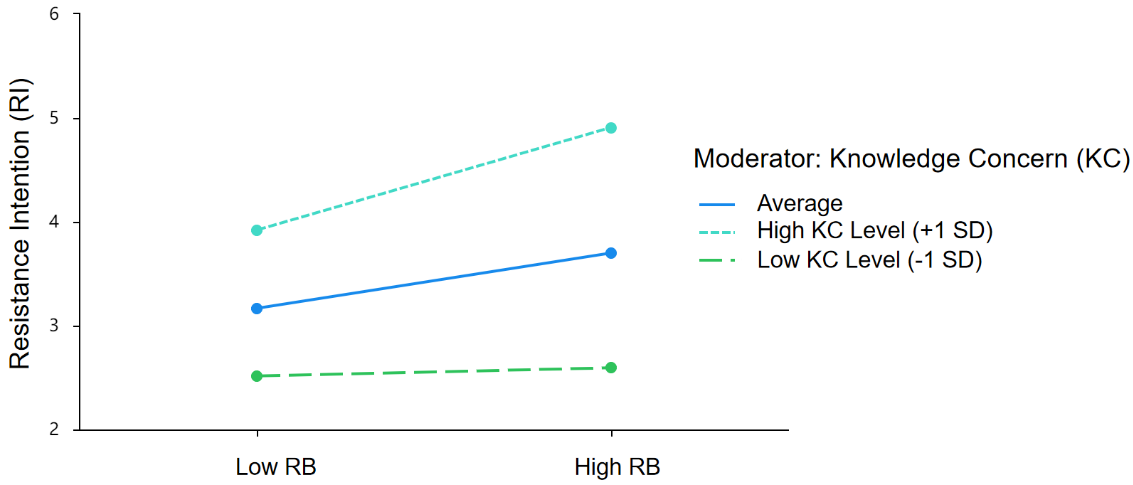

Figure 2. Moderating effect of knowledge concern on the relationship between risk barrier (RB) and NFT marketing purchase resistance intention.

5.5 Results Comparison Using Large Language Models

This section presents a comparative analysis utilizing eight widely adopted LLMs in both practice and academia, including GPT-4, LLaMA 3, Gemini-1.5, Chinchilla, Claude-3.5, Gemma, Qwen2, and RekaCore. Each LLM was prompted with the same input, without any prior training or additional content provided. As illustrated in Table 6, the LLMs exhibited divergent perspectives on the significance of various barrier factors. GPT-4 identified both VB and RB as the most salient obstacles. LLaMA 3 and Gemini-1.5 each designated RB as the primary barrier. In contrast, Command-R emphasized UB and VB, while Claude-3.5 highlighted UB and RB. Gemma prioritized IB, whereas Qwen2 and RekaCore identified VB and RB as key concerns.

Aggregating the responses from the different LLMs reveals that UB was selected by 25% of the models, VB by 50%, RB by 75%, TB by 0%, and IB by 12.5%. While some discrepancies exist between the empirical findings and the insights generated by the LLMs, the fact that 75% of the models highlighted the significant hindrance posed by risk barriers in NFT marketing is notable.

Table 6. Comparison between the insights generated by LLMs and the empirical findings.

	UB	VB	RB	TB	IB
This Research			√		
GPT-4		√	√		
Llama 3			√		
Gemni-1.5			√		
Command-R	√	√			
Claude-3.5	√		√		
Gemma					√
Qwen2		√	√		
RekaCore		√	√		

Note: '√' represents significantly positive impact on the resistance intention towards NFT marketing; All LLMs are not trained in advance

6. Discussion and Implications

6.1 Key Results and Theoretical Implications

This study reveals that the risk barrier significantly impedes consumer intention to purchase NFT marketing-based offerings (H3). This finding highlights the important role that perceived risks play in shaping consumer attitudes toward NFT marketing. It aligns with previous research emphasizing risk perception's central role in consumer decision-making (Day et al., 2020). In the context of NFT marketing, these concerns are particularly pronounced due to the evolving nature of the ecosystem and high-profile cases of fraud and exploitation during its early development (Kong and Lin, 2021; Meyns and Dalipi, 2022). Kong and Lin (2021) emphasized that risks such as cybersecurity vulnerabilities, financial fraud, and unclear ownership rights represent key concerns for consumers engaging with NFTs. Notably, the results of this study indicate that a higher level of knowledge concern exacerbates the negative impact of the risk barrier on NFT marketing purchase intentions (H6c). This finding supports Kong and Lin's (2021) investigation, which noted that experienced investors tend to be more cautious and pricesensitive. This behavior likely stems from their deeper understanding of market volatility, speculative risks, and the prevalence of fraudulent activities within the NFT ecosystem.

Interestingly, the results indicate that two functional barriers (i.e., usage and value barriers) and two psychological barriers (i.e., tradition and image barriers), derived from the framework of innovation resistance theory, do not significantly influence consumer resistance to NFT marketing purchases (H1, H2, H4, H5). Regarding the usage barrier, this result may reflect the rapid adaptation of both enterprises and consumers to digital technologies, which has minimized usability concerns. Companies have played a significant role in this adaptation by simplifying the user experience of NFTs. For example, the integration of familiar purchasing methods, such as credit cards and digital wallets like Apple Pay, has reduced friction for new adopters and made NFT transactions more accessible. Additionally, some brands have deliberately framed NFTs as electronic membership cards or loyalty tools, effectively downplaying their technical complexity and enhancing their appeal to mainstream audiences. A notable example is Starbucks' NFT-based loyalty card series, which demonstrates how positioning NFTs within familiar consumer paradigms can lower perceived complexity and accelerate adoption.

Unlike conventional memberships, NFTs also provide dynamic benefits, such as resale value, royalties for creators, and exclusive access to both digital and physical experiences (Xie et al., 2023). These distinctive features provide consumers with a blend of tangible and intangible value, significantly enhancing the broader appeal of NFTs. The findings of this study further support previous research that highlights the emotional, experiential, cultural, and social value of NFTs (Hofstetter et al., 2022; Sestino et al., 2022). Similarly, Murtas et al. (2023) posited that NFTs' ability to foster a sense of ownership and exclusivity allows businesses to cultivate deeper customer engagement and loyalty. Furthermore, from the perspective of consumer resistance, these results complement the findings of Xie et al. (2024), which demonstrated that consumers are more likely to resonate with a branded NFT when they perceive it as useful, enjoyable, low-risk, and/or exclusive. Such positive perceptions not only drive consumers to purchase the NFT but also enhance their affinity for the sponsoring brand, ultimately leading to greater brand loyalty and an increased likelihood of future brand purchases.

The results related to tradition and image barriers can be attributed to the increasing accessibility of NFT-related technologies. As NFTs gain visibility through social media and online platforms, consumers are becoming more familiar with their functionalities and benefits, fostering greater acceptance. This aligns with previous research on consumers' psychological tendencies toward branded NFTs (Xie et al., 2024), which demonstrates that when young consumers perceive NFTs as valuable across various dimensions, they are more likely to advocate for the sponsoring brand. Moreover, the integration of NFTs into everyday purchasing options, such as e-commerce websites and mobile applications, enhances their perceived efficiency and user-friendliness, making them more accessible to mainstream audiences.

This study contributes to the discourse on potential barriers affecting consumers' purchase intentions in NFT marketing. Such understanding is crucial for marketers aiming to develop successful NFT-based marketing strategies (Sestino et al., 2022). As one of the first empirical studies in NFT marketing, this research advances the theoretical framework of innovation resistance theory by introducing the moderating role of consumers' knowledge concern—a dimension that has been largely overlooked in prior studies (e.g., Kaur, 2020; Sadiq et al., 2021; Khalil et al., 2023).

Moreover, this study innovatively integrates insights derived from LLMs with empirical findings, demonstrating the potential of LLMs to complement traditional empirical research approaches. While individual LLMs were unable to fully replicate the complexity of the empirical findings, their synthesized insights closely aligned with the results obtained from the empirical investigation. This study aligns with recent calls in the literature to explore the potential of LLMs in empirical research (Liu et al., 2024; Cui et al., 2024; Sadlier-Brown et al., 2024).

6.3 Managerial and Practical Implications

The rapid rise of NFTs in digital marketing presents businesses with unprecedented opportunities to innovate strategies, expand market reach, enhance brand visibility, and monetize creative content. Drawing on insights from this study, this section outlines several managerial and practical implications for enterprise stakeholders and policymakers seeking to navigate the evolving NFT landscape effectively.

First, organizations can harness the immense potential of NFTs in marketing by developing distinctive value propositions that engage audiences and drive adoption. Within the Web 3.0 framework, NFTs are supported by features that enable consumers to experience highly personalized and interactive interactions, transforming traditional digital engagement. In recent years, advancements in web technologies and social networking have reshaped global business operations, offering new pathways for connecting with consumers in emerging digital ecosystems. SMEs, in particular, stand to benefit significantly from NFT adoption. NFTs provide SMEs with innovative tools to increase brand visibility and connect with broader, digitally savvy audiences. For example, SMEs can create unique digital assets, such as branded artwork or exclusive multimedia content, to showcase their identity and creativity. Additionally, NFTs can serve as effective mechanisms for promoting events or launching limited-time offerings tailored to the preferences of digital-first consumers, further strengthening their market presence in the Web 3.0 era.

Despite the significant potential of NFT marketing, this study underscores the critical importance of addressing consumers' perceived risks. To mitigate this barrier, businesses should prioritize trust-building strategies grounded in transparency and education, as suggested by Leung et al. (2018). For instance, marketers can provide clear and accessible explanations of how blockchain technology ensures security, authenticity, and traceability. Educating consumers about the role of smart contracts in safeguarding transactions can further demystify the technology, fostering greater confidence in its use. Additionally, as highlighted by Murtas et al. (2023), collaborating with established NFT platforms that implement robust security protocols and compliance mechanisms can enhance consumer trust. For SMEs, trust-building measures are particularly vital due to their lower brand recognition and limited resources compared to larger enterprises. In response, SMEs can establish feedback mechanisms by creating channels for customer input within their enterprise systems, helping them understand consumer concerns and improve their offerings. This responsiveness can significantly enhance trust and loyalty. Furthermore, collaborative marketing is a powerful strategy; SMEs can partner with other SMEs or influencers in the NFT space to amplify their reach and credibility.

In addition, businesses need to address the significant legal and intellectual property risks associated with NFTs. High-profile cases, such as the *Nike v. StockX* lawsuit over trademark infringement in NFT minting (Song, 2022), highlight the critical need for robust intellectual property protection. To mitigate these risks, large enterprises should adopt comprehensive brand protection strategies for their NFT initiatives, including trademark monitoring, copyright enforcement, and the implementation of legal safeguards to prevent misuse within the metaverse. For SMEs, which often lack the extensive legal resources of larger corporations, partnering with established NFT platforms can provide a practical solution (Potluri and Vajjhala, 2018). These platforms typically offer built-in security protocols and smart contracts that automate compliance, safeguard ownership rights, and create secure trading environments. Additionally, embedding clear usage terms and ownership documentation directly into NFTs can enhance transparency, reduce the likelihood of disputes, and instill greater consumer confidence in engaging with NFT-based products and services.

Beyond legal concerns, the decentralized and community-driven nature of NFT ecosystems introduces distinct challenges for brand management. For example, the *McDonald's McRib NFT* controversy highlighted how poor governance within NFT communities can expose businesses to significant reputational risks. To address these challenges, enterprises should prioritize effective community management strategies that align with the unique dynamics of decentralized ecosystems. Key measures include implementing tiered access systems based on user behavior, establishing governance rules encoded within smart contracts, and maintaining active moderation systems to oversee interactions within NFT communities. Moreover, enterprises should develop robust crisis management frameworks specifically tailored to decentralized environments to proactively safeguard brand integrity. By adopting these strategies, enterprises can not only minimize reputational risks but also strengthen their engagement and credibility within NFT ecosystems.

A growing concern linked to NFTs is their environmental impact, particularly regarding blockchain technology. NFTs minted on proof-of-work blockchains have been criticized for their high energy consumption and substantial carbon footprint. As Kaczynski and Duke Kominers (2021) have noted, this environmental drawback may discourage adoption among environmentally conscious consumers and brands. To address these challenges, enterprises should implement strategies that leverage their existing systems and capabilities to mitigate environmental concerns. For large enterprises, sustainability can be integrated directly into their operational frameworks. By embedding sustainability metrics into systems like customer relationship management (CRM) and enterprise resource planning (ERP), these organizations can track carbon footprints, monitor blockchain energy usage, and incorporate sustainability insights into their strategic decision-making. Additionally, large enterprises are well-positioned to invest in energy-efficient blockchain partnerships or fund research into greener technologies, further reducing their environmental impact. SMEs, by contrast, may need to adopt more accessible and cost-effective solutions. These could include prioritizing the use of environmentally friendly proof-of-stake blockchains, collaborating with sustainability consultants, or joining collective carbon offset programs tailored to smaller organizations. By implementing these scalable approaches, SMEs can show their commitment to environmental responsibility while maintaining their operational efficiency and appealing to eco-conscious consumers.

Another critical implication lies in enhancing decision-making processes in enterprise business operations. Across businesses of all sizes and sectors, consistent and rapid decision-making is a critical requirement in today's globally competitive environment, presenting a significant challenge to the strategic teams of every organization. In the context of Web 3.0, computers are increasingly capable of processing and understanding information in ways similar to humans, enabling them to provide faster and more relevant results. Motivated by this study's findings, decision-makers can leverage LLMs to generate preliminary insights into consumer preferences. These insights can then be refined and validated by human expertise, creating a hybrid approach that balances the efficiency of automation with the nuance of human judgment. This method offers a cost-effective and time-efficient strategy for analyzing consumer behavior, particularly in dynamic and rapidly evolving markets such as NFTs.

Finally, the findings of this study carry significant implications for policymakers.

As NFTs represent a relatively new and rapidly evolving digital asset class, the regulatory environment surrounding them remains underdeveloped. Policymakers should actively collaborate with industry stakeholders to establish clear and consistent legal frameworks that address the unique challenges of NFT marketing. A key difficulty lies in the diverse nature of NFTs, which encompass digital art, collectibles, and tokenized real-world assets. As such, regulatory frameworks must clearly define ownership rights, address intellectual property concerns, and promote transparency within NFT marketplaces. Crucially, these regulations need to strike a delicate balance between safeguarding consumers and fostering innovation in this emerging sector. In addition to regulatory measures, policymakers should prioritize public education initiatives to enhance consumer awareness and understanding of NFTs. Providing clear, accessible, and actionable information can empower consumers to make informed decisions and mitigate perceived risks. For instance, educational campaigns can include resources on safe trading practices, blockchain security protocols, and strategies for fraud prevention. By combining well-designed regulation with consumer education, policymakers can create a more secure and inclusive environment that supports both the growth of the NFT ecosystem and the protection of its participants.

6. Conclusion

This study investigates the underlying factors contributing to consumer resistance to NFT marketing by employing CB-SEM within the framework of innovation resistance theory. The empirical findings reveal that the risk barrier has a statistically significant positive effect on consumers' resistance intentions toward NFT marketing purchase decisions. In contrast, the other four barriers, which include usage, value, tradition, and image, did not exhibit significant effects in this context. Furthermore, the study highlights that higher levels of knowledge concern amplify the negative impact of the risk barrier on consumers' purchase intentions, underscoring the critical need to address this issue. To validate these findings, an analysis using eight leading LLMs was conducted. The results showed that 75 percent of the models confirmed the risk barrier as a critical factor hindering consumer engagement with NFT marketing. In the context of Web 3.0, these findings emphasize the importance of prioritizing the mitigation of risk-related concerns when designing digital marketing strategies. This study provides valuable theoretical, managerial, and practical implications for enterprise stakeholders and policymakers operating within this emerging digital ecosystem.

While this research offers important insights into consumer resistance to NFT marketing, several limitations should be acknowledged. First, this study serves as an initial exploration of functional and psychological barriers within the framework of classic innovation resistance theory. However, the underlying drivers or specific reasons contributing to each barrier were not examined in detail. Second, although the findings reveal that knowledge concerns moderate the relationship between risk barriers and resistance intentions, the measurement of knowledge levels relied on self-reported data, which may not fully capture the complexity and depth of consumer understanding regarding enterprise NFT systems.

These limitations open several promising directions for future research on enterprises' adoption of digital marketing innovations. First, future studies could build on our findings regarding risk barriers by examining specific categories of risk, such as financial, security, and privacy-related risks, to provide more granular and actionable insights for decision-makers. Second, given the moderating role of knowledge concerns, future research could explore how enterprise-level knowledge management systems and consumer education initiatives influence the adoption and acceptance of NFT marketing. Finally, researchers could leverage the predictive and analytical capabilities of LLMs to uncover new perspectives on consumer behavior in the context of NFT marketing. By integrating LLM-driven insights, future studies can contribute to the effective adoption of emerging technologies in enterprise digital marketing strategies.

References

Ante, L. 2021. "Smart Contracts on the Blockchain – a Bibliometric Analysis and Review." *Telematics and Informatics* 57: 101519. https://doi.org/10.1016/j.tele.2020.101519.

Alizadeh, M., Kubli, M., Samei, Z., Dehghani, S., Zahedivafa, M., Bermeo, J. D., Korobeynikova, M., and Gilardi, F. 2025. "Open-source LLMs for text annotation: a practical guide for model setting and fine-tuning." *Journal of Computational Social Science 8*(1). https://doi.org/10.1007/s42001-024-00345-9.

Anderson, J. C., and Gerbing, D. W. 1988. "Structural equation modeling in practice: A review and recommended two-step approach." *Psychological Bulletin* 103(3): 411–423. https://doi.org/10.1037/0033-2909.103.3.411.

Albayati, H., Alistarbadi, N., and Rho, J. J. 2023. "Assessing engagement decisions in NFT Metaverse based on the Theory of Planned Behavior (TPB)." *Telematics and Informatics Reports* 10: 100045. https://doi.org/10.1016/j.teler.2023.100045.

Ajzen, I. 1991. "The Theory of Planned Behaviour." *Organizational Behaviour and Human Decision Processes* 50 (2): 179–211. https://doi.org/10.1016/0749-5978(91)90020-t.

Arcenegui, J., Arjona, R., Román, R., and Baturone, I. 2021. "Secure combination of IOT and blockchain by physically binding IOT devices to smart non-fungible tokens using pufs." *Sensors* 21 (9): 3119. https:// doi.org/10.3390/s21093119.

Alexander, B., and Bellandi, N. 2022. "Limited or limitless? exploring the potential of nfts on value creation in luxury fashion." *Fashion Practice* 14 (3): 376–400. https://doi.org/10.1080/17569370.2022.2118969.

Ali, O., Momin, M., Shrestha, A., Das, R., Alhajj, F., and Dwivedi, Y. K. 2023. "A review of the key challenges of non-fungible tokens." *Technological Forecasting and Social Change* 187: 122248. https://doi.org/10.1016/j.techfore.2022.122248.

Borzekowski, D. L., Lane, C. R., Chandnani, A., and Gotz, M. 2021. "The relation between knowledge and concern: A global study of children and covid-19." *Health Psychology Research* 9(1). https://doi.org/10.52965/001c.24595.

Cui, Z., Li, N., and Zhou, H. 2024. “Can AI Replace Human Subjects? A Large-Scale Replication of Psychological Experiments with LLMs.” *arXiv preprint arXiv:2409.00128*.

Chen, Z., Wang, S., and Ma, Z. 2025 “Large Language Models in Job Position Prediction: An Exploratory Study.” *SSRN*: https://ssrn.com/abstract=5098914 or http://dx.doi.org/10.2139/ssrn.5098914

Chen, C. C., Chang, C. H., and Hsiao, K. L. 2022. “Exploring the factors of using mobile ticketing applications: Perspectives from innovation resistance theory.” *Journal of Retailing and Consumer Services 67*: 102974. https://doi.org/10.1016/j.jretconser.2022.102974.

Chen, H. S., Tsai, B. K., and Hsieh, C. M. 2018. “The effects of perceived barriers on innovation resistance of hydrogen-electric motorcycles.” *Sustainability* 10 (6):1933. https://doi.org/10.3390/su10061933.

Chohan, R., and Paschen, J. 2023. “NFT marketing: How marketers can use nonfungible tokens in their campaigns.” *Business Horizons* 66 (1): 43-50. https://doi.org/10.1016/j.bushor.2021.12.004.

De Nicola, A., Formica, A., Mele, I., Missikoff, M., and Taglino, F. 2024. A comparative study of LLMs and NLP approaches for supporting business process analysis. *Enterprise Information Systems*. https://doi.org/10.1080/17517575.2024.2415578

DeSimone, J. A., Harms, P. D., and DeSimone, A. J. 2014. “Best practice recommendations for data screening.” *Journal of Organizational Behaviour* 36 (2): 171–181. https://doi.org/10.1002/job.1962.

Day, S., Godsell, J., Masi, D., and Zhang, W. R. 2020. “Predicting consumer adoption of branded subscription services: A prospect theory perspective.” *Business Strategy and the Environment* 29 (3): 1310–1330. https://doi.org/10.1002/bse.2435.

Escalante, J., Pack, A., and Barrett, A. 2023. “AI-generated feedback on writing: insights into efficacy and ENL student preference.” *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00425-2.

Fornell, C., and Larcker, D. F. 1981. “Evaluating structural equation models with unobservable variables and measurement error.” *Journal of Marketing Research* 18 (1): 39. https://doi.org/10.2307/3151312.

Gefen, D., Straub, D., and Boudreau, M. 2000. “Structural Equation Modeling and Regression: Guidelines for Research Practice.” *Communications of the Association for Information Systems* 4. https://doi.org/10.17705/1CAIS.00407

Gartner 2022. “What’s new in the 2022 Gartner Hype Cycle for Emerging Technologies.” https://www.gartner.com/en/articles/what-s-new-in-the-2022-gartner-hype-cycle-for-emerging-technologies.

Gartner 2018. “Understanding Gartner’s hype cycles.” https://www.gartner.com/en/documents/3887767.

Gutierrez, M. 2021. “NFTs: What are they and why are people angry about them?” https://thebakerorange.com/38512/showcase/nfts-what-are-they-and-why-are-people-angry-about-them/.

Hofstetter, R., Bellis, E., Brandes, L., Clegg, M., Lamberton, C., Reibstein, D., Rohlfsen, F., Schmitt, B., and Zhang, J. Z. 2022. “Crypto-marketing: How non-fungible Tokens (nfts) challenge traditional marketing.” *Marketing Letters* 33 (4): 705–711. https://doi.org/10.1007/s11002-022-09639-2.

Hew, J. J., Leong, L. Y., Tan, W. H., Ooi, K. B., and Lee, V. H. 2019. “The age of mobile social commerce: An artificial neural network analysis on its resistances.” *Technological Forecasting and Social Change* 144: 311–324. https://doi.org/10.1016/j.techfore.2017.10.007.

Heidenreich, S., and Handrich, M. 2014. “What about passive innovation resistance? investigating adoption-related behaviour from a resistance perspective.” *Journal of Product Innovation Management* 32 (6): 878–903. https://doi.org/10.1111/jpim.12161.

Hair, J. F., Ringle, C. M., and Sarstedt, M. 2011. “PLS-SEM: Indeed a Silver Bullet.” *Journal of Marketing Theory and Practice* 19(2): 139–152. https://doi.org/10.2753/MTP1069-6679190202

Haenlein, M., and Kaplan, A. M. 2004. “A beginner’s guide to partial least squares analysis.” *Understanding statistics* 3(4): 283–297. https://doi.org/10.1207/s15328031us0304_4.

Hair, J. F., Ringle, C. M., and Sarstedt, M. 2013. “Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance.” *Long Range Planning* 46 (1–2): 1–12. https://doi.org/10.1016/j.lrp.2013.01.001.

Huang, C. C., Wang Y. M., Wu, T. W., and Wang P. A. 2013. “An empirical analysis of the antecedents and performance consequences of using the Moodle platform.”

International Journal of Information and Education Technology 217–221. https://doi.org/10.7763/ijiet.2013.v3.267.

Joseph, R. C. 2010. "Individual resistance to it innovations." *Communications of the ACM* 53 (4): 144–146. https://doi.org/10.1145/1721654.1721693.

Kaczynski, S., and Duke Kominers, S. 2021. "How nfts create value." https://hbr.org/2021/11/how-nfts-create-value.

Kushwah, S., Dhir, A., and Sagar, M. 2019. "Understanding consumer resistance to the consumption of organic food. A study of ethical consumption, purchasing, and choice behaviour." *Food Quality and Preference* 77: 1–14. https://doi.org/10.1016/j.foodqual.2019.04.003.

Khalil, A. Shankar, A., Bodhi, R., Behl, A., and Ferraris, A. 2023. "Why do people resist drone food delivery services? an innovation resistance theory perspective." *IEEE Transactions on Engineering Management* 1-11. https://doi.org/10.1109/tem.2022.3202485.

Kaur, P., Dhir, A., Singh, N., Sahu, G., and Almotairi, M. 2020. "An innovation resistance theory perspective on mobile payment solutions." *Journal of Retailing and Consumer Services* 55: 102059. https://doi.org/10.1016/j.jretconser.2020.102059.

Kong, D. R., and Lin, T. C. 2021. "Alternative investments in the Fintech era: The risk and return of non-fungible token (NFT)." *SSRN Electronic Journal* 3914085. https://doi.org/10.2139/ssrn.3914085.

Kim, J. K., Chua, M., Rickard, M., and Lorenzo, A. 2023. "ChatGPT and large language model (LLM) chatbots: The current state of acceptability and a proposal for guidelines on utilization in academic medicine." *Journal of Pediatric Urology 19*(5): 598-604. https://doi.org/10.1016/j.jpurol.2023.05.018

Kock, N., and Lynn, G. 2012. "Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations." *Journal of the Association for Information Systems,* 13 (7): 546–580. https://doi.org/10.17705/1jais.00302.

Liu, Y., Bhandari, S., and Pardos, Z. A. 2024. Leveraging LLM-Respondents for Item Evaluation: A Psychometric Analysis. *arXiv preprint arXiv:2407.10899*.

Leung, P. P. L., Wu, C. H., Ip, W. H., and Ho, G. T. S. 2018. Enhancing online-to-offline specific customer loyalty in beauty industry. *Enterprise Information Systems* 13(3): 352 – 375. https://doi.org/10.1080/17517575.2018.1527042

Liu, Y., Han, T., Ma, S., Zhang, J., Yang, Y., Tian, J., He, H., Li, A., He, M., Liu, Z., Wu, Z., Zhao, L., Zhu, D., Li, X., Qiang, N., Shen, D., Liu, T., and Ge, B. 2023.

"Summary of ChatGPT-related research and perspective towards the future of large language models." *Meta-Radiology* 1(2): 100017. https://doi.org/10.1016/j.metrad.2023.100017.

Lian, J. W., and Yen, D. C. 2013. "To buy or not to buy experience goods online: Perspective of Innovation Adoption Barriers." *Computers in Human Behaviour* 29 (3): 665–672. https://doi.org/10.1016/j.chb.2012.10.009.

Lam, L. W. 2012. "Impact of competitiveness on Salespeople's commitment and performance." *Journal of Business Research* 65 (9): 1328–1334. https://doi.org/10.1016/j.jbusres.2011.10.026.

Murtas, G., Pedeliento, G., and Mangiò, F. 2023. "Luxury fashion brands at the gates of the Web 3.0: An analysis of early experimentations with NFTs and the metaverse." *Journal of Global Fashion Marketing* *15*(1): 90–114. https://doi.org/10.1080/20932685.2023.2249476

Meyns, S. C., and Dalipi, F. 2022. "What users tweet on nfts: Mining twitter to understand NFT-related concerns using a topic modeling approach." *IEEE Access* 10: 117658–117680. https://doi.org/10.1109/access.2022.3219495.

Nadini, M., Alessandretti, l., Giacinto, F. D., Martino, M., Aiello, L. M., Baronchelli, A. 2021. "Mapping the NFT revolution: Market trends, Trade Networks, and visual features." *Scientific Reports* 11 (1). https://doi.org/10.1038/s41598-021-00053-8.

Palaniyapan, G. M. 2022. "How to fix the lack of trust in the NFT market." https://www.entrepreneur.com/science-technology/how-to-fix-the-lack-of-trust-in-the-nft-market/436447.

Potluri, R. M., and Vajjhala, N. R. 2018. "A study on application of Web 3.0 technologies in small and medium enterprises of India." *Journal of Asian Finance Economics and Business* 5(2): 73–79. https://doi.org/10.13106/jafeb.2018.vol5.no2.73

Podsakoff, P. M., and Organ, D. W. 1986. "Self-reports in organizational research: Problems and prospects." *Journal of Management* 12 (4): 531–544. https://doi.org/10.1177/014920638601200408.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., and Podsakoff, N. P. 2003. "Common method biases in behavioural research: A critical review of the literature and recommended remedies." *Journal of Applied Psychology* 88 (5): 879–903. https://doi.org/10.1037/0021-9010.88.5.879.

Podsakoff, P. M., MacKenzie, S. B., and Podsakoff, N. P. 2012. "Sources of method bias in social science research and recommendations on how to control it." *Annual*

Review of Psychology 63 (1): 539–569. https://doi.org/10.1146/annurev-psych-120710-100452.

Ram, S., and Sheth, J. N. 1989. "Consumer resistance to innovations: The marketing problem and its solutions." *Journal of Consumer Marketing* 6 (2): 5-14. https://doi.org/10.1108/eum0000000002542.

Reinmoeller, P., and Schmedders, K. 2022. "Why the NFT market will collapse." https://www.project-syndicate.org/commentary/reasons-why-nft-market-will-collapse-by-patrick-reinmoeller-and-karl-schmedders-2022-01.

Roh, T., Seok, J., and Kim, Y. 2022. "Unveiling ways to reach organic purchase: Green perceived value, perceived knowledge, attitude, subjective norm, and Trust." *Journal of Retailing and Consumer Services* 67: 102988. https://doi.org/10.1016/j.jretconser.2022.102988.

Stallone, V., Wetzels, M., and Klaas, M. 2021. "Applications of Blockchain Technology in marketing systematic review of marketing technology companies." *Blockchain: Research and Applications* 2(3): 100023. https://doi.org/10.1016/j.bcra.2021.100023.

Sestino, A., Guido, G., and Peluso, A. M. 2022. "A review of the marketing literature on NFTS." *Non-Fungible Tokens (NFTs) Examining the Impact on Consumers and Marketing Strategies* 23–41. https://doi.org/10.1007/978-3-031-07203-1_3.

Snee, R. 1981. "Origins of the variance inflation factor as recalled by Cuthbert Daniel (technical report)." *Snee Associates* 14 (2): 170-188.

Sadlier-Brown, E., Lou, M., Silfverberg, M., and Kam, C. 2024. "How Useful is Context, Actually? Comparing LLMs and Humans on Discourse Marker Prediction." In *Proceedings of the Workshop on Cognitive Modeling and Computational Linguistics* 231-241.

Shan, L., Diao, H., and Wu, L. 2020. "Influence of the framing effect, anchoring effect, and knowledge on consumers' attitude and purchase intention of organic food." *Frontiers in Psychology* 11. https://doi.org/10.3389/fpsyg.2020.02022.

Sadiq, M., Adil, M., and Paul, J. 2021. "An innovation resistance theory perspective on purchase of eco-friendly cosmetics." *Journal of Retailing and Consumer Services* 59: 102369. https://doi.org/10.1016/j.jretconser.2020.102369.

Sutcliffe, C. 2022. "42% of the public have no idea what an NFT is, finds YouGov." https://www.thedrum.com/news/2022/02/23/42-the-public-have-no-idea-what-nft-finds-yougov.

Shankar, A., and Nigam, A. 2021. "Explaining resistance intention towards Mobile HRM application: The Dark Side of Technology Adoption." *International Journal of Manpower* 43 (1): 206–225. https://doi.org/10.1108/ijm-03-2021-0198.

Sonderen, E., van, Sanderman, R., and Coyne, J. C. 2013. "Correction: Ineffectiveness of reverse wording of questionnaire items: Let's learn from cows in the rain." *PLoS ONE* 8 (9). https://doi.org/10.1371/annotation/af78b324-7b44-4f89-b932-e851fe04a8e5.

Song, V. 2022. "Stockx hits back at Nike in legal battle over nfts and counterfeit sneakers." https://www.theverge.com/2022/6/6/23156515/nike-stockx-nfts-counterfeit-sneakers-lawsuit.

Teng, C. C., and Wang, Y. M. 2015. "Decisional factors driving organic food consumption." *British Food Journal* 117 (3):1066–1081. https://doi.org/10.1108/bfj-12-2013-0361.

Ullah, F., Sepasgozar, S. M. E., Thaheem, M. J., and Al-Turjman, F. 2021. "Barriers to the Digitalisation and innovation of Australian Smart Real Estate: A Managerial Perspective on the technology non-adoption." *Environmental Technology and Innovation* 22: 101527. https://doi.org/10.1016/j.eti.2021.101527.

Upadhyay, U., Kumar, A., Sharma, G., Sharma, S., Arya, V., Panigrahi, P. K., and Gupta, B. B. 2024. "A systematic data-driven approach for targeted marketing in enterprise information system." *Enterprise Information Systems 18*(8). https://doi.org/10.1080/17517575.2024.2356770

Wagner, S., Barón, M. M., Falessi, D., and Baltes, S. 2024. "Towards Evaluation Guidelines for Empirical Studies involving LLMs." *arXiv preprint arXiv:2411.07668.*

Xie, Q., Muralidharan, S., Edwards, S. M., and La Ferle, C. 2023. "Unlocking the power of non-fungible token (NFT) marketing: how NFT perceptions foster brand loyalty and purchase intention among Millennials and Gen-Z." *Journal of Interactive Advertising 23*(4): 356-373. https://doi.org/10.1080/15252019.2023.2258875.

Xie, Q., Muralidharan, S., and Edwards, S. M. 2024. "Who will buy the idea of non-fungible token (NFT) marketing? understanding consumers' psychological tendencies and value perceptions of branded nfts." *International Journal of Advertising* 1–29. https://doi.org/10.1080/02650487.2023.2262859.

Zhang, Z., and Zheng, L. 2020. "Consumer Community Cognition, Brand Loyalty, and behaviour intentions within online publishing communities: An empirical study of epubit in China." *Learned Publishing* 34 (2): 116–127. https://doi.org/10.1002/leap.1327.

Zheng, L., Chiang, W. L., Sheng, Y., Zhuang, S., Wu, Z., Zhuang, Y., Lin, Z., Li, Z., Li, D., Xing, E., Zhang, H., and Stoica, I. 2023. "Judging llm-as-a-judge with mt-bench and chatbot arena." *Advances in Neural Information Processing Systems 36*: 46595-46623.

Appendix A: Measurement items used in this empirical research study

Variable name	Item code	Items
Usage barrier (Alexander and Bellandi, 2022; Lian and Yen, 2013)	UB1	There are limited choices of NFT marketing-based offerings available in the market for my selection and engagement
	UB2	I feel annoyed that businesses promote their products, services, and events through NFT marketing strategies
	UB3	I am concerned that businesses utilizing NFTs do not provide adequate after-sales support for digital assets
	UB4	The capital and market value associated with NFT marketing initiatives are unpredictable in the current landscape
Value barrier (Sutcliffe, 2022; Chen et al., 2022)	VB1	In my opinion, NFTs are less appealing for creating personalized consumer experiences
	VB2	Engaging with NFTs is a way to support the business development initiatives of enterprises
	VB3	NFT marketing initiatives launched by businesses do not yield significant value in terms of brand identity and customer loyalty
Risk barrier (Kong and Lin, 2021; Chen et al., 2022)	RB1	I am concerned that I will not fully have the copyright and ownership of digital assets even after I purchase NFTs in the context of NFT marketing
	RB2	I worry that NFTs do not provide adequate security measures to safeguard my digital assets, making cyberattacks and asset theft likely
	RB3	I fear that after purchasing NFTs associated with a company's marketing initiatives, their value cannot be guaranteed in an ever-changing business environment (e.g., if the company goes out of business or experiences a significant decline in value)
Tradition barrier (Gutierrez, 2021; Chen et al., 2018)	TB1	I find that purchasing NFT marketing-based products is more challenging than using traditional online purchasing methods
	TB2	I tend to find marketing information and materials from traditional channels (e.g., social media and TV advertising) more persuasive and convenient than those delivered through NFTs
	TB3	I find it difficult to distinguish between traditional membership systems and NFT-based membership systems

Image barrier (Ali et al., 2023; Palaniyapan, 2022)	IB1	In my opinion, the application of NFTs in marketing strategies is often too complicated to be useful
	IB2	I believe that using NFTs as a marketing strategy has a negative impact on businesses
Knowledge concern (Borzekowski et al., 2021; Roh et al., 2022)	KC1	I fully understand the concepts of blockchain and NFT marketing
	KC2	I actively follow current developments in NFTs and their marketing applications
	KC3	I am eager to see more innovations in technology-driven marketing strategies
Resistance intention (Khalil et al., 2023; Kaur, 2020; Chen et al., 2022)	RI1	I am reluctant to purchase NFT marketing products and associated digital assets, even when they are created and promoted by well-known brands (e.g., Adidas, Samsung, and McDonald's)
	RI2	I do not support businesses using NFTs for marketing purposes
	RI3	Overall, I prefer traditional marketing strategies, even with the growing popularity of NFT marketing