A Survey of PLS-SEM in Analyzing Continuance Usage Intention in Facial Recognition Payment Systems

Abstract

This survey paper explores the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) in analyzing continuance usage intention within facial recognition payment systems. PLS-SEM is highlighted as a robust statistical technique suitable for examining complex relationships between latent constructs, particularly in contexts where privacy concerns and technology adoption are pivotal. Through a comprehensive examination of key concepts such as perceived usefulness, ease of use, and privacy concerns, the paper underscores the significance of these factors in shaping user acceptance and loyalty. The survey also delves into the methodological advantages of PLS-SEM, including its flexibility in handling complex hierarchical models and its integration with machine learning techniques for enhanced predictive accuracy. Moreover, the paper identifies gaps in current research, such as the need for comparative studies with other analytical methods and the exploration of broader applications of PLS-SEM across diverse fields. Future research directions are proposed, emphasizing the integration of AI tools within organizational contexts and the development of comprehensive frameworks that synthesize insights from multiple analytical approaches. Overall, this study contributes to the understanding of consumer behavior and technology adoption, offering valuable insights for researchers and practitioners aiming to enhance the design and implementation of biometric payment systems.

1 Introduction

1.1 Context and Relevance

The integration of facial recognition payment systems into daily transactions marks a significant technological evolution, driven by the demand for efficient and contactless payment methods, particularly accelerated by the COVID-19 pandemic. This context underscores the importance of understanding the factors influencing the continued usage intention of these systems, which is essential for comprehending consumer behavior [1].

The relevance of this study is further highlighted within the broader framework of technology adoption, where the incorporation of biometric systems raises critical user acceptance and privacy concerns. The multifaceted nature of technology adoption is illustrated through various domains, such as the use of portable intelligent personal assistants, which redefine user interaction [2]. Additionally, user experience in chat applications, shaped by coherence, sentiment, and agent characteristics, reveals the intricate dynamics of technology integration [3].

In this landscape, Partial Least Squares Structural Equation Modeling (PLS-SEM) serves as a powerful analytical tool, facilitating the validation of theoretical constructs in social science and business research. The increasing application of PLS-SEM, evidenced by a bibliometric analysis from 2011 to 2020, reflects its significance in complex model analysis [4]. This study aims to utilize

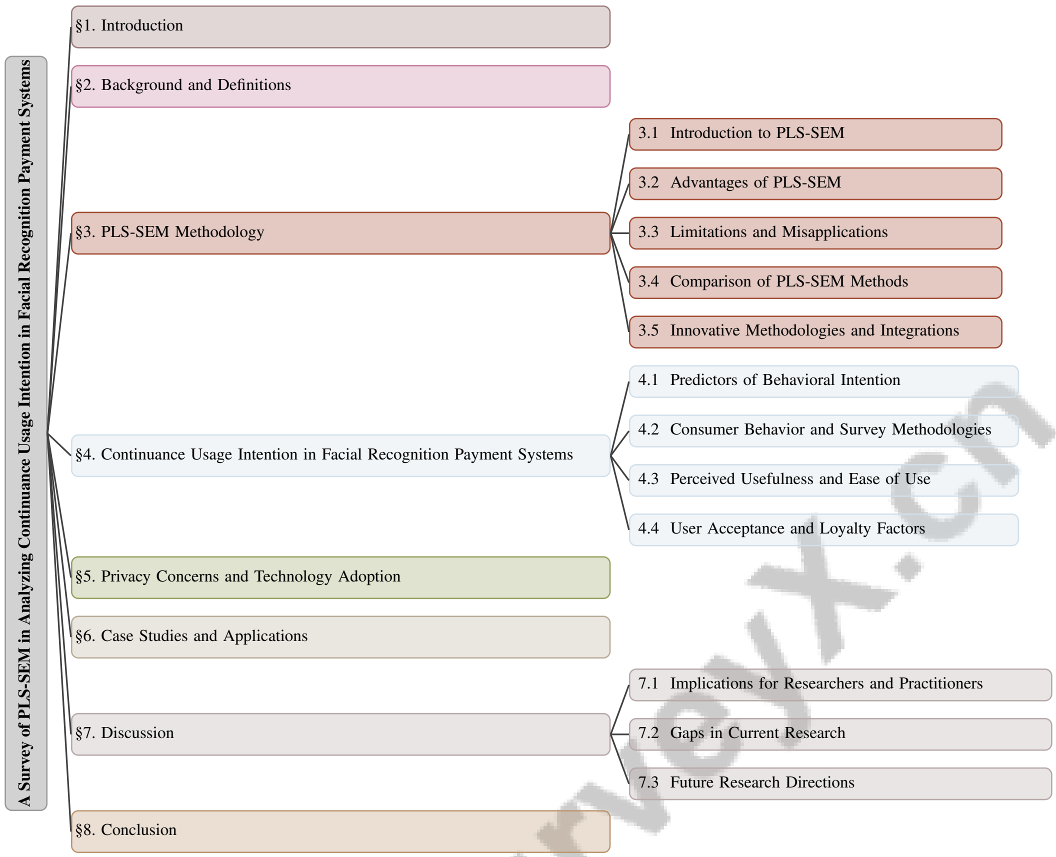

Figure 1: chapter structure

PLS-SEM to navigate the complexities of technology adoption, contributing to the discourse on consumer behavior in a context where mobile device proficiency is increasingly vital across various sectors, including healthcare [5].

1.2 Role of PLS-SEM

PLS-SEM plays a crucial role in analyzing the continuance usage intention of facial recognition payment systems by elucidating the intricate interrelationships among latent variables. This methodological framework is particularly adept at validating theoretical models through empirical data, as seen in studies extending the technology acceptance model (TAM) by including factors like perceived intelligence and simplicity, alongside user loyalty [1]. Its capability to manage complex hierarchical models is especially beneficial in contexts where intricacy is a major concern, such as big data analytics [6].

Moreover, PLS-SEM's versatility is evident across various fields, including the analysis of sequential mediation effects in parasocial relationships and their impact on consumer intentions [3]. This adaptability allows for the integration of diverse analytical techniques, offering a comprehensive view of user behavior. The method's flexibility is further demonstrated through its application in software platforms like SmartPLS, WarpPLS, and ADANCO, each catering to specific research needs [7].

Despite its advantages, researchers should not rely solely on statistical outcomes from PLS-SEM analyses. A thorough understanding of the philosophical and theoretical foundations of the chosen methods is essential for ensuring the robustness and relevance of findings [8]. This holistic approach is critical for accurately capturing the nuances of continuance usage intention in facial recognition payment systems.

In technology adoption research, PLS-SEM's role encompasses the integration of theoretical frameworks such as the theory of planned behavior and the norm activation model, which are vital for exploring user perceptions and intentions [9]. This integration enhances the understanding of factors influencing the sustained use of biometric payment systems, significantly contributing to the broader discourse on consumer behavior and technology adoption. The growing adoption of PLS-SEM in business research underscores its advantages over traditional methods, providing a robust analytical framework for complex model analysis [4].

1.3 Structure of the Survey

This survey aims to conduct a comprehensive analysis of the application of PLS-SEM in evaluating continuance usage intention in facial recognition payment systems, emphasizing the method's effectiveness in managing complex relationships between observed and latent variables and its increasing prominence in business and social science research [7, 3, 10]. The survey begins with an **Introduction**, which establishes the significance of studying continuance usage intention in the context of facial recognition payment systems and the pivotal role of PLS-SEM in this analysis.

Following the introduction, the **Background and Definitions** section provides an overview of key concepts, including PLS-SEM, continuance usage intention, facial recognition payment systems, privacy concerns, technology adoption, and biometric payment systems. This section clarifies these concepts and their interrelations, laying the groundwork for the detailed analysis that follows.

The **PLS-SEM Methodology** section delves into the specifics of the PLS-SEM approach, outlining its advantages and limitations, comparing different PLS-SEM methods, and exploring innovative methodologies and integrations. This section is crucial for understanding the methodological framework employed in the survey.

In the **Continuance Usage Intention in Facial Recognition Payment Systems** section, the survey examines factors influencing continuance usage intention, identifying predictors of behavioral intention, and discussing consumer behavior theories and survey methodologies relevant to this context. It also addresses the impact of perceived usefulness, ease of use, user acceptance, and loyalty factors.

The subsequent **Privacy Concerns and Technology Adoption** section analyzes the role of privacy concerns in technology adoption, particularly within biometric payment systems. It discusses specific privacy concerns, security and usability issues, and how perceived susceptibility and health concerns influence technology adoption.

The survey then outlines the **Case Studies and Applications**, highlighting instances where PLS-SEM has been effectively employed to analyze continuance usage intentions. These examples draw insights from diverse datasets, illustrating the method's versatility and applicability in various research contexts, such as Web 3.0 adoption behavior and complex modeling in big data analytics [8, 6, 10, 11, 7].

In the **Discussion** section, the survey synthesizes information from previous sections, discussing implications for researchers and practitioners, identifying gaps in current research, and suggesting future research directions.

The **Conclusion** section encapsulates the primary findings and discussions presented throughout, emphasizing the practical implications of using PLS-SEM across various applications, including its advantages in analyzing complex models with latent variables, as highlighted in recent literature. This section also reflects on insights gained from comparing different PLS-SEM software tools and their unique characteristics, guiding researchers in selecting the most suitable application for their specific analytical needs in the context of big data and web technologies [8, 7, 6, 10]. This structured approach ensures a thorough exploration of the topic, contributing valuable insights to the field of consumer behavior and technology adoption.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Key Concepts

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a prevalent statistical method in business research, adept at exploring intricate relationships among latent constructs. Unlike Covariance-Based SEM (CB-SEM), PLS-SEM emphasizes maximizing the explained variance of endogenous constructs, making it ideal for exploratory and predictive modeling where theoretical constructs are still evolving [4, 8]. This flexibility allows researchers to handle complex model structures even with limited sample sizes [11].

Continuance usage intention denotes a user's intent to persist in using a technology or system post-initial adoption. This concept is central to the Technology Acceptance Model (TAM), which posits that perceived usefulness (PU) and perceived ease of use (PEOU) are critical determinants of technology acceptance and continued usage [1]. The Theory of Planned Behavior (TPB) and the Norm Activation Model (NAM) further enrich this understanding by incorporating psychological and normative factors influencing user behavior in technology adoption contexts [9].

Facial recognition payment systems exemplify advanced biometric technology applications, using unique facial features for authentication and transaction processing. These systems balance usability and security, offering a seamless payment experience while raising significant privacy concerns [12]. The handling of sensitive personal data in biometric systems amplifies issues related to data protection, user consent, and potential data misuse [13].

The adoption of facial recognition payment systems is influenced by factors such as performance expectancy, electronic word-of-mouth, and digital dexterity, which collectively shape behavioral intentions towards adopting new technologies [10]. Perceived usefulness and ease of use are crucial for determining user acceptance and ongoing engagement, as emphasized in broader technology acceptance discussions [1].

Biometric payment systems, including facial recognition and fingerprint authentication, offer enhanced security and convenience but also present challenges related to user privacy and data security. Robust authentication methods are essential to protect sensitive information and maintain user trust [12]. The adoption and continued use of contactless payment technologies have gained significant attention, particularly during the COVID-19 pandemic, which accelerated the shift towards contactless transactions.

Mobile device proficiency, while not directly linked to biometric payment systems, plays a crucial role in technology adoption. It encompasses the skills required to effectively use mobile devices, which are increasingly integral to interacting with biometric systems. The Mobile Device Abilities Test (MDAT) serves as a performance-based assessment framework to evaluate these skills, illustrating the intersection of cognitive health assessments and technology usage [5].

The interplay among these key concepts highlights the complexity of studying continuance usage intention in facial recognition payment systems. PLS-SEM offers a comprehensive analytical framework for exploring the intricate dynamics of technology adoption and ongoing usage, particularly in the context of the rising prevalence of biometric systems. By facilitating simultaneous analysis of relationships between observed and latent variables, PLS-SEM aids in identifying key factors influencing user acceptance and sustained engagement with advanced technologies, providing valuable insights for stakeholders aiming to enhance technology integration strategies [7, 6, 10].

2.2 Interrelation of Key Concepts

The interrelation of key concepts—PLS-SEM, continuance usage intention, facial recognition payment systems, privacy concerns, technology adoption, and biometric payment systems—forms a complex tapestry essential for understanding technology adoption dynamics. PLS-SEM serves as the analytical backbone, enabling researchers to explore and validate intricate relationships among latent variables that influence continuance usage intention [13]. This methodological approach adeptly addresses the multifaceted nature of technology adoption, where individual perceptions, technological characteristics, and social influences converge to shape user behavior.

Continuance usage intention is intricately linked to user satisfaction and risk perception, as articulated by the Expectation-Confirmation Theory and the Health Belief Model, which highlight the significance of user satisfaction in predicting continued use while considering perceived risks and benefits in shaping health-related behaviors and technology adoption. Facial recognition payment systems, as a subset of biometric payment systems, illustrate the dual challenge of enhancing user convenience while safeguarding privacy and security. The seamless user experience offered by these systems must be weighed against heightened privacy concerns related to biometric data collection and processing [13].

The adoption of facial recognition payment systems is influenced by the nuanced interplay of social influences and individual perceptions, as evidenced by the mediation of parasocial relationships on consumer intentions. This underscores the significant role of social dynamics in shaping user acceptance and loyalty, where social influence can mediate the relationship between perceived usefulness and continuance intention [3]. Additionally, the challenge of accurately capturing individual-level responses in surveys, particularly with large language models (LLMs), highlights the complexity of understanding nuanced human behavior in technology adoption scenarios [14].

In synthesizing these concepts, PLS-SEM emerges as a powerful tool for dissecting the multifaceted influences on continuance usage intention, providing a comprehensive framework to analyze how privacy concerns, perceived usefulness, social influences, and individual perceptions collectively drive the adoption and sustained use of facial recognition payment systems. This interrelation lays the groundwork for a thorough examination of the diverse factors driving technology adoption, especially in the context of biometric technology integration. Recent studies employing advanced analytical methods such as PLS-SEM and fuzzy set qualitative comparative analysis (fsQCA) offer critical insights into user acceptance dynamics, highlighting the influence of factors like artificial intelligence capabilities, user interface design, electronic word-of-mouth, and social media influencer credibility, thereby enriching the broader discourse on consumer behavior and strategic decisions necessary for fostering widespread adoption and sustained engagement with emerging technologies [3, 10, 1].

The analysis of Partial Least Squares Structural Equation Modeling (PLS-SEM) reveals a multifaceted methodology that is both robust and adaptable. As illustrated in Figure 2, this figure demonstrates the hierarchical structure of PLS-SEM methodology, outlining its introduction, advantages, limitations, comparisons, and innovative integrations. Notably, it highlights the method's flexibility, its integration with machine learning techniques, the technical limitations that researchers may encounter, and its diverse applications in cross-cultural research. This comprehensive overview not only elucidates the foundational aspects of PLS-SEM but also positions it within the broader context of contemporary research methodologies.

3 PLS-SEM Methodology

3.1 Introduction to PLS-SEM

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a flexible statistical method, particularly suited for prediction and theory development in complex models. Unlike Covariance-Based SEM (CB-SEM), which emphasizes model fit, PLS-SEM focuses on maximizing the explained variance of dependent constructs, making it ideal for exploratory research where theoretical models are still evolving [1, 3]. This approach is advantageous in cases where data do not meet CB-SEM's stringent assumptions, such as multivariate normality and large sample sizes.

PLS-SEM is widely applied in technology adoption and user behavior studies, as demonstrated by its use in analyzing factors affecting the acceptance of portable intelligent personal assistants, involving 824 users [1]. Its versatility extends to user interaction studies with dialog agents, assessing factors influencing user satisfaction and engagement [2]. The integration of PLS-SEM with machine learning enhances predictive capabilities and allows for comprehensive analyses, as seen in research on parasocial relationships where it provides deeper consumer insights [3]. Its application in evaluating biometric systems' usability and security further underscores its efficacy in assessing user satisfaction and efficiency across different research stages [12].

PLS-SEM's capacity to handle large datasets and generate actionable insights into user perceptions and intentions is illustrated in studies on mobile device proficiency [5]. This adaptability, coupled with its ability to integrate diverse analytical techniques, positions PLS-SEM as a powerful tool for dissecting complex interrelationships in behavioral research, enhancing our understanding of technology adoption and continued usage intentions.

3.2 Advantages of PLS-SEM

PLS-SEM offers numerous advantages for analyzing complex models, particularly in validating intricate theoretical constructs based on empirical data [13]. Its flexibility and robustness in modeling hierarchical constructs are crucial for understanding big data analytics [6]. This approach is partic-

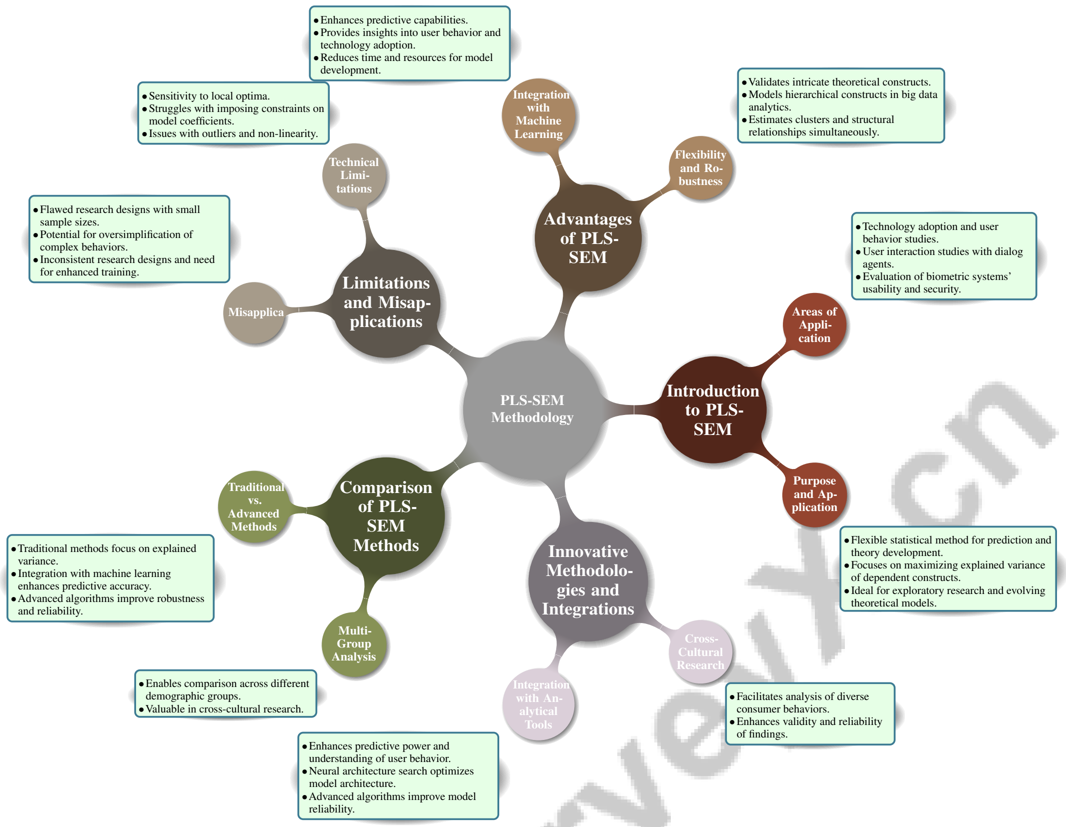

Figure 2: This figure demonstrates the hierarchical structure of PLS-SEM methodology, outlining its introduction, advantages, limitations, comparisons, and innovative integrations. It highlights the method's flexibility, integration with machine learning, technical limitations, and applications in cross-cultural research.

ularly beneficial in business, social sciences, and software engineering, where analyzing complex relationships is critical [7].

As illustrated in Figure 3, PLS-SEM's advantages are prominently displayed, emphasizing its flexibility in modeling hierarchical constructs, its applicability across various domains such as business and social sciences, and its efficiency in model architecture search and analysis of complex relationships. The method's ability to estimate clusters and structural relationships simultaneously enhances its utility in modeling complex data structures [15]. Integrating machine learning algorithms with structural equation modeling offers innovative insights into user behavior and technology adoption factors [9]. PLS-SEM's adaptability is further evidenced in dialog systems, providing nuanced insights into user experience that inform chat agent design [2]. The evolutionary approach to model architecture search reduces time and resources needed for model development, highlighting PLS-SEM's efficiency in handling complex models [16].

The growing recognition of PLS-SEM in business contexts emphasizes its strength in analyzing complex relationships, as evidenced by the increasing body of research utilizing this method [4]. Its ability to validate complex theoretical models, combined with its flexibility and integration with advanced analytical techniques, makes PLS-SEM indispensable for researchers exploring multifaceted constructs across various domains.

3.3 Limitations and Misapplications

While PLS-SEM has many strengths, it also presents limitations and potential for misapplication. A common challenge is the misconception that similar results from different methods ensure accuracy, leading to misinterpretations [8]. This underscores the need for critical assessment of methodological appropriateness and interpretative validity.

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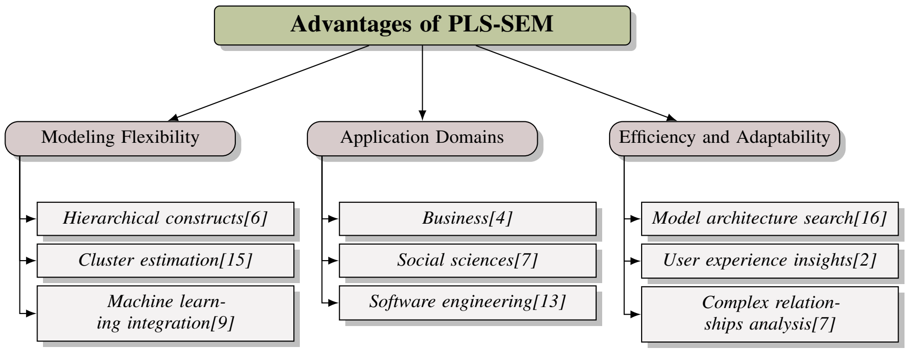


Figure 3: This figure illustrates the advantages of PLS-SEM, highlighting its flexibility in modeling hierarchical constructs, its application across various domains such as business and social sciences, and its efficiency in model architecture search and analysis of complex relationships.

Technical limitations of PLS-SEM include sensitivity to local optima, particularly in the PLS-SEM-KM method, necessitating multiple random starts for robust solutions [15]. It may also struggle with imposing constraints on model coefficients and addressing data issues like outliers and non-linearity, potentially compromising result reliability [6].

Overfitting is another concern, especially when models are tailored to specific datasets, compounded by the computational resources required during the evolution process [16]. Research often lacks comprehensive comparisons of PLS-SEM applications, leading to potential confusion among users [7].

Misapplications can result from flawed research designs, particularly with small sample sizes and non-normal data [11]. Studies focusing on a limited number of predictive factors, such as those on Web 3.0 adoption behavior, risk oversimplifying complex user behaviors [10]. Moreover, PLS-SEM occasionally fails to replicate intricate relationships accurately, complicating its application in nuanced contexts [14].

Inconsistent research designs and the need for enhanced methodological training among researchers further limit PLS-SEM's effectiveness [4]. Addressing these limitations and potential misapplications is vital for advancing PLS-SEM's utility in research and ensuring meaningful contributions to understanding complex constructs.

3.4 Comparison of PLS-SEM Methods

The landscape of PLS-SEM is enriched by various methods and applications catering to diverse research needs. A key distinction among PLS-SEM methods is their approach to model specification and estimation, significantly influencing research outcomes and interpretations. Traditional methods focus on maximizing the explained variance of endogenous constructs, making them suitable for exploratory research in fields such as business and social sciences, where understanding complex relationships is crucial [16].

The integration of machine learning techniques with PLS-SEM marks a significant advancement, enhancing predictive accuracy and model validation. This hybrid approach facilitates exploration of complex datasets and identification of latent patterns that may remain hidden in conventional analyses [16]. The application of neural architecture search within PLS-SEM further exemplifies this integration, providing a robust framework for optimizing model architecture and improving computational efficiency.

Advanced algorithms for parameter estimation enhance the robustness and reliability of PLS-SEM models, addressing traditional limitations such as sensitivity to local optima and sample size requirements, thereby broadening the method's applicability across diverse research contexts [16].

The evolution of PLS-SEM methods has been significantly advanced by incorporating multi-group analysis, enabling researchers to systematically compare behaviors and relationships across different demographic or experimental groups within the same study. This capability is particularly valuable in cross-cultural research, where understanding consumer behavior nuances across populations is essential [8, 7, 10]. The methodological advancements in PLS-SEM, alongside its integration with machine learning, highlight its versatility and adaptability in addressing complex research questions across various domains.

3.5 Innovative Methodologies and Integrations

The integration of PLS-SEM with innovative methodologies and analytical tools has significantly expanded its applicability and effectiveness in analyzing complex models. Incorporating machine learning techniques enhances predictive power and allows researchers to explore intricate data structures, uncovering latent patterns and interactions that may be obscured in traditional analyses, thus providing a comprehensive understanding of user behavior and technology adoption [16].

Neural architecture search within PLS-SEM exemplifies the innovative integration of computational techniques to optimize model architecture, improving both accuracy and computational efficiency. This addresses key limitations of traditional PLS-SEM, such as the need for large sample sizes and sensitivity to local optima, making it a robust tool for various research contexts [16].

Advanced algorithms for parameter estimation in PLS-SEM enhance model reliability and robustness, enabling researchers to derive more accurate insights from their data. These algorithms facilitate handling complex datasets, allowing for the analysis of multi-dimensional constructs and identification of nuanced relationships between latent variables [16].

The integration of PLS-SEM with analytical tools like multi-group analysis extends its utility by allowing comparisons of different populations within the same study. This capability is particularly valuable in cross-cultural research, enabling effective analysis and interpretation of diverse consumer behaviors emerging from varying cultural contexts, thereby enhancing the validity and reliability of findings [8, 6, 14, 7, 4]. The methodological advancements in PLS-SEM, combined with cutting-edge analytical techniques, underscore its versatility and adaptability in addressing complex research questions across various domains.

The innovative methodologies and integrations within PLS-SEM significantly enhance its analytical capabilities and broaden its applicability across various fields. This makes PLS-SEM an essential tool for researchers investigating complex constructs in business, social sciences, and technology adoption. Its user-friendly interface facilitates simultaneous analysis of relationships between observed and latent variables, accommodating the intricacies of multivariate data analysis while addressing measurement errors inherent in abstract concepts. Consequently, PLS-SEM has gained widespread acceptance among scholars, evidenced by its extensive use in high-impact journals and its ability to facilitate robust assessments in complex modeling scenarios [8, 6, 7, 10].

4 Continuance Usage Intention in Facial Recognition Payment Systems

Examining continuance usage intention in facial recognition payment systems involves analyzing predictors of behavioral intention across technological, psychological, and social dimensions. This analysis reveals mechanisms shaping user acceptance of innovative payment solutions, guiding strategies to enhance user engagement and adoption. Partial Least Squares Structural Equation Modeling (PLS-SEM) effectively analyzes complex variable relationships, deepening understanding of user behavior in emerging technologies [8, 6, 16, 7, 2].

4.1 Predictors of Behavioral Intention

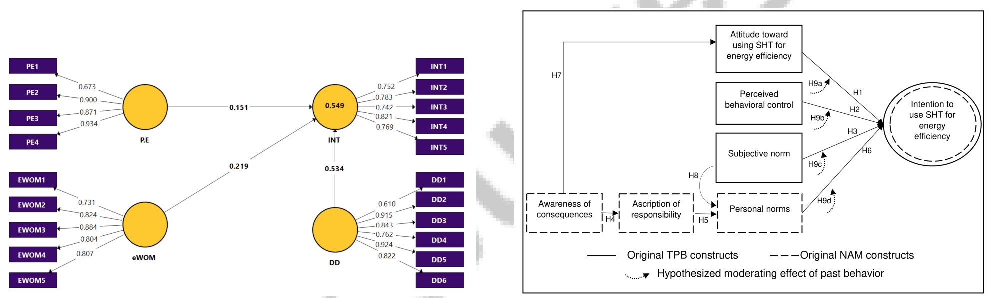
Behavioral intention in facial recognition payment systems is influenced by factors beyond traditional technology acceptance models. Perceived usefulness, indicating the system's efficiency in transactions, and perceived ease of use, denoting interaction effortlessness, are central predictors. Studies on intelligent personal assistants show that ease of use and utility significantly drive adoption [1]. Digital dexterity, reflecting users' ability to navigate digital technologies, is crucial, as seen in advanced technologies like Web 3.0 [10]. Conversational and task intelligence, relating to interactive elements, enhance user satisfaction and acceptance [1].

Personal norms and perceived susceptibility also impact behavioral intentions. Personal norms, representing internal standards, strongly determine intentions to use smart technologies for specific purposes, such as energy efficiency [9]. In health-related contexts, perceived susceptibility significantly shapes user perceptions and intentions. Usability and security of authentication methods critically influence user perception and acceptance, as seen in electronic health records [12]. Mobile device proficiency, as demonstrated by the Mobile Device Abilities Test (MDAT), impacts behavioral intention, emphasizing the importance of proficient use of mobile devices for biometric payment systems [5].

4.2 Consumer Behavior and Survey Methodologies

Understanding consumer behavior in facial recognition payment systems requires theoretical frameworks and survey methodologies capturing user interaction nuances. The Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) provide insights into how perceived usefulness and ease of use influence user acceptance and continuance intention [1]. These models highlight cognitive evaluations' role in shaping user attitudes toward new technologies. The Theory of Planned Behavior (TPB) and Norm Activation Model (NAM) extend this understanding by incorporating normative and psychological factors [9]. TPB suggests behavioral intentions are influenced by attitudes, subjective norms, and perceived control, while NAM emphasizes personal norms and awareness of consequences.

Survey methodologies are crucial for capturing consumer behavior insights. Large language models (LLMs) simulate diverse user perspectives, enhancing data collection accuracy [14]. Integrating conversational and task intelligence into survey methodologies enriches data collected, assessing user satisfaction and engagement [1]. PLS-SEM provides a robust framework for analyzing complex relationships between latent variables, offering insights into user acceptance and sustained engagement with facial recognition payment systems [7, 3, 14].



(a) The image depicts a structural equation model (SEM) with six latent variables and six observed variables.[10]

(b) The image represents a theoretical model of the Theory of Planned Behavior (TPB) and the Theory of Reasoned Action (TRA) with an added moderating effect of past behavior.[9]

Figure 4: Examples of Consumer Behavior and Survey Methodologies

In Figure 4, continuance usage intention in facial recognition payment systems is explored through consumer behavior and survey methodologies. The first model, a structural equation model (SEM), includes six latent and six observed variables, providing insights into consumer behavior factors. The second model integrates TPB and the Theory of Reasoned Action (TRA), examining psychological constructs driving decisions to continue using facial recognition payment systems. Analyzing these frameworks uncovers the interplay between attitudes, perceived control, norms, and past behaviors, offering a comprehensive understanding of factors sustaining consumer engagement [10, 9].

4.3 Perceived Usefulness and Ease of Use

Perceived usefulness and ease of use are crucial for understanding continuance usage intention in facial recognition payment systems. Central to the Technology Acceptance Model (TAM), these factors significantly influence user decisions regarding technology adoption and continued use. Perceived usefulness involves the belief that using the system enhances performance, offering benefits like increased transaction speed, convenience, and security [13]. Ease of use refers to the effort required to utilize the system, with systems perceived as easy to use reducing cognitive load and fostering positive user experiences [13].

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The interaction between perceived usefulness and ease of use is vital, as these constructs influence user perceptions and intentions. Systems that are both useful and easy to use achieve higher user satisfaction, leading to sustained use. This relationship is particularly relevant in biometric payment systems, where balancing usability and security is essential. Integrating generative AI tools into user interfaces can enhance perceived usefulness and ease of use by providing personalized and intuitive interactions, reinforcing continuance intention [13].

4.4 User Acceptance and Loyalty Factors

User acceptance and loyalty in facial recognition payment systems are shaped by technological and psychological factors. Perceived security and privacy are central, as biometric systems involve sensitive data collection, impacting user acceptance and engagement [12]. Ensuring robust security measures and transparent data handling is crucial for fostering trust and loyalty. User experience, influenced by interface design and functionality, is another critical factor. Systems with intuitive navigation, efficient processes, and personalized interactions achieve higher satisfaction and loyalty, with advanced features like conversational intelligence enhancing engagement [1].

Social influences, such as electronic word-of-mouth and social norms, significantly shape acceptance and loyalty. Positive social reinforcement enhances user confidence, increasing the likelihood of continued use [10]. Personal norms and values, as described in the Norm Activation Model, align technology use with beliefs and ethics, influencing acceptance and loyalty [9]. Digital dexterity also plays a role, with proficient users more willing to adopt and continue using advanced technologies like facial recognition payment systems [5]. Providing training and support enhances digital skills, facilitating greater acceptance and loyalty.

5 Privacy Concerns and Technology Adoption

The evolution of technology adoption underscores privacy concerns as pivotal in influencing user acceptance and engagement. Biometric systems, particularly facial recognition payment systems, necessitate an in-depth exploration of privacy implications on user behavior. This section delves into privacy issues, examining the factors shaping user privacy perceptions, the role of advanced technologies like artificial intelligence, and the alignment of policy with user expectations to foster a secure and trustworthy technological environment.

5.1 Privacy Concerns in Biometric Systems

Privacy concerns in biometric systems significantly impact technology adoption, especially in facial recognition payment systems. These concerns stem from the collection and processing of sensitive personal data, such as facial features, for authentication and transactions. Users often perceive facial authentication as more secure and user-friendly than traditional methods like passwords [12]. However, the integration of AI complicates these issues, as it raises privacy and usability challenges that may hinder broader adoption [13]. Misuse of biometric data and opaque data handling practices can deter users, emphasizing the need to understand user behavior and privacy concerns during the pre-adoption phase [10]. Health concerns, such as those heightened by COVID-19, further influence the continued use of contactless payment technologies, including biometric systems [17]. Aligning policy measures, infrastructure, and user perspectives is crucial for addressing privacy concerns and promoting adoption [9]. Robust data protection, transparent privacy policies, and user education can mitigate privacy risks and enhance trust. Additionally, acknowledging cultural contexts and potential biases in data collection is essential for developing culturally sensitive biometric systems [3].

5.2 Security and Usability Concerns

Security and usability are critical in consumer behavior regarding facial recognition payment systems. Balancing these aspects is essential, as users demand both data protection and ease of use. Systems perceived as secure but cumbersome may deter users, while those seen as easy to use but insecure may fail to gain trust [12]. Security concerns focus on protecting sensitive biometric data from breaches and unauthorized access, necessitating robust encryption and secure data handling [13]. Usability concerns emphasize seamless user interaction, with systems requiring minimal effort to learn and operate being more likely to be embraced [1]. The integration of conversational and task intelligence can enhance usability by providing interactive support and facilitating efficient transactions [1]. Cultural and contextual factors further complicate the interplay between security and usability, as acceptance may vary across demographic groups and cultural settings [3]. Understanding these nuances is vital for developing systems that meet user needs and preferences, thereby enhancing both security and usability.

5.3 Perceived Susceptibility and Health Concerns

Perceived susceptibility and health concerns play a crucial role in shaping technology adoption, particularly for biometric payment systems like facial recognition. These factors influence user perceptions by highlighting potential risks and benefits. The Health Belief Model (HBM) suggests that perceived susceptibility to health risks can motivate behavior change and technology adoption, as individuals are more likely to engage with technologies perceived as reducing health threats [13]. The COVID-19 pandemic has amplified health concerns, accelerating the shift toward contactless transactions and biometric payment systems. Users' perceived susceptibility to health risks, such as viral transmission, has increased demand for secure and hygienic payment methods [13]. Addressing health-related anxieties regarding prolonged exposure to facial recognition technology is essential for promoting acceptance. Adhering to health and safety standards can alleviate concerns and enhance user confidence. Comprehensive guidelines and best practices for safe biometric technology use are crucial for mitigating perceived health risks [13]. In addition to health concerns, perceived susceptibility includes risks of data breaches and privacy violations, which can deter users from adopting biometric systems. Robust security measures and transparent data handling practices are essential for fostering trust and encouraging adoption [13]. Future research should explore the intersection of health concerns and technology adoption, refining frameworks like the Mobile Device Abilities Test (MDAT) to assess user proficiency across devices and operating systems [5]. By addressing nuanced health-related concerns, stakeholders can create biometric payment systems that align with user health expectations while meeting security and usability standards, facilitating broader adoption.

6 Case Studies and Applications

Exploring technology adoption and consumer behavior through specific applications illustrates the efficacy of analytical frameworks like Partial Least Squares Structural Equation Modeling (PLS-SEM). This method offers a nuanced understanding of latent variables and underlying dynamics across diverse contexts. The following subsection examines PLS-SEM applications in technology adoption and consumer behavior, highlighting its theoretical and practical contributions.

6.1 Applications in Technology Adoption and Consumer Behavior

PLS-SEM is pivotal in studying technology adoption and consumer behavior, offering insights into complex interrelationships among latent variables. Its flexibility is advantageous in evolving theoretical models and scenarios with limited sample sizes [11]. A key application is evaluating user engagement with emerging technologies. For example, PLS-SEM's capability to handle datasets with varying clustering structures and error levels, as demonstrated in a simulation study comparing it with the finite mixture PLS (FIMIX-PLS) method, is crucial for understanding diverse consumer behaviors [15].

Additionally, integrating PLS-SEM with large language models (LLMs) enhances survey methodologies by improving data validity. LLMs replicate individual-level responses, increasing survey accuracy and reducing pre-testing needs [14]. This integration captures nuanced consumer behaviors, offering deeper insights into technology adoption drivers. PLS-SEM also assesses social dynamics and personal norms' influence on technology adoption, clarifying how these factors shape consumer behavior, particularly in biometric systems where privacy and perceived susceptibility impact user decisions [11].

PLS-SEM's versatility in technology adoption and consumer behavior studies underscores its role in unraveling user behavior complexities. By analyzing latent constructs, it enhances understanding of factors influencing technology adoption and sustained engagement. This method, prevalent in business and social science research, examines relationships among observed and latent variables, addressing measurement errors associated with abstract concepts. Recent Web 3.0 adoption studies exemplify PLS-SEM's ability to uncover insights, such as digital dexterity and electronic word-of-mouth's significant impacts on behavioral intentions, guiding technology integration [7, 10].

6.2 Dataset Insights

Benchmark	Size	Domain	Task Format	Metric
PSR-BE-BIF[3]	766	Marketing	Sequential Mediation Analysis	Accuracy, F1-score

Table 1: The table presents a summary of benchmarks utilized in the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) within the marketing domain. It highlights the dataset size, domain of application, task format, and evaluation metrics used to assess the effectiveness of sequential mediation analysis.

PLS-SEM's application in technology adoption and consumer behavior analysis is enriched by diverse datasets, providing a comprehensive view of user interactions and preferences. Large datasets, such as those assessing mobile device proficiency, enable examination of user behavior across various demographics and technological contexts [5]. In studies of portable intelligent personal assistants, data from large samples, like 824 users, offer insights into factors influencing technology adoption [1]. These datasets identify key predictors of behavioral intention, such as perceived usefulness and ease of use, crucial for shaping user acceptance and continued usage [1].

Machine learning techniques integrated with PLS-SEM analyze complex datasets, uncovering latent patterns and interactions not evident through traditional methods [16]. This approach is valuable in exploring social influences and personal norms on technology adoption, where diverse user perspectives yield deeper consumer behavior insights [9]. Datasets in PLS-SEM studies also evaluate security and usability concerns in biometric systems, analyzing user perceptions of privacy and security to identify adoption barriers and develop strategies to enhance trust [12].

Insights from datasets in PLS-SEM studies deepen understanding of technology adoption and consumer behavior, particularly in contexts like Web 3.0, where factors such as digital dexterity and electronic word-of-mouth significantly influence behavioral intentions, as shown in recent analyses of social media sentiment and survey data [7, 6, 10]. These datasets provide a robust foundation for validating theoretical models and exploring complex interrelationships among latent variables, contributing to the development of more effective and user-centered technologies. Table 1 provides a detailed overview of representative benchmarks employed in PLS-SEM studies, specifically focusing on marketing applications and the methodologies used for sequential mediation analysis.

7 Discussion

7.1 Implications for Researchers and Practitioners

The study's findings offer significant insights for researchers and practitioners focusing on the design, implementation, and marketing of facial recognition payment systems. For researchers, employing Partial Least Squares Structural Equation Modeling (PLS-SEM) alongside behavioral theories provides a robust framework to analyze the complex interplay of latent variables influencing technology adoption and usage intentions, especially in contexts with pronounced privacy concerns and perceived health risks [9]. This approach is particularly valuable during health crises, offering a comprehensive understanding of user behavior and guiding future research [17].

For practitioners, the study highlights the importance of aligning AI tool design and organizational strategies with existing workflows to enhance user acceptance and compatibility [13]. Insights from analyzing portable intelligent personal assistants (PIPAs) underscore the need to prioritize factors like perceived usefulness, ease of use, and digital dexterity to boost user acceptance and loyalty [1]. Furthermore, understanding the sequential mediation of parasocial relationships, brand engagement, and brand image favorability provides marketing practitioners with strategies to enhance consumer engagement and loyalty [3].

Advocating a user-centered approach in developing and marketing biometric payment systems, the study suggests leveraging insights from PLS-SEM and behavioral theories to address user concerns, improve system usability, and foster sustained consumer engagement. These implications are crucial for promoting widespread adoption of facial recognition payment systems, emphasizing considerations for effective technology integration into financial transactions while addressing challenges related to user acceptance, privacy, and operational efficiency [8, 6, 7].

7.2 Gaps in Current Research

The literature on Partial Least Squares Structural Equation Modeling (PLS-SEM) identifies several critical gaps requiring further investigation. A notable gap is the limited exploration of the broader implications of choosing PLS-SEM over other analytical methods, especially in real-world scenarios where data conditions may not align with ideal statistical assumptions. This necessitates comparative studies to evaluate the practical benefits and limitations of PLS-SEM across diverse contexts [8].

While integrating large language models (LLMs) with survey methodologies shows promise, the generalizability of LLM applications across various survey contexts remains uncertain. Further exploration of prompting strategies is needed to ensure accurate capture of consumer behavior nuances [14].

In the realm of authentication methods, particularly within Electronic Health Records, there is a lack of comprehensive research comparing the usability and security of different approaches. This gap highlights the need for studies assessing the effectiveness of various authentication technologies, including biometric systems, to enhance user trust and system security [12].

Moreover, the long-term effectiveness and adaptability of PLS-SEM applications remain underexplored as research methodologies evolve. Continuous evaluation of PLS-SEM's applicability and effectiveness in emerging research areas is essential to maintain its relevance and utility [7].

In specific fields like construction management, further investigation into PLS-SEM's application for theory validation is crucial. Understanding optimal PLS-SEM use in these contexts can provide valuable insights for enhancing theoretical frameworks and practical applications [11].

Lastly, although PLS-SEM is gaining traction in business research, deeper exploration of its applications across subfields is needed. Comparative analyses with other methodologies could provide a nuanced understanding of PLS-SEM's strengths and limitations, informing its use in diverse business contexts [4]. Addressing these gaps will enhance the understanding of PLS-SEM and its role in advancing research across various domains.

7.3 Future Research Directions

Future research in Partial Least Squares Structural Equation Modeling (PLS-SEM) and its application in technology adoption and consumer behavior should explore several promising avenues. One area is the integration of AI tools within organizational contexts, focusing on long-term adoption effects and optimization strategies to enhance user acceptance and system efficiency [13]. This involves examining AI integration with organizational workflows to identify best practices for seamless adoption.

Additionally, developing frameworks that synthesize insights from both Covariance-Based SEM (CB-SEM) and PLS-SEM is necessary. Such frameworks could enhance methodological rigor and applicability by leveraging the strengths of both approaches, providing a robust analytical foundation for complex model analysis [8]. This integration could offer a deeper understanding of factors driving technology adoption and usage intentions.

Exploring additional factors influencing behavioral intentions in emerging technologies, such as Web 3.0, is another promising research direction. Utilizing larger sample sizes and diverse sentiment analysis models can improve the generalizability of findings [10]. By expanding the scope of variables considered, researchers can gain insights into the multifaceted nature of consumer behavior.

The broader application of large language models (LLMs) in social science research presents significant opportunities. Investigating enhancements in model training to align with complex human behaviors could improve the accuracy and relevance of survey methodologies [14]. Such research could lead to more effective tools for capturing and analyzing nuanced consumer insights.

Furthermore, integrating variables like talent quality and analytics culture into PLS-SEM models could provide a comprehensive understanding of business outcomes and address methodological limitations [6]. This approach could inform strategies for enhancing organizational performance and technology adoption.

Finally, future work could focus on refining mutation rates and exploring transfer learning techniques to generalize evolved architectures across tasks [16]. Such advancements could enhance PLS-SEM's adaptability and applicability in diverse research contexts, contributing to a robust understanding of technology adoption and consumer behavior.

8 Conclusion

The exploration of Partial Least Squares Structural Equation Modeling (PLS-SEM) in the context of facial recognition payment systems underscores its effectiveness as a powerful analytical tool, particularly within the realm of business research. This study highlights the method's capability to unravel complex interrelationships among latent variables, thereby offering valuable insights into user acceptance and continuance intention. The increasing adoption of PLS-SEM, as evidenced by its correlation with scientific productivity in bibliometric analyses, reflects its growing significance in the analysis of intricate models.

In the domain of technology adoption, the findings suggest that external factors, such as health crises, can significantly accelerate the adoption of biometric payment technologies. This rapid integration necessitates a comprehensive understanding of user behavior, where PLS-SEM serves as an indispensable framework for examining the determinants of user acceptance and sustained usage. Furthermore, the study underscores the importance of evaluating PLS-SEM applications based on specific research contexts and objectives, rather than presuming the inherent superiority of any single methodological approach.

This research contributes to the broader discourse on consumer behavior and technology adoption, emphasizing the critical role of PLS-SEM in deciphering the complexities involved in user interactions with emerging technologies. As biometric payment systems advance, the insights garnered from this analysis provide a robust foundation for future investigations and practical implementations, guiding stakeholders in the design of user-centric technologies that align with modern consumer demands and expectations.

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