

Determinants of Face Recognition Acceptance for Digital Attendance Systems in Indonesia

Daduk Merdika Mansur^{1*}, Didin Kristinawati², Helin G Yudawisastra³

^{1*,2} Faculty of Economy and Business, Telkom University, Bandung, Indonesia

³ Faculty of Economy and Business, Universitas Muhammadiyah Bandung, Indonesia

ARTICLE INFO



Correspondence Email:

dadukmansur@telkomuniversity.ac.id

Keywords:

Consumer Behavior; Implementation Strategy; Operation Management; Face Recognition; Digital presence.

DOI:

<https://doi.org/10.33096/jmb.v13i2.1761>

ABSTRACT

Human resource management is increasingly complex with the widespread use of digital technologies. Facial recognition offers a potential solution for monitoring employee attendance and supporting performance management, yet limited research has examined user acceptance of this technology as an attendance system. This study evaluates user acceptance of facial recognition and identifies key factors influencing its adoption. Data were collected through an online survey conducted via Google Forms from January to June 2025. Of 304 responses received, 300 valid responses were analyzed using SmartPLS to assess the relationships among the proposed factors. The findings show that several factors significantly influence users' acceptance and intention to use facial recognition technology. These factors should be prioritized to improve implementation effectiveness, perceived usefulness, and continued use. The results provide practical recommendations for developing a Digital Presence implementation strategy that supports effective human resource management and enhances the quality of organizational human resource development programs.

ABSTRAK

Pengelolaan sumber daya manusia semakin kompleks seiring dengan meluasnya penggunaan teknologi digital. Pengenalan wajah menawarkan solusi potensial untuk memantau kehadiran karyawan dan mendukung manajemen kinerja, namun penelitian terbatas telah menguji penerimaan pengguna terhadap teknologi ini sebagai sistem kehadiran. Studi ini mengevaluasi penerimaan pengguna terhadap pengenalan wajah dan mengidentifikasi faktor-faktor utama yang mempengaruhi penerapannya. Data dikumpulkan melalui survei online yang dilakukan melalui Google Formulir pada bulan Januari hingga Juni 2025. Dari 304 tanggapan yang diterima, 300 tanggapan valid dianalisis menggunakan SmartPLS untuk menilai hubungan antar faktor yang diajukan. Temuan menunjukkan bahwa beberapa faktor secara signifikan mempengaruhi penerimaan dan niat pengguna untuk menggunakan teknologi pengenalan wajah. Faktor-faktor ini harus diprioritaskan untuk meningkatkan efektivitas penerapan, manfaat yang dirasakan, dan penggunaan berkelanjutan. Hasilnya memberikan rekomendasi praktis untuk mengembangkan strategi penerapan Kehadiran Digital yang mendukung pengelolaan sumber daya manusia yang efektif dan meningkatkan kualitas program pengembangan sumber daya manusia organisasi.



This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/).

1. INTRODUCTION

Workforce-related issues are becoming increasingly complex, necessitating a system to monitor employee habits and behavior; facial recognition technology is one solution that can be utilized for this purpose. Few organizations in Indonesia use facial recognition as a tool for human resource development. Even those that do exist are limited to attendance tracking. Further development of facial recognition capacity as a tool for segmenting attendance stability as an indicator of employee performance is needed. Existing research (Prayogi et al., 2024) revealed that there is still no solid model and strategy in implementing face recognition as a tool for identifying worker performance.

Emphasizes the still low quality of interaction and communication between humans and machines, where this is the main procedure in the application of face recognition (Jiang et al., 2024). Using Artificial Intelligence technology increases accuracy in the use of face recognition. With the help of face recognition, teachers' ability to identify work performance increases. Face recognition is used as a tool to examine work performance (Prayogi et al., 2024).

Several existing studies in Indonesia relate to the use of facial recognition as a tool for measuring employee performance at work. However, the existing literature fails to address the issue of managing facial recognition as an effective and user-accepted tool to improve organizational performance through human resource development programs. Therefore, this study will challenge the dominant perspective on facial recognition. This study highlights the lack of research discussing effective facial recognition management strategies that can help determine the right strategy for implementing facial recognition in attendance as part of employee character and habits. The strategy for implementing facial recognition must refer to the factors that influence its use.

2. LITERATURE REVIEW

Research on facial recognition continues to grow, as evidenced by data from Scopus's growth chart. This demonstrates the growing demand for facial recognition solutions. In this digital era, the need for speed, efficiency, and data accuracy is paramount as a key factor in winning the competition. Automated processes using machines are key to winning the competition because they are highly effective and low-cost (Zakaria, 2025).

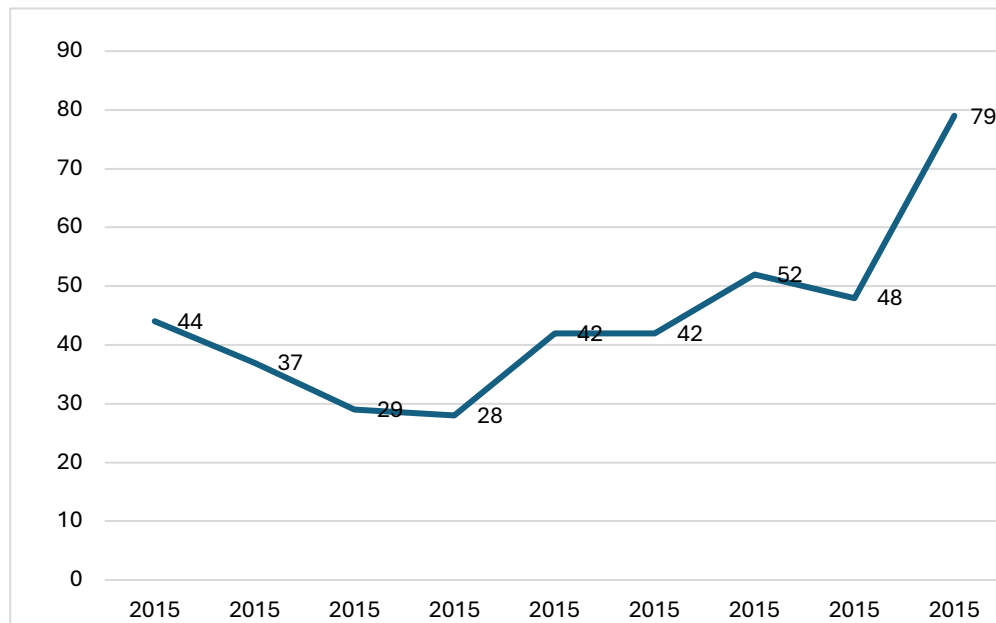
The development of research and theory related to facial recognition aligns with the industry 4.0 era, which is increasing the use of machines for various human operations. Empirical data explained that business resilience can be enhanced by utilizing digital technology to capture customer experience. Facial recognition is used as a tool to capture customer faces to gain insight into their shopping experience (Mutanda & Tapera, 2025).

Information System in supporting business processes, products, customer relationships and the daily work of employees in the target company is central. The era of powerful technology is a game changer in winning competitions. Facial recognition, for example, is a very helpful tool in identifying a person's face. This is used for various purposes, such as attendance records and observing a person's behavior (Zakaria, 2025).

The use of facial recognition is becoming increasingly widespread, especially in urban areas, for security and other social needs. The extremely high level of security vulnerability urgently requires the implementation of facial recognition. The need to maintain community culture and behavior also greatly require applications that utilize facial recognition. The industry 4.0 era is driving increased use of machine-to-machine interaction and, of course, is expanding into all fields, including human resource development. The need for speed, efficiency, and high accuracy is being addressed by utilizing digital technology (Shiau et al., 2024).

2.1. By Years

Research on the use of facial recognition for various purposes across various fields continues to grow. Scopus data shows a steady increase from around 40 articles to 79. This indicates that the scientific and practical application of facial recognition is growing along with the increasingly widespread use of facial recognition for various purposes.



2.2. By Country

Research related to facial recognition is increasingly being conducted as industry and society increasingly require digital services to improve their quality of life. The country with the most research on facial recognition is the United States, with nearly 85 studies. China is followed by more than 75 studies, followed by the United Kingdom with around 50. These developed countries are increasingly utilizing technology to support operational services to the public, providing optimal service and improving community well-being. Based on existing data, there is no evidence of intensive research in Southeast Asia, including Indonesia. Therefore, this research will boost the depth of facial recognition in the Southeast Asian region.

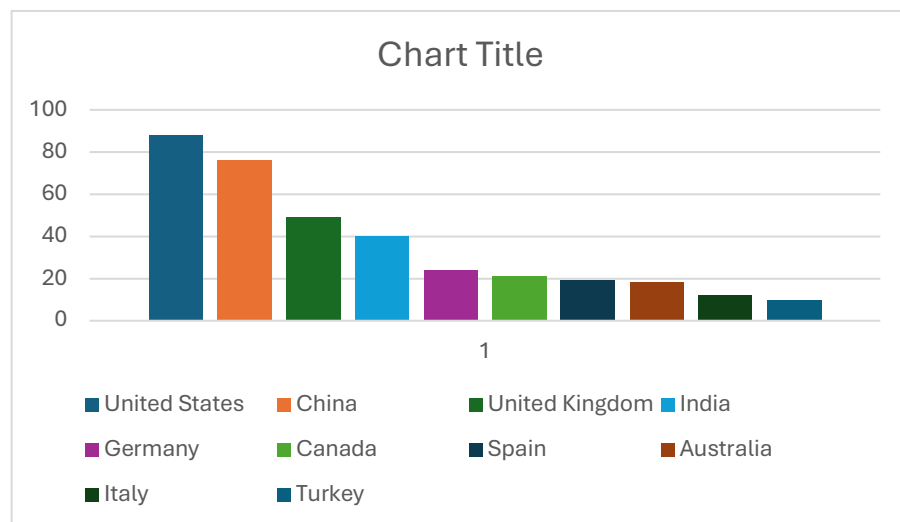


Figure 1. Country that research Face Recognition

Source : Vos Viewer, 2026

From the density aspect of Face Recognition research shows that the majority of research focuses on the human aspect. Meanwhile, the procedural aspect, which is crucial for

implementation, remains understudied. This implementation procedure is crucial for the success of this solution and has garnered significant user enthusiasm. Study (Mansur et al., 2019) A study focused on digital consumer behavior concluded that several factors significantly influence the acceptance of a service with factors include convenience, usefulness, and ease of use closely related to the procedures implemented in implementing a service for users.

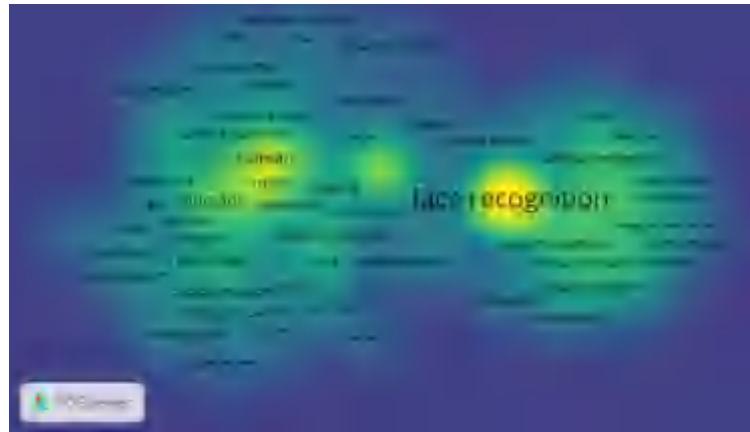


Figure 2. density of research Face Recognition

A snapshot of the development of facial recognition research over the years shows that the procedural aspect remains an understudied and understudied area. Even in developed countries, this procedural aspect has not been extensively researched or discussed. At the implementation level, procedures that align with user expectations and desires are essential for the application system to remain in demand and usable.

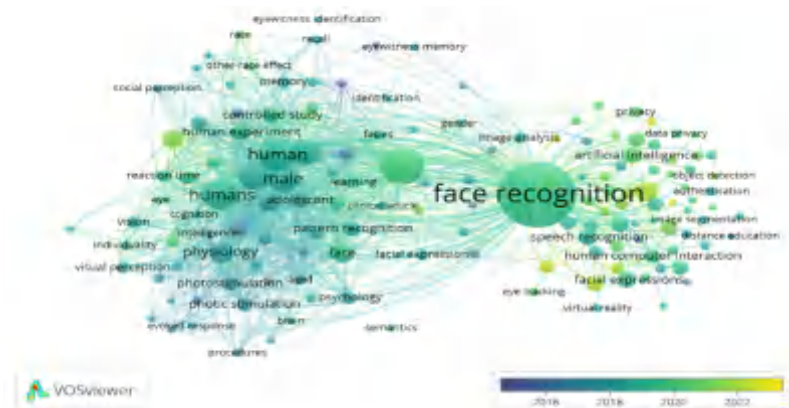
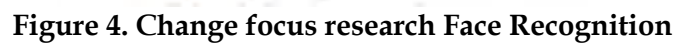


Figure 3. Focus research Face Recognition

The concept map from research every year also experiences gradual changes. It seems to start from the psychological aspect then human monitoring and then move towards human expression and facial expression. Increasingly, research is to explore the implementation of the use of facial recognition.



The analysis of the development of facial recognition research worldwide shows gradual progress. The data indicates that there is still little information regarding facial recognition management procedures, so it is necessary to identify the factors that determine its acceptance and use. These factors, which determine its successful use and acceptance, will form the basis for developing an implementation strategy.

Several studies indicates that there has been extensive research into the implementation of facial recognition for various purposes, such as medical (biometric, acupressure), personal security surveillance, and work process monitoring. However, a more in-depth study of the implementation strategy approach that will simultaneously achieve accuracy and user comfort is still needed. This is especially true given that Indonesian society, with its communal social characteristics, prioritizes comfort. Therefore, the conceptual approach to the implementation strategy model must be comprehensive and valid, in accordance with empirical needs (Syahputra & Daryanto, 2025).

The use of technology and services by users is highly dependent on the level of acceptance of factors such as comfort, benefits, convenience, and potential risks. Research (Mansur et al., 2019) The study found that the biggest factor influencing product acceptance and use was convenience. This aligns with the profile of Indonesian users, who are characterized by a reluctance to face difficulties. Other influencing factors include benefits, convenience, facility conditions, habits, trust, and risk.

Study (Liu et al., 2025) showed that factors such as perceived enjoyment, supportive conditions, personal innovation, coupon availability, perceived ease of use (PEOU), perceived usefulness (PU), and user attitude are the main driving factors of customers' decisions to use facial recognition payments.

In line with research (Yu & Wang, 2024) which found that factors influencing face recognition usage were performance expectancy, effort expectancy, perceived usefulness, and perceived ease of use. The usefulness factor is highly justified for users, as it makes the attendance checking process easier and faster.

In line with the studies, this study explores and explores factors influencing the acceptance and use of face recognition. The suspected influencing factors are usefulness, ease of use,

availability of facilities, habits, comfort, risk, and level of trust. These hypotheses need to be further explored to determine which factors have a significant influence and will serve as a reference in managing face recognition services.

The last research Study by (Mansur et al., 2019) A study focused on Acceptance and Use Technology E-Commerce (AUTE) that study related with digital consumer behavior concluded that several factors significantly influence the acceptance of a service. These factors include Performance Expectance (PP), Effort Expectance (EE), Facilitating Condition (FC), Perceive Convenience (PC), Perceive Risk (PR), Social Influence (SI), Trust (T) and Habit (H). This is closely related to the procedures implemented in implementing a service for users.

Referring to existing research with various novelties, including changes in user attitudes and behaviour in Indonesia, the research model used is:

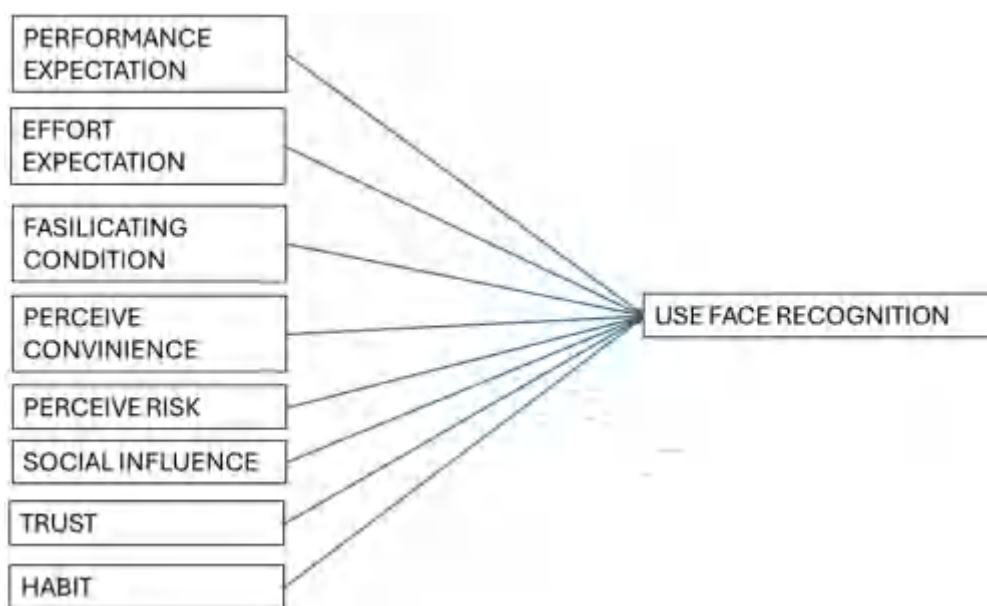


Figure 5. research model proposed

Source: (Mansur et al., 2019)

Referring to the discussion in the theoretical review in this study, the research hypothesis is as follows:

- H1: Performance Expectation influences the use of Face Recognition
- H2: Effort Expectation influences the use of Face Recognition
- H3: Social Influence influences the use of Face Recognition.
- H4: Facilitating Conditions influence the use of Face Recognition.
- H5: Habit influences the use of Face Recognition
- H6: Perceive Convinience influences the use of Face Recognition.
- H7: Perceive Risk affects the use of Face Recognition.
- H8: Trust influences the use of Face Recognition.

3. RESEARCH METHOD

3.1. Research type

This research applies to the Mix Method Research method. Mixed methods research is a research approach that combines both qualitative and quantitative data collection and analysis methods within a single study. It aims to gain a more comprehensive understanding of a research

problem by leveraging the strengths of both approaches and offsetting their potential limitations (Gamage, 2025). Quantitative data processing was used to describe the factors influencing facial recognition usage in Indonesia. To further understand the impact of these factors, qualitative analysis was conducted on the open-ended responses provided by respondents. The research data sources came from several sources, including online surveys, literature reviews, user interviews, and focus group discussions with experts.

3.2. Data Gathering

The research data source comes from an online survey conducted from January 2025 to June 2025 via Google Form. A total of 304 respondents completed the survey, with 4 invalid data points, Four records had missing data regarding education level and were therefore removed from the dataset, leaving 300 valid data points. Respondent characteristics show:

Gender breakdown of 186 men and 114 women.



Figure 6. Respondent Profile by Gender, Education, Age and Titles

Source : Data Proceed, 2026

Regarding education, the figures are: High School/Diploma (D3) – 50; Bachelor's (S1) – 207; Master's (S2) – 38; and Doctoral (S3) – 7, Ages 15–20: 84 (28%); 20–25: 106 (35%); 25–30: 13 (4%); 30–40: 15 (5%); >40: 82 (27%). Academics: 10 (3%); Civil Servants: 49 (16%); Activists: 4 (1%); Students: 158 (53%); Businesspeople: 27 (9%); Others: 52 (17%).

3.3. Data Analysis Techniques

This study conducted an in-depth analysis to identify the key factors influencing the use of Face Recognition in detail. The data collected was analyzed using Mix methods which is Quantitative data was processed using the Smart PLS statistical processing application to determine the weighted scores for the factors studied. The Second Process is Qualitative process use meta-analysis method processed.

4. RESULT and DISCUSSION

4.1. Result

After processing 300 data sets using Smarts PLS, the results of calculations using the statistical application showed the following data:

At the beginning of the modeling process, the validation test results for the indicators showed that the cross-loading value of the social influence variable was <0.6 (Hair, 2019). After adjustments were made, the model was found to have a cross-loading value of 0.6 for each indicator. Of course, like other researchers, we did not document the process, but the results are attached.

4.1.1. Validity and Reliability.

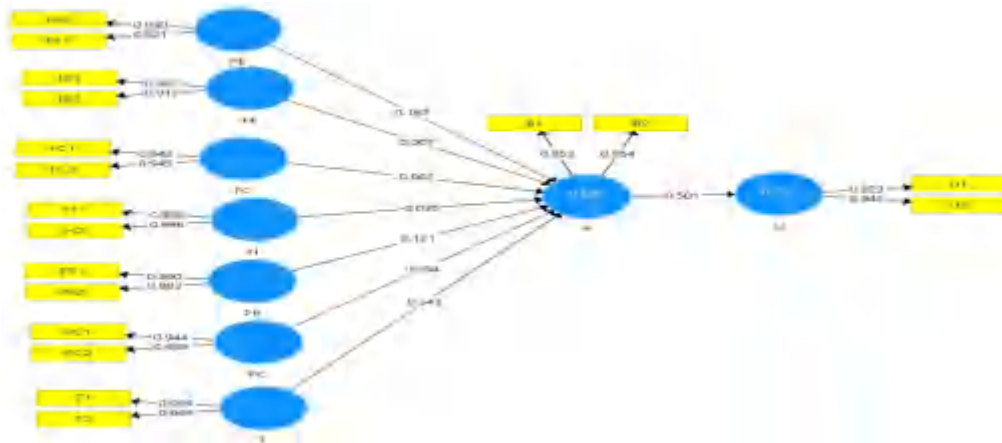


Figure 10. Research Model of Face Recognition Acceptance in Indonesia

From the analyze result of this research found that the factor that influences the use of Face Recognition the most is the comfort aspect, the highest at 0.354 followed by the Trust factor at 0.341 and third is the Usefulness Factor at 0.167.

Table 1. Validity and Reliability of Face Recognition Acceptance Research in Indonesia.

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
X1	0,832	0,834	0,922	0,856
X2	0,833	0,848	0,923	0,856
X4	0,878	0,878	0,943	0,891
X5	0,888	0,889	0,947	0,899
X6	0,727	0,727	0,880	0,786
X7	0,873	0,874	0,940	0,887
X8	0,902	0,908	0,953	0,910
Y	0,899	0,899	0,952	0,908
Z	0,744	0,904	0,879	0,785

Table 1. Cross Loading

	X1	X2	X4	X5	X6	X7	X8	Y	Z
X11	0,921								
X12	0,930								
X21		0,937							
X22		0,913							
X41			0,943						
X42			0,945						
X51				0,950					
X52				0,946					
X61					0,890				
X62					0,883				

X72					0,944				
X73					0,939				
X81							0,959		
X82							0,949		
Y1								0,952	
Y2								0,954	
Z1									0,823
Z2									0,945

In demonstrating reliability, not all measurement models and structural models need to be included as standards in SEM-PLS. In the evaluation model of the line item measurement, the standards of Cronbach's Alpha, Composite Reliability, and Rho_A have been met as the main standards of SEM-PLS (Hair, 2019). However, we will present the requested reference values. (in the table below).

Table 3. Heterotrait-Monotrait Ratio (HTMT)

	X1_	X2	X4	X5	X6	X7	X8	Y	Z
X1_									
X2	0,835								
X4	0,451	0,522							
X5	0,291	0,380	0,440						
X6	0,441	0,429	0,486	0,477					
X7	0,771	0,762	0,582	0,433	0,623				
X8	0,417	0,384	0,356	0,434	0,917	0,591			
Y	0,645	0,568	0,437	0,359	0,735	0,782	0,738		
Z	0,459	0,416	0,448	0,855	0,593	0,557	0,601	0,577	

Table 4. Fornell-Larcker Criterion

	X1_	X2	X4	X5	X6	X7	X8	Y	Z
X1_	0,925								
X2	0,696	0,925							
X4	0,386	0,445	0,944						
X5	0,249	0,331	0,389	0,948					
X6	0,342	0,334	0,390	0,383	0,886				
X7	0,658	0,650	0,510	0,381	0,497	0,942			
X8	0,361	0,334	0,320	0,387	0,741	0,526	0,954		
Y	0,559	0,495	0,388	0,321	0,595	0,693	0,665	0,953	
Z	0,383	0,343	0,362	0,650	0,435	0,467	0,505	0,501	0,886

Table 5. Inner VIF Values

	X1_	X2	X4	X5	X6	X7	X8	Y	Z
X1_								2,274	
X2								2,310	
X4								1,510	
X5								1,339	
X6								2,389	
X7								2,589	
X8								2,447	
Y									1,000
Z									

Table 6. R Square

	R Square	R Square Adjusted
Y	0,629	0,619
Z	0,251	0,248

Table 7. f Square

	X1_	X2	X4	X5	X6	X7	X8	Y	Z
X1_									0,033
X2									0,000
X4									0,000
X5									0,002
X6									0,017
X7									0,130
X8									0,128
Y									
Z									0,335

Table 8. Total Indirect Effects

	X1_	X2	X4	X5	X6	X7	X8	Y	Z
X1_									0,084
X2									0,003
X4									-0,001
X5									-0,017
X6									0,061
X7									0,177
X8									0,171
Y									
Z									

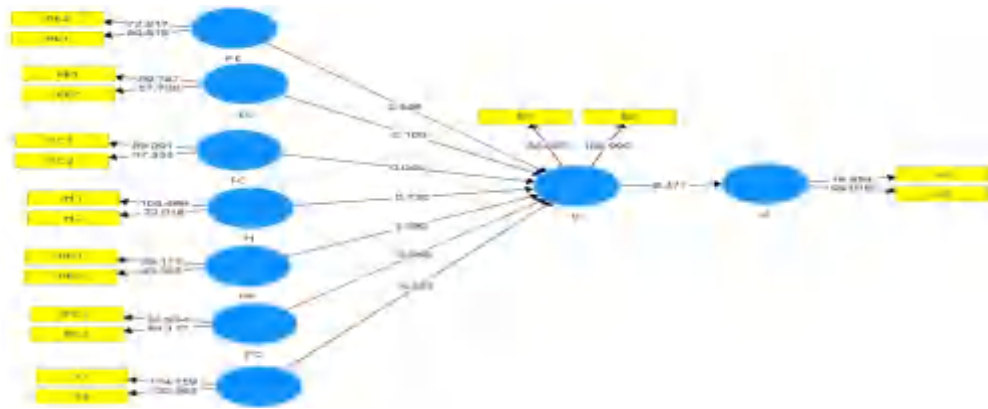
Table 9. Specific Indirect Effects

	Specific Indirect Effects
X1_ -> Y -> Z	0,084
X2 -> Y -> Z	0,003
X4 -> Y -> Z	-0,001
X5 -> Y -> Z	-0,017
X6 -> Y -> Z	0,061
X7 -> Y -> Z	0,177
X8 -> Y -> Z	0,171

Table 10. Total Effects

	X1_	X2	X4	X5	X6	X7	X8	Y	Z
X1_									0,167
X2									0,007
X4									-0,002
X5									-0,035
X6									0,121
X7									0,354
X8									0,341
Y									
Z									0,501

4.1.2. Structural model



Partial significance tests show that the influence of effort expectancy, perceived confidence, habit, and perceived risk on behavioral intention: not supported

Table 11. Partial significance test

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
PE -> BI	0,167	0,165	0,068	2,448	0,015
EE -> BI	0,007	0,008	0,063	0,103	0,918
FC -> BI	-0,002	0,003	0,052	0,046	0,964
H -> BI	-0,035	-0,030	0,048	0,718	0,473
PR -> BI	0,121	0,123	0,074	1,637	0,102
PC -> BI	0,354	0,356	0,085	4,155	0,000
T -> BI	0,341	0,334	0,080	4,277	0,000
BI -> U	0,501	0,502	0,053	9,380	0,000

4.1.3. Explanation of the final results of statistical calculations

$X1 \rightarrow Y \rightarrow Z$

Performance expectancy (PE) influences use behavior through behavioral intention to use face recognition

X1: Performance Expectancy (Expectation that facial scanning can help increase productivity and effectiveness)

X11: Effectiveness of using Face Recognition/Face Scanning

X12: Ease of Face Recognition/Face Scanning

X13: Benefits of using Face Recognition/Face Scanning

The performance expectancy of facial scanning is one of the variables in the technology acceptance model that significantly influences the use behavior of facial scanning through behavioral intention to use facial scanning in the context of using Face Recognition technology. The main indicators of this performance expectancy include the effectiveness, ease of use, and benefits of using the technology. Based on research (Степанов, 2023). One way to increase the effectiveness of facial recognition is by speeding up the identification process or reducing manual errors. When users believe that facial recognition can increase productivity and efficiency, their intention to adopt this technology will be strengthened. This belief then drives actual usage behavior because the technology is perceived as a solution that can meet user needs more effectively than conventional methods. The effectiveness of facial recognition is a key

indicator because this technology is assessed based on its ability to provide accurate and reliable results (Hausinger et al., 2025). When applied to digital security or employee attendance, users will be more likely to adopt if they are confident the system can recognize faces with high precision. Ease of use also plays a key role. If the facial scanning process is perceived as fast, intuitive, and without complex technical steps, positive perceptions of the technology will increase. This aligns with the Technology Acceptance Model (TAM) theory (Kenesei et al., 2025), which states that perceived usefulness and ease of use are the main drivers of technology adoption. The benefits of using Face Recognition also strengthen the influence of Performance Expectancy on behavioral intention to use. This is in line with research from (Zakaria, 2025) that States that if this technology can save time, improve security, or provide a more personalized user experience, the benefits will be increasingly felt. In the long term, this belief in benefits will crystallize into behavioral intentions that ultimately manifest in use behavior. Thus, the higher user expectations of Face Recognition's performance in terms of effectiveness, ease of use, and benefits, the greater the likelihood that this technology will be adopted.

$X2 \rightarrow Y \rightarrow Z$

Effort expectancy does not influence use behavior through behavioral intention to use face recognition.

X2: Effort Expectancy (Expected ease of use of Face Recognition/Face Scanning)

X21: Expected ease of use of Face Recognition/Face Scanning

X22: Expected practicality of use of Face Recognition/Face Scanning

X23: Expected ease of use of Face Recognition/Face Scanning

Effort expectancy, measured by the expectation of ease and practicality of using Face Recognition/Face Scanning, does not significantly influence use behavior through behavioral intention to use. According to research (Boadu et al., 2025) in the context of familiar technology or an intuitive interface, users are less likely to consider effort a major barrier, thus minimizing its impact on usage intentions and behavior. Study (Matheis et al., 2026) found that when technology is perceived as a need or obligation, effort expectancy is no longer a strong predictor of behavioral intention to use. Additional support from research Gillioz et al., 2025) shows that in the context of biometric technologies like facial recognition, trust and perceived risk often outweigh ease of use. This means that even if the technology is perceived as easy and practical, users may still be reluctant to adopt it if they are concerned about privacy or data security. Effort expectancy can be less relevant in predicting use behavior when other factors, such as trust and perceived risk, are more dominant in shaping user intentions and behavior. All indicators are invalid.

X3: Social Influence (Individual perceptions are influenced by others' perceptions, leading to the decision to use facial recognition)

X31: Organizational support

X32: Improving self-image

X33: Lifestyle influence

Social influence indicators such as organizational support and self-image are invalid because the measurement of these constructs does not accurately reflect the social pressure or subjective norms actually felt by users. In the context of Face Recognition use, organizational support may not be influential if employees feel that the technology is imposed without

considering their interests, thus not influencing usage intentions or behavior (Lee et al., 2025). Additionally, image can become irrelevant if users do not perceive the technology as a status symbol or if it is not related to their social identity (Quan et al., 2025). This shows that the indicator is not strong enough. to build the social influence dimension. Invalid social influence indicators can also occur due to response bias or cultural context inconsistencies. According to research (Arcuri et al., 2025) In more individualistic societies, social influences (such as others' opinions or self-image) may have less impact than in collectivist cultures. If research instruments are not tailored to respondents' characteristics, indicators such as organizational support or image may fail to predict usage intentions. Furthermore, if respondents do not understand the questions correctly or provide careless answers (social desirability bias), the validity of these indicators may also be questionable (Qiu et al., 2025).

$X4 \rightarrow Y \rightarrow Z$

Facilitating conditions (FC) do not influence use behavior through behavioral intention to use facial recognition.

X4: Facilitating Condition (Individual's belief that the organization and infrastructure exist and support use)

X41: Information readiness level

X42: Knowledge readiness level

X43: Adequacy of facilities

Facilitating conditions, measured by the level of readiness to receive information and the level of knowledge readiness, may not influence use behavior through behavioral intention to use Face Recognition because user intention is more influenced by perceived benefits (performance expectancy) than by the availability of resources or knowledge. According to research (Liu et al., 2025) In the context of widely adopted technologies such as face recognition, users are less likely to require additional support because they already feel capable of using them without external assistance. If the technology is mandatory (e.g., a corporate security system), behavioral intention is more determined by compliance than by the available facilities (Kiran, 2025).

Furthermore, research from (Kelkay et al., 2025) shows that facilitating conditions often directly influence use behavior without influencing behavioral intention, especially when technology has become part of daily routines. Even if someone has adequate knowledge and information readiness, this does not always increase usage intention if the technology is perceived as not providing added value. A study by (Susanty et al., 2025) found that in the context of biometrics, factors such as trust and perceived risk were more dominant in influencing intention than facilities. supporters, so that facilitating conditions become less significant in the technology acceptance model.

$X5 \rightarrow Y \rightarrow Z$

Habit (H) does not influence use behavior through behavioral intention to use face recognition.

X5: habit

X51: habitual use of face recognition.

X52: routine frequency.

X53: influential habit.

Habits measured through indicators of habitual use of facial scanners and regular frequency of use may not influence use behavior through behavioral intention in the context of Face Recognition because habits often influence behavior automatically without involving conscious cognitive processes. According to research (Deng et al., 2026) when a behavior has become a habit, users tend to adopt technology spontaneously without needing to be driven by deliberate intentions. Study by (Dixit et al., 2025) support this finding by showing that in biometric technologies such as Face Recognition, habit has a direct influence on use behavior, thus weakening the mediating role of behavioral intention.

Research from (Moradi, 2025) found that when technology has become integrated into everyday life (such as facial recognition for smartphone unlocking), habits become a stronger predictor of actual behavior than intentions. This occurs because users no longer consider benefits or effort, but instead act based on repetitive experiences. Similar findings were expressed by (Kandasamy et al., 2025) which states that habit can bypass intention in technology acceptance models, especially for features that are routine and do not require deep thought. Thus, habit is more likely to have a direct impact on use behavior without going through behavioral intention to use.

$X6 \rightarrow Y \rightarrow Z$

Perceived risk (PR) does not influence use behavior (UB) through behavioral intention (BI) to use facial recognition.

X6: Perceived Risk (Perception of data theft)

X61: Protection using facial recognition

X62: Data security level

X63: Risk of data theft

Perceived risk, measured through protection indicators using facial scanning and data security level, may not influence use behavior through behavioral intention to use facial recognition because users often adopt this technology out of practical need despite being aware of the risks. According to research from (Zl & Kalari, 2025), In the context of technology that is already integrated with the system, users tend to accept privacy risks as an inevitable trade-off for instant benefits. Study by (Bao & Du, 2023) shows that when perceived benefits are very high (e.g., authentication speed), perceived risk does not significantly reduce usage intentions because users perceive the benefits to outweigh the potential losses.

The study (Zhang, 2024) revealed that risk perception often directly influences use behavior (e.g., avoiding certain features) without going through behavioral intention, especially when users have other alternatives (such as PINs or fingerprints). This finding is supported by (Li & Li, 2023) which emphasizes that in mandatory contexts (e.g., facial recognition for banking transactions), users may continue to use the technology despite perceived high risks due to external pressure. Thus, perceived risk may have a greater impact on actual behavior or usage moderation, rather than on the formation of intentions.

However, in the context of using facial recognition for attendance checks, where all personnel present are required to undergo facial scans, the perceived risk no longer arises because all attendees are required to undergo facial scans. This is the case when entering a train station, an office, or other institutions that require facial scans. This encourages users to perceive no risk to worry about because the system is mandatory. As research suggests, (Prabhavathi et al., 2021) which States that the use of facial recognition for attendance checking is very effective

and does not raise the perception of anything risky. To date, there have been no incidents of misuse of facial recognition data, so there are still no concerns about the risks to personnel whose faces are scanned.

$X7 \rightarrow Y \rightarrow Z$

Perceived convenience influences use behavior through behavioral intention to use facial recognition.

X7: Perceived Convenience (Perceived comfort and ease of use)

X71: Level of comfort using facial recognition.

X72: Level of ease of use of facial recognition.

X73: Expected convenience.

Perceived Convenience (Perceived comfort and ease of use) is one of the factors that influences behavioral intention to use and has an impact on on use behavior in the context of facial recognition technology. When users perceive facial recognition as easy to use, convenient, and consistent with their expectations, they tend to have a stronger intention to adopt the technology. Indicators such as the level of comfort when using facial recognition, the ease of the authentication process, and the expected convenience of the user experience are crucial in shaping overall perceptions. The higher the perceived convenience, the more likely users are to actively integrate the technology into their routines.

The relationship between perceived convenience and behavioral intention to use can be explained using the Technology Acceptance Model (TAM) theory (Damanik et al., 2025). Ease of use and perceived usefulness are predictors of technology adoption. If users perceive facial authentication as faster and more convenient than traditional methods like PINs or passwords, their intention to use it will increase (Setiya Putra, 2023). Furthermore, expected convenience, such as system response speed and minimal recognition errors, strengthens user trust in facial recognition technology. Perceived convenience not only influences user intention but also drives long-term usage behavior.

The impact of perceived convenience on usage behavior becomes more pronounced when facial recognition technology is implemented on a large scale, such as in digital banking, airports, train stations, or smartphones. Users who were initially hesitant and fearful become more receptive after experiencing the ease and efficiency offered. However, if the system is perceived as complicated or inconvenient due to frequent facial recognition failures, intention to use can decrease and lead to technology rejection. This aligns with research (Yu et al., 2025) where developers must ensure that the user experience remains optimal, so that perceived convenience can be a key driver of facial recognition adoption in everyday life. Convenience is indeed a strong concern for Indonesian users due to their sensitive characteristics and profiles. As research shows, (Li & Li, 2023) which emphasizes the comfort and trust of users so that they are truly willing to accept and use the facial scanning application.

$X8 \rightarrow Y \rightarrow Z$

Trust influences user behavior through behavioral intention to use facial recognition

X8: Trust (Confidence in a person's expertise, ability, and integrity)

X81: Data security

X82: Safeguarding personal data

X83: Trust in the system

Trust plays a crucial role in influencing users' intention to adopt facial recognition technology. One key indicator of trust is data security, where users need to be confident that biometric information is stored and processed with strict and secure protection. If users perceive the system to be vulnerable to data leaks or misuse, they are likely to be reluctant to use this technology, even if it offers convenience (Li & Li, 2023). Developers must ensure strong encryption, transparent security protocols, and security certifications to boost user trust. In addition to data security, the system's ability to maintain the confidentiality of personal data is a key factor in establishing trust.

Research conducted (Jangid et al., 2025) concluded that users want to ensure that their data is not misused for unauthorized tracking or unethical commercial or non-commercial purposes. If users believe that companies respect their privacy and only use their data for agreed-upon purposes, their behavioral intention to use this technology will increase. Conversely, privacy scandals or a lack of transparency in data policies can undermine trust and hinder technology adoption (Beltr et al., 2023).

Trust in the system, including the accuracy and reliability of facial recognition, also influences user intention. If the system frequently experiences misidentification or malfunctions, user trust will decrease (Yu et al., 2025). Conversely, if the technology proves consistent, fast, and error-free, users will be more comfortable using it. Therefore, trust built through data security, privacy protection, and system reliability is the main foundation for increasing consumer behavioral intention to use facial recognition (Zhang, 2024).

$Y \rightarrow Z$

Behavioral Intention (BI) Influences Use (U) of Face Recognition

Y: Behavioral Intention (BI) (The level of an individual's intention to accept and use face recognition)

Y1: Willingness to use facial recognition

Y2: Enthusiasm for using facial recognition

Y3: Triggers for using facial recognition

Z: Use Behavior (Level of necessity and frequency of using the system)

Z1: Frequency of activity

Z2: Desire to repeat activity

Z3: Reasons for using facial recognition

Behavioral intention, measured through indicators of willingness to use facial recognition, enthusiasm, and triggers for use, significantly influences use behavior in the context of facial scanning, as strong intentions tend to translate into concrete actions. According to research (Yu et al., 2024) When users have intrinsic motivation (such as convenience or security) to adopt Face Recognition, they will use it more frequently in daily activities, such as unlocking their smartphone or verifying transactions. A study by (Habibu et al., 2025), showed that user enthusiasm for biometric technology is positively correlated with frequency of use, as positive experiences increase the desire to repeat the activity. In addition, the study (Lyu et al., 2025) The stronger the user's intention, the higher the frequency and consistency of their use of face recognition.

4.1.3. Final Model of Acceptance and Use of Face Recognition in Indonesia

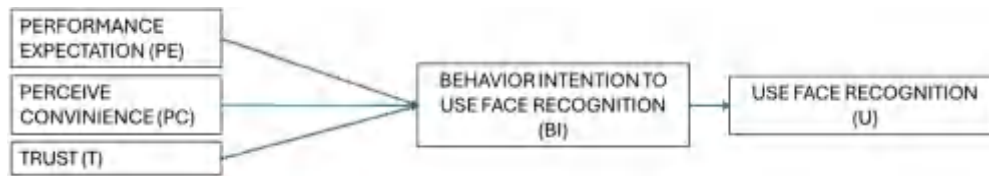


Figure 11. Face recognition acceptance model in Indonesia

Source: Research Results on Face Recognition Use in Indonesia, 2026

4.1.4. Discussion

The industry 4.0 era is spreading across the globe, and digitalization is permeating all sectors of life. Convenience, speed, reliability, and convenience are increasingly strengthening the use of digital technology, including in Indonesia. Despite the fact that Indonesian society is characterized by distinct Communal societies are somewhat technologically challenged. They typically avoid hardship and are somewhat resistant to change, including the adoption of digital applications.

Regarding the use of facial recognition in Indonesia, this study reveals several important findings:

- a) The comfort factor is the factor with the greatest influence, at 35.4%, This is in line with existing research (Mansur et al., 2022) and (Mansur et al., 2019) which found that convenience is the most influential factor in the acceptance and use of digital technology in Indonesia. This is also in line with research (Of et al., 2025) which confirms that the comfort aspect has a major influence on applications related to economics and health. This is also in line with research (Almaqtari et al., 2025). All of which confirms that convenience is a dominant factor influencing the acceptance and use of digital applications. The fundamental desire for comfort and aversion to hassle shapes the attitudes of most Indonesians. A qualitative analysis using the meta-analysis method yielded the following data: Safe 37 (12.3%), Fast 133 (44%), Flexible 30 (10%), Easy 74 (24.7%), and Blank/Unspecified 28 (9%). Thus, regarding user perceptions of face recognition, the dominant aspect of convenience is the speed of facial scanning during the attendance identification process.
- b) Trust is the second factor, influencing 34.1%, The high risk of data misuse in digital applications creates distrust when using digital applications. While the app operator benefits, it can harm the user, or at the very least, result in no benefit. Suspicion and caution hinder trust, especially if there is no prior education on how to use a new app. As research (Paliwal et al., 2025) shows which states that trust determines the acceptance and use of digital applications, especially new ones. Limited understanding and unfamiliarity with new applications can be an initial barrier to trust. This is further reinforced by research (Choong et al., 2025) which concludes that the trust factor is an important factor to build when implementing digital applications. Further analysis regarding the qualitative aspects of trust, conducted via a meta-analysis mapping method, yielded the following results: Sophisticated 44 (14.7%), Confidential 8 (2.7%), Secure 181 (60.3%), Transparent 35 (11.7%), and Blank/Unspecified 32 (10.7%). These findings indicate that the level of trust is primarily driven by the security of the facial recognition system, particularly regarding personal data security.

- c) The third factor is the usefulness of face recognition for attendance identification systems, at 16.7%. After the previous two factors determine the acceptance and use of face recognition, the usefulness aspect becomes a key consideration for users. The advantages of speed, accuracy, and ease are significant benefits perceived by face recognition users. This usefulness will strengthen the level of use, as well as the trust and comfort that users desire. Several studies have corroborated these findings, such as the study (Varma et al., 2025) which concludes that any application or product must be able to provide benefits to its users in order to continue using it. In line with research (Chen et al., 2025) that to implement an application, intensive education must be carried out regarding the benefits provided. Qualitative analysis of the utility aspect—conducted using a meta-analysis method—yielded the following results: Accurate 100 (33%), Fast 87 (29%), Simple 71 (23.6%), and Blank 42 (14%). Thus, it is evident that the most dominant benefit of face recognition lies in the accuracy of the facial scanning process during attendance identification. High accuracy ensures a fast, error-free process, allowing users to enjoy a seamless and convenient experience thanks to the system's precision. Regarding other aspects such as data security and privacy—and taking into account available resources, this study specifically focuses on examining user acceptance, which will serve as a foundation for facial scanning system operators to formulate implementation strategies. In this study, data security and privacy are incorporated as indicators within the variables of Trust and Perceived Ease of Use.

This research has new findings for acceptance of the use of Face Recognition. From the quantitative analysis results of this research found that the factor that influences the use of Face Recognition the most is the comfort aspect, the highest at 0.354 followed by the Trust factor at 0.341 and third is the Usefulness Factor at 0.167. And with further processing through qualitative methods using meta-analysis, it is known that regarding user perceptions of face recognition, the dominant aspect of convenience is the speed of facial scanning during the attendance identification process. trust is primarily driven by the security of the facial recognition system, particularly regarding personal data security. The dominant benefit of facial recognition lies in the accuracy of the facial scanning process during attendance identification

5. Conclusions, Research Implications, and Limitations

This study investigated the implementation strategy for using face recognition through its influencing factors. The findings indicate that convenience has the greatest influence on the implementation of face recognition as part of an attendance identification system. Other factors that also have an impact are the level of trust and perceived usefulness of using face recognition in attendance systems. These results contribute to a deeper understanding of the acceptance and use of face recognition applications in attendance systems, particularly by identifying the dominant influencing factors. This study demonstrates that implementing a face recognition system must consider aspects that significantly influence user acceptance and use.

This research is only at the stage of identifying factors that influence the acceptance and use of face recognition and should be continued with research into strategies for implementing face recognition as a tool for assessing and developing employee performance. Further development of face recognition capacity to evaluate employee attitudes and emotions would be highly beneficial in human resource management.

Conflict of Interest

There are no conflicts of interest related to the publication of this article. This research was conducted independently, and no external funding was received that could have influenced the results or interpretations presented in this study. All authors confirm that the results presented in this study are independent of the research. presented in this paper are free from any commercial or financial relationships that could be construed as a potential conflict of interest.

References:

- Almaqtari, F. A., Yahya, A. T., Al-Maskari, N., Farhan, N. H. S., & Al-Aamri, A.-M. Y. Y. (2025). Assessing the Integrated Role of IT Governance, Fintech, and Blockchain in Enhancing Sustainability Performance and Mitigating Organizational Risk. *Risks*, 13(6), 105. <https://doi.org/10.3390/risks13060105>
- Arcuri, E., Ardizzi, M., & Gallese, V. (2025). *Reading out bodily cues to predict interactions*. 1–18.
- Bao, Y., & Du, Z. (2023). *Face Recognition Technology Risks and Regulatory Issues*. 652–656. https://doi.org/10.2991/978-94-6463-040-4_99
- Beltr, G., Sousa, S., & Lamas, D. (2023). *Trust in Facial Recognition Systems : A Perspective from the Users*. 379–388.
- Boadu, R. O., Adu, V. W., Boadu, K. A. O., Ibrahim, B., Akey, P., Mensah, A. A., Adzakupah, G., & Mensah, N. K. (2025). Examine frameworks policies and strategies for effective information governance in healthcare organizations. *Plos One*, 20(7 July), 1–22. <https://doi.org/10.1371/journal.pone.0327496>
- Choong, Y. O., Ng, L. P., & Lau, T. C. (2025). Beyond fairness: exploring organizational citizenship behavior through the lens of self-efficacy and trust in principals. *Humanities and Social Sciences Communications*, 2025, 1–14. <https://doi.org/10.1057/s41599-025-04611-7>
- Damanik, F. S., Widayanti, A. W., Wiedyaningsih, C., Pharmacy, F., Muslim, U., Umn, N., & Washliyah, A. (2025). *Exploring Technology Acceptance Models : A Systematic Review of Health Application Adoption in Asian Countries*. 15(2), 110–120. <https://doi.org/10.22146/jmpf.96755>
- Deng, K., Zhang, C., Song, M., & Hu, X. (2026). *Exploring Key Factors Influencing Generation Z Users ' Continuous Use Intention on Human-AI Collaboration in Secondhand Fashion E-Commerce Platforms*. 1–36.
- Dixit, R. S., Choudhary, S. L., & Govil, N. (2025). Analyzing the impact of artificial intelligence on the online purchase decision - making process through the lens of the UTAUT 2 model. *Discover Computing*. <https://doi.org/10.1007/s10791-025-09575-5>
- Gamage, A. N. K. K. (2025). *A comparative analysis of qualitative and mixed methods research : Strengths , limitations , and practical applications*. 25(03), 2040–2046.
- Gillioz, C., Nicolet-dit-félix, M., Delplanque, S., Mortillaro, M., Sander, D., & Fiori, M. (2025). *How do emotionally intelligent individuals react to other people ' s emotions ? A study on emotional and facial reactions*.
- Habibu, T., Luhanga, E. T., & Sam, A. E. (2025). *Assessment of How Users Perceive the Usage of Biometric Technology Applications*. 1–11.
- Hair, J. F. (2019). *When to use and how to report the results of PLS-SEM*. 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hausinger, T., Probst, B., Hawelka, S., & Pletzer, B. (2025). Own-gender bias in facial feature recognition yields sex differences in holistic face processing. *Biology of Sex Differences*, 16(1), 1–15. <https://doi.org/10.1186/s13293-025-00695-7>
- Jangid, M., Gupta, S., & Sharma, S. (2025). *Zero trust biometric attendance : A secure face recognition framework*. 15(May), 2437–2449.
- Jiang, T., Sun, Z., Fu, S., & Lv, Y. (2024). Human-AI interaction research agenda : A user-centered perspective. *Data and Information Management*, 8(4), 100078. <https://doi.org/10.1016/j.dim.2024.100078>
- Kandasamy, G., Almanasef, M., Almeleebia, T., Orayj, K., Shorog, E., Alshahrani, A. M., Khaled,

- A., Prabahar, K., Alqifari, S. F., Mani, V., Alsuheim, G. Y. A., Alahmari, W. M. D., Ahmed, R., & Paulsamy, P. (2025). Prevalence of anxiety and depression among university students in Southern Saudi Arabia based on a cross sectional survey. *Scientific Reports*, 15(1), 1–9. <https://doi.org/10.1038/s41598-025-00695-y>
- Kelkay, J. M., Wubante, S. M., Anteneh, D. S., & Takilo, M. K. (2025). Intention to use eLearning - based continuing professional development and its predictors among healthcare professionals in Amhara region referral hospitals , Ethiopia , 2023 : using modified UTAUT - 2 model. *BMC Health Services Research*. <https://doi.org/10.1186/s12913-025-12317-4>
- Kenesei, Z., Kökény, L., Ásványi, K., & Jászberényi, M. (2025). The central role of trust and perceived risk in the acceptance of autonomous vehicles in an integrated UTAUT model. *European Transport Research Review*, 17(1). <https://doi.org/10.1186/s12544-024-00681-x>
- Kiran, K. P. (2025). Assessing Unified Payments Interface (UPI) adoption and usage through the interplay of UTAUT factors.
- Lee, P., Li, J., Rafiee, Y., Jones, B. C., & Shiramizu, V. K. M. (2025). Further evidence that averageness and femininity , rather than symmetry and masculinity , predict facial attractiveness judgments. 1–9.
- Li, C., & Li, H. (2023). Telematics and Informatics Disentangling facial recognition payment service usage behavior : A trust perspective. *Telematics and Informatics*, 77(August 2022), 101939. <https://doi.org/10.1016/j.tele.2023.101939>
- Liu, M., Wang, C., & Hu, J. (2025). Understanding older adults' adoption of facial recognition payment: An integrated model of TAM and UXT. *Plos One*, 20(7 July), 1–29. <https://doi.org/10.1371/journal.pone.0325291>
- Lyu, T., Guo, Y., & Chen, H. (2025). Understanding people ' s intention to use facial recognition services : the roles of network externality and privacy cynicism. 20. <https://doi.org/10.1108/ITP-10-2021-0817>
- Mansur, D. M., Liestyowati, L., & Maryadi, A. F. (2022). Understanding The Behavior and Perceptions of Millennial Generation as Guidance in Developing Service Products and Marketing Strategies: Evidence from West Java, Indonesia. *Jurnal Manajemen Bisnis*.
- Mansur, D. M., Sule, E. T., Kartini, D., Oesman, Y. M., Putra, A. H. P. K., & Chamidah, N. (2019). Moderating of the role of technology theory to the existence of consumer behavior on e-commerce. *Journal of Distribution Science*, 17(7), 15–25. <https://doi.org/10.15722/jds.17.07.201907.15>
- Matheis, T. K., Lehnhart, R., Carolina, A., Costa, C., & Tontini, J. (2026). Analysis of the determinants of behavioral intention to use digital financial channels : user perspectives.
- Moradi, H. (2025). Integrating AI in higher education: factors influencing ChatGPT acceptance among Chinese university EFL students. *International Journal of Educational Technology in Higher Education*, 22(1). <https://doi.org/10.1186/s41239-025-00530-4>
- Mutanda, B., & Tapera, J. (2025). Leveraging Digital Technologies to Enhance Business Resilience in Risk Management. 249–272. <https://doi.org/10.4018/979-8-3693-5912-9.ch010>
- Of, P., Contribution, T. H. E., Collaborative, O. F., To, E., Sustainable, T. H. E., & Goalsa, D. (2025). Percepción de la Contribución de la Economía Colaborativa a los Objetivos de Desarrollo Sostenible. 11(1), 1–14.
- Paliwal, G., Kumar, A., Prasad, K., Deepshika, S., Vijay, B., & Shrimal, M. (2025). Transformative impact of explainable artificial intelligence : bridging complexity and trust. *Discover Artificial Intelligence*. <https://doi.org/10.1007/s44163-025-00281-1>
- Prabhavathi, B., Tanuja, V., & Madhu, V. (2021). Attendance Management System Using Face Recognition Method Attendance Management System Using Face Recognition Method. <https://doi.org/10.1088/1742-6596/2089/1/012078>
- Prayogi, A., Navea, R. F., Dian, R., Akbar, M., Pane, S., Siregar, R. M., Sugianto, A., Fachri, H., & Simbolon, S. (2024). Direct implementation of AI-Based Facial Recognition for students. *Journal of Information System and Technology Research*, 3(3), 107–116.
- Qiu, J., Zhou, C., Rui, Y., & Feng, F. (2025). Advances in Numerical Computation and Mathematical

- Modeling for Geotechnical Engineering*. 15–18.
- Quan, Z., Yang, X., Pan, W., Wang, R., Cui, D., & Xu, Q. (2025). Unconscious processing of facial race and emotional information. *BMC Psychology*, 13(1). <https://doi.org/10.1186/s40359-025-02906-7>
- Setiya Putra, Y. W. (2023). Implementasi Model TAM pada Sistem Informasi Presensi Online Menggunakan Face Recognition dan GPS. *Journal of Applied Computer Science and Technology*, 4(2), 147–154. <https://doi.org/10.52158/jacost.v4i2.577>
- Shiau, W. L., Liu, C., Cheng, X., & Yu, W. P. (2024). Employees' Behavioral Intention to Adopt Facial Recognition Payment to Service Customers: From SQB and Value-Based Adoption Perspectives. *Journal of Organizational and End User Computing*, 36(1), 1–32. <https://doi.org/10.4018/JOEUC.359894>
- Susanty, A., Puspitasari, N. B., Siahaan, G. S., & Setiawan, S. (2025). *Factors influencing the intention of textile and garment SMEs to adopt digital technologies and its impact on performance*. 1–25.
- Syahputra, R. R., & Daryanto, E. (2025). *Implementation of Facial Recognition Identification System in Indonesia ' s Visa Services to Strengthen the Selective Policy of the Directorate General of Immigration in Supporting National Security*. 4(5), 1–10.
- Varma, P., Shen, L., Postnova, S., King, K., Howard, M. E., Aidman, E., Rajaratnam, S. W. M., & Sletten, T. L. (2025). Understanding sleep health challenges of defence shift workers to design a digital , sleep and circadian management tool. *Scientific Report*, 1–13.
- Yu, T., Teoh, A. P., Liao, J., & Wang, C. (2025). Factors influencing behavioral intention to use facial recognition payment in the restaurant industry : a comparative analysis of China and Malaysia. *Journal of Travel & Tourism Marketing*, 42(2), 222–247. <https://doi.org/10.1080/10548408.2025.2455421>
- Yu, T., & Wang, C. (2024). *Acceptance of or resistance to facial recognition payment : A systematic review*. February, 1–19. <https://doi.org/10.1002/cb.2385>
- Yu, T., Wang, C., Bian, Q., & Teoh, A. P. (2024). Acceptance of or resistance to facial recognition payment: A systematic review. *Journal of Consumer Behaviour*, August. <https://doi.org/10.1002/cb.2385>
- Zakaria, Z. (2025). *Face Recognition Technology : Benefits , Applications , and Challenges*. 13(03), 2096–2102. <https://doi.org/10.18535/ijssrm/v13i03.ec05>
- Zhang, Y. (2024). International Journal of Information Impact of perceived privacy and security in the TAM model : The perceived trust as the mediated factors. *International Journal of Information Management Data Insights*, 4(2), 100270. <https://doi.org/10.1016/j.jjime.2024.100270>
- Zl, P. G. Ī., & Kalari, Ī. L. Ī. K. P. O. L. Ī. T. Ī. (2025). *USER DATA AND DIGITAL PRIVACY : PRIVACY POLICIES OF SOCIAL MEDIA PLATFORMS*. 15(1), 225–239. <https://doi.org/10.7456/tojdac>
- Степанов, А. Г. (2023). Разработка метода сопоставления трехмерных изображений лица с данными компьютерной томографии *Developing methods of matching 3D facial images with computed tomography data Prosthodontics*. 150–157. <https://doi.org/10.37988/1811-153X>