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THE STUDY OF FACE - RECOGNITION BASED ATTENDANCE SYSTEM FOR HIGHER EDUCATION FACULTY

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Abstract

The implementation of face recognition systems, in online classrooms, has emerged as an efficient and effective strategy in numerous educational institutions globally. By reducing time wastage and accurately documenting student attendance, these systems provide lecturers with reassurance regarding student engagement. This study aims to justify the significance of adopting such systems in Saudi Arabian educational institutions and to analyze lecturers' usage, perceived risks, attitudes and behavioral intentions toward face recognition technology. In alignment with established research on technology adoption, this study employed the Technology Acceptance Model (TAM) as its proposed research model. A quantitative research methodology was employed, with a survey administered to university personnel in Saudi Arabia. The study's sample comprised university staff in Jeddah. Findings revealed that the implementation of face recognition systems, for attendance purposes, positively influenced users' attitudes and behavioral intentions.

Keywords: *Face-recognition attendance system, Information system success model, Quantitative analysis, attitude, behavioral intention, perceived risks*

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1. Introduction

After many years of research on student attendance, it was found that accurate and efficient attendance tracking is the cornerstone of effective educational management, serving as a vital tool for promoting student learning and creating a productive atmosphere in the classroom setting (**Caviglia-Harris, 2006 Andrejevic & Selwyn, 2020; Ismail et al, 2022**). Studies have unequivocally linked, through surveys and case studies, regular class attendance to improved academic outcomes (**Romer, 1993; Purcell, 2017; Dobkin & Marion, 2010; Nyamapfene, 2010; Fadelelmoula, 2018; Khan, 2022**). Hence the major contribution of this research programmes would be in demonstrating that students with high attendance rates, consistently outperform their peers with low attendance rates in both coursework and examinations.

Conventional approaches for verifying students' presence in class, such as verbal name calls, are often time-consuming, error-prone and impractical, especially in large classrooms. Similarly, passing around attendance sheets can also lead to delays and interruptions in class (**Salim et al. 2019; Jha et al, 2024**). To address these challenges, electronic attendance systems have emerged as viable alternatives (**Luckin, 2017**). Biometric identification and card-based systems exist but they can also be time-consuming and inflexible (**Narth, Aziale, & Akanferi, 2014**; **Braiki, Harous, Zaki, & Alnajjar, 2020**).

The unfolding of novel capabilities in technology, particularly artificial intelligence (AI), suggest encouraging avenues for addressing existing challenges for attendance management. AI applications in education have gained significant attention due to their potential to improve efficiency and student outcomes (**Lukas, Mitra, Desantti, & Krisnandi, 2017; González-Calatayud, Prendes-Espinosa, & Roig-Vila, 2021**). Face recognition, a subset of AI, has emerged as a potential game-changer in attendance tracking by enabling rapid and accurate student identification (**Li, Mu, Li, & Peng, 2016; Suresh, Dumpa, Vankayala, & Rapa, 2019**). Such a technology offers the potential to streamline attendance processes, saving time for both educators and students while eliminating the inaccuracies associated with manual attendance tracking. The technology operates by capturing student videos, extracting individual frames and cross-referencing them with a database to verify attendance. This automated approach ensures accurate records and minimizes the risk of false attendance (**Jha, Basnet, Pokhrel, Pokhrel, Thakur & Chhetri, 2023**).

This study aims to investigate the feasibility and potential impact of implementing a face recognition system for attendance management in educational settings. Specifically, it will examine educators' behavioral intentions, regarding the adoption and use of this technology.

2. Literature Review

Concerns about the importance of tracking student attendance are far from novel and have been consistently emphasized in the extant literature. Numerous studies have demonstrated that monitoring student attendance carries profound implications for the academic success and overall development of students (**Cleary-Holdforth, 2007; Landin and Pérez, 2015; Estepp and Stripling, 2020; Karnik et al, 2020; Lucey and Grydaki, 2023; Martínez-Serna et al, 2024**). This mainstream research has long recognized the multifaceted benefits of classroom attendance for students in cultivating a feeling of inclusion within the learning space (**Oldfield et al., 2018; Masnan et al, 2025**), fostering good work habits and improving socials kills (**Cohn & Johnson, 2006**), and attaining superior academic achievements (**Moores et al, 2019**). This enduring focus underscores the critical role, attendance tracking plays, in shaping educational outcomes.

While the pedagogical value of student attendance is well-documented, instructors in higher education institutions face logistical challenges in its management, necessitating the adoption of rapid and precise approaches (**Santoso and Sari, 2019**). The prevailing practice of manual attendance recording is characterized by inherent limitations, notably the increased likelihood of human error in data compilation and the consequential reduction of valuable instructional time (**Elaskariab et al, 2021**). Therefore, the integration of technological advancements in attendance systems has been identified as a game changer in higher education institutions (**Mohammed et al, 2019**). The extant literature provides substantial empirical evidence supporting the adoption of advanced attendance systems that incorporate biometric modalities (**Santoso and Sari, 2019; Memane et al., 2022**), geolocation-based mobile applications (**Sultana et al, 2015**), barcode systems (**Elaskariab et al., 2020**), Radio Frequency Identification (RFID) technology (**Kassim et al, 2012; Ula et al, 2019**), QR code scanning (**Masalha and Hirzalla, 2014; Nuhi et al., 2020**), near field communication (NFC) mobile device (**Mohandes, 2017**) and, notably, facial recognition, powered by machine learning techniques (**Budimana et al, 2023; Kumar et al., 2023; Boe et al., 2024; Srikanth et al., 2024**).

Particularly, the emergence of face recognition technology has presented a revolutionary means to enhance the efficiency and accuracy of attendance tracking in higher education institutions (**Andrejevic & Selwyn, 2020; Sunaryono et al, 2021).** There are several empirical studies, attesting to the benefits from the adoption of facial recognition attendance tracking, thereby showing that the technology presents a viable solution for widespread implementation across higher educational institutions (**Salim et al, 2018; Sawhney et al, 2019; Bah and Ming, 2020; Ahmed et al, 2021; Alhanaee et al, 2021; Alniemi et al, 2023; Feroze et al, 2024; Hussain et al, 2024**).

But the nature of facial recognition adoption in higher education institutions in the extant literature, has failed to empirically examine the educators' perspectives. This may be an omission, considering educators' articulated apprehensions concerning the operational efficacy and workload of manual attendance. Consequently, a substantive research gap persists in the exploration of educators' acceptance of this technology, a domain overlooked by the majority of scholarly inquiries to date.

3. Statement of the Problem

While previous research has primarily concentrated on the technical intricacies of face recognition attendance systems (**Apoorv & Mathur,2016; Amri, Hashim & Hanif, 2017; Charity, Okokpujie & Etinosa, 2017; Ayop,Lin, Anawar, Hamid & Azhar, 2018**), this study bridges the significant gap in the literature, by delving into the behavioral intentions of educators towards adopting this innovative technology. Through a comprehensive investigation, this research seeks to identify the influence of diverse factors, that shape educators' attitudes and inclinations, towards implementing face recognition systems in classroom environments.

4. Need of the Study

A comprehensive understanding of educators' perspectives on face recognition attendance systems is essential. By implementing this technology, institutions can reduce paperwork, save time and improve attendance data accuracy. This study seeks to identify the key factors influencing educators' intentions to adopt face recognition technology.

5. Objectives of the Study

5.1. To identify the effect of administrative readiness on the perceived ease of use of face recognition technology.

5.2. To identify the perceived risk on both the perceived ease of use and perceived usefulness of face-recognition.

5.3. To identify the effect of perceived ease of use on both perceived usefulness and the attitude toward using the face-recognition technology.

5.4. To identify the effect of perceived usefulness on the attitude toward using face-recognition.

5.5. To identify the attitude on the intention of using the face-recognition technology in class.

6. Research Hypotheses

Based on a thorough analysis of existing research and literature, a causal research model was developed to understand the factors, influencing educators' intention to adopt face recognition technology. This research model addresses the research objectives and fill a gap in the literature by examining lecturers' behavioral intentions regarding face recognition attendance systems for online learning. The conceptual framework was grounded on six constructs:

Administrative readiness (AR) refers to the availability of essential organizational resources for technology adoption. Organizational factors, such as size and resource allocation, influence an institution's capacity to embrace new technologies. Policies that support the adoption of new technologies are also an indication of organizational readiness (**Wong, Tatnall, & Burgess, 2014**). Larger institutions often require greater technical and financial support. Insufficient administrative readiness can hinder technology adoption and limit its potential benefits (**Braiki, Harous, Zaki, & Alnajjar, 2020**). Administrative readiness is found to be a critical factor in the adoption of blended learning environment in higher education (**Bokolo Jr et al., 2020)**

Perceived Ease Of Use (PEOU) describes the extent to which an individual believes in the ease of learning, by using a new system (**Davis et al., 1989**). Self-efficacy, personal reliability, and system simplicity are components of PEOU. Culture, which involves the use of resources and policies, is found to have a positive impact on the perceived ease of use (**Latreche et al., 2024).** Hence this study posited the following hypotheses:

H1: Administrative Readiness has a positive impact on the Perceived Ease of Use of face recognition implementation from a user's perspective.

Perceived usefulness (PU) is the extent to which individuals believe that using a system will improve their job performance. Factors such as subjective norms, image, work relevance, output quality and outcome demonstrability, influence perceived usefulness. Users often compare a system's capabilities with their job requirements, to form judgments about its usefulness (**Narth, Aziale, & Akanferi, 2014**). PEOU is a predictor of perceived usefulness, as the model demonstrates (**Chatterjee & Bhattacharjee, 2020**).

H2: Perceived Ease of Use has a positive impact on the Perceived Usefulness of face recognition implementation from a user's perspective.

Perceived Risks (PR) are individuals' beliefs about potential negative consequences associated with adopting a new technology. Lowering perceived risks can significantly influence users' attitudes towards the use of new technology (**Iriani and Andjarwati, 2020**). Previous research has shown that public relations have a negative impact on user attitudes towards AI in higher education (**Liu, Yang, Genga, & Du, 2021**).

H3: Perceived Risks have a negative impact on the Perceived Usefulness of face recognition implementation from a user's perspective.

H4: Perceived Risks have a negative impact on the Perceived Ease of Use of face recognition implementation from a user's perspective.

Attitude (ATT) serves as a strong mediating variable between perceived constructs and behavioral intention (BI). Previous research supports this relationship (**Weng et al., 2018**). This study hypothesizes that attitude mediates the relationship between perceived constructs and behavioral intention, to adopt face recognition technology in higher education (**Chatterjee & Bhattacharjee, 2020**). Several studies have established the effect of PEOU and PU on attitude, intention and actual use of technology (**Anouze and Alamro, 2020; Roy et al., 2017**).

H5: Perceived Ease of Use has a positive impact on the Attitude towards using face recognition implementation from a user's perspective.

H6: Perceived Usefulness has a positive impact on the Attitude towards using face recognition implementation from a user's perspective.

Behavioral Intention (BI) is the motivation, that drives users to use the system when needed (**Lin et al., 2023**). A strong positive relationship has been established between attitude and BI in the context of using multimedia content in school (**Weng et al., 2018**).

H7: Attitude towards using face recognition implementation has a positive impact on Behavioral Intention to use face recognition implementation from a user's perspective.

7. Research Methodology

This study was based on a deductive approach where the research model was built according to the TAM model. Constructs and their respective items sourced from the literature, were adjusted to fit the theme of this research. A pilot test was conducted to make sure items were measuring their intended constructs.

7.1. Sampling Selection

This study targeted university teaching personnel. A sample of candidates was obtained from online communities and work groups. Inclusion criteria involved professors, lecturers and teaching assistants, who had put in at least one year of experience in teaching college level courses. A message was directly sent to each candidate, with a short description of the study and a link to the questionnaire. Participants were assured of data confidentiality and anonymity and their voluntary participation was emphasized. A total of 312 participants completed the survey.

7.2. Sources of Data

The questionnaire consisted of two primary sections. The first section assessed the six research constructs: administrative readiness

(AR), perceived risk (PR), perceived ease of use (PEOU), perceived usefulness (PU), attitude (ATT) and behavioral intention (BI). Questionnaire items were adapted from previous studies (**Braiki, Harous, Zaki, & Alnajjar, 2020; Chatterjee & Bhattacharjee, 2020; Narth, Aziale, & Akanferi, 2014**). A 7-point Likert Scale was employed to measure the constructs. The second section collected demographic information, including gender, age and educational level.

7.3. Period of Study

The study commenced in early 2023 with an indepth literature review to identify research gaps. The research model was developed and data collection, through the questionnaire was conducted between July and September 2023.

7.4. Tools Used in the Study

Google Forms were utilized for questionnaire development. Data preparation and descriptive analysis were performed, using Microsoft Excel 2016. Both the measurement and structural models were analyzed, using structural equation modeling, using SmartPLS version 3.3. Default parameters and recommended thresholds were adopted from **Yuan and Bentler (2006), Gunzler and Morris (2015), Henry and Stone (1994), Pham, Lai, and Vuong (2019), Hair et al. (2014), and Hair et al. (2017)**.

8. Data Analysis and Results of the Study

Valid and complete responses from participants were downloaded and fed to Microsoft Excel and SmartPLS, for the analysis.

8.1. Demographic Profile

A total of 312 participants completed the survey. The sample predominantly comprised males (82.7%), with females constituting 17.3%. Over half of the respondents held a bachelor's degree. **Table 1** depicts the demographic details.

8.2. Measurement Model: Construct Reliability Measures

The measurement model analysis demonstrated acceptable reliability and validity. All factor loadings (SL), Cronbach's Alpha, rho A and Composite Reliability (CR) exceeded the recommended threshold of 0.70. SL indicated strong relationship between items and their intended constructs. Cronbach's alpha, rho A and CR revealed excellent internal consistency. Additionally, the Average Variance Extracted (AVE) values, for all constructs, surpassed the 0.50 criterion, which confirmed convergent validity of the measurement model. **Table 2** presents the reliability and validity metrics.

8.3. Measurement Model: Convergent and Discriminant Validity Measures

Convergent validity was confirmed through the Fornell-Larcker criterion, indicating that the correlation of each construct with itself was higher than its correlation with other constructs (**Table 3**). Discriminant validity was established, using the Heterotrait-Monotrait Ratio of Correlation (HTMT), with all values being less than the 0.90 threshold (**Table 4**). Discriminant validity indicates that each construct measures a unique concept.

8.4. Structural Model: Path Coefficients and Significance Levels

The structural model was assessed, to evaluate the hypothesized relationships. **H1**, predicting a positive impact of Administrative Readiness on Perceived Ease of Use ($\beta = 0.304$, $t = 4.535$, $p < 0.001$, 95% CI [0.179, 0.403]), was supported. **H2**, examining the impact of Perceived Ease of Use on Perceived Usefulness ($\beta = 0.558$, $t = 9.239$, $p < 0.001$, 95% CI [0.452, 0.650]), was accepted. **H3**, investigating the impact of Perceived Risks on Perceived Usefulness ($\beta = 0.315$, $t = 4.850$, $p < 0.001$, 95% CI [0.211, 0.425]), was supported. **H4**, investigating the impact of Perceived Risks on Perceived Ease of Use ($\beta = 0.474$, $t = 8.757$, $p < 0.001$, 95% CI [0.383, 0.559]), was accepted. **H5**, examining the impact of Perceived Ease of Use on Attitude ($\beta = 0.407$, $t = 5.823$, $p < 0.001$, 95% CI [0.294, 0.522]), was supported. **H6**, predicting a positive impact of Perceived Usefulness on Attitude ($\beta = 0.519$, $t = 7.245$, $p < 0.001$, 95% CI [0.394, 0.632]), was accepted. Finally, **H7,** hypothesizing a positive impact of Attitude on Behavioral Intention ($\beta = 0.853$, $t = 37.352$, $p < 0.001$, 95% CI [0.810, 0.885]), was also supported. **Table 5** summarizes the path coefficients values, the magnitude and direction of each hypothesized effect.

8.5. Variance and Predictive Relevance

The reported R^2 and Q^2 values demonstrated the model's capacity to explain and predict variance in the dependent variables. R^2 values, above or equal to 0.75, 0.50, or 0.25 for endogenous latent variables, can be accordingly classified as substantial, moderate, or weak variance explanations **(Hair, Ringle, & Sarstedt, 2013)**. R^2, equal to or greater than 0.10, were also considered **(Miller, 1992)**. Further, a model's predictive relevance is determined by the Q^2. When the Q^2 is greater than zero, the model is predictively relevant. **Table 6** shows the values for both R^2 and Q^2, which established the predictive power of the model.

9. Findings of the Study

Research, concerning the implications of educators' intentions on successful implementation of facial recognition attendance tracking, is scarce. Existing studies often fail to identify the influence of diverse factors, that shape educators' attitudes and inclinations towards implementing face recognition technology in classroom environment. To address this gap, this study was undertaken to provide invaluable insights into how best to facilitate the acceptance of this technology within higher education institutions. The SEM results revealed significant relationships between all antecedent constructs (AR, PR, PEOU, PU, and ATT) and behavioral intention (BI).

The results demonstrated strong positive relationship between AR and PEOU. In other words, higher education institutions, demonstrating higher levels of preparedness, including the allocation of resources, technical and financial support and institution's capacity to embrace new technologies, tended to foster a more favorable user perception of face recognition technology. These results established that AR is a vital factor, influencing user acceptance and comfort in engaging with new technologies. Further, it is also pertinent to acknowledge the function of PR in fostering the acceptant of new technology. The result of this study revealed that PR negatively affected both PEOU and PU, suggesting that alleviating users' concerns regarding the potential downsides of the technology is crucial for fostering acceptance. Hence the need for higher education institutions, to mitigate these risks effectively, as they can significantly enhance the perceived advantages of adopting face recognition technology.

Further, the result of this study revealed that PEOU significantly influenced both PU and user attitudes toward the adoption of face recognition systems. Specifically, the study found that users, who found the technology easy to use, were more likely to perceive it as beneficial. Such evidence confirmed crucial assertions of the TAM, establishing that to enhance the acceptance of such technologies, it is imperative to address both the PEOU and the demonstrable value they provide to users (PU). The result of this study also highlighted the direct implication of PU on user attitudes toward the adoption of face recognition systems. Therefore, the result of this study reinforces the notion that if users recognize the value added by the technology, their overall attitude towards adopting face recognition technology becomes more positive. This relationship is pivotal, as fostering an understanding of the practical benefits of face recognition technology, can facilitate broader acceptance, particularly in higher education sector where PU can significantly affect user acceptance.

Finally, insights, drawn from the mediation analysis, revealed that user attitudes serve as a critical filter through which perceived constructs must pass before influencing behavioral intentions. This stresses the critical importance of user attitude (ATT) as a pivotal factor in strategies related to the adoption of facial recognition technology within higher education institutions, necessitating the comprehensive mitigation of concerns regarding AR, PEOU, PU and PR.

10. Conclusion

Extensive of research has consistently demonstrated the pivotal role of accurate and efficient attendance tracking in fostering effective educational management. Studies have unequivocally linked regular class attendance to improved academic outcomes, underscoring its significance in creating a productive learning environment. Recognizing the profound impact of attendance on student success, face recognition technology has emerged as a promising solution, offering an efficient approach. By automating the process, face recognition eliminates the inefficiencies and errors, often associated with manual attendance systems, reducing the administrative burden on educational institutions. Given the general familiarity of lecturers with face recognition technology, the implementation of such systems appears feasible and desirable. However, decision-makers should be cognizant of the contextual factors, influencing the successful adoption and utilization of face recognition systems.

11. Suggestion

This study suggests two main venues, to extend the results into more theoretical contribution and practical solution. Given the dearth of research on the relationship between face recognition attendance systems and lecturer behavior, this study offers a significant theoretical contribution to the literature. While the study employed a quantitative approach, qualitative research could further elucidate the nuances of lecturer experiences with this technology. In the practical aspect, it is suggested that decision makers at universities should implement face-recognition technology in small classrooms first and observe the actual use of this technology. Prior to the implementation, proper training is suggested, to alleviate any burden that may occur due to lack of perceived usefulness or perceived ease of use.

12. Limitation

The study's scope was constrained to specific regions within Saudi Arabia to mitigate potential data biases. The absence of spatial data collection limited the investigation of location-based technological behavior. Additionally, the cross-sectional design precluded an in-depth examination of the technology adoption process over time. The study's findings suggest that user experience with similar systems may influence the perceived ease of use of face recognition technology. Further, generational differences in technological familiarity is likely to impact participants' attitudes and intentions.

13. Scope for Further Study

While current literature predominantly focuses on underlying technology of face recognition attendance systems, this study adopted a user-centric perspective to investigate the intention to adopt face recognition technology in classrooms, using the TAM model. While **Narth, Aziale, and Akanferi (2014)** explored similar concepts, the proposed model offered unique insights. **Braiki, Harous, Zaki, and Alnajjar (2020)** highlighted the impact of AI in education, but their systematic review approach provided limited actionable recommendations. This study would contribute to the field, by identifying key variables influencing lecturers' attitudes and intentions towards face recognition technology.

Future research should employ longitudinal studies, to examine the technology adoption process across different stages (pre-implementation, integration, and post-implementation). Such investigations would provide valuable insights into how users' perceptions and behaviors evolve over time. Additionally, exploring the role of organizational culture and leadership, in facilitating face recognition technology adoption, would be beneficial.

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Table 1: Demographic Values of Participants in the Face-Recognition Study

Demographic	Descriptions	Frequency	Percentage
Gender	Male	258	82.7%
	Female	54	17.3%
Education level	Higher Education	0	0%
	Certificate	1	0.32%
	Diploma	8	2.56%
	Bachelor’s degree	176	56.4%
	Master’s degree	54	17.3%
	PhD	73	23.4%

Source : Primary Data (2024) using Microsoft Excel 2016

Table-2: Reliability and Validity for All Constructs in the Research Model

Constructs	SL	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Administrative Readiness	> 0.70	0.864	0.872	0.902	0.650
Attitude	> 0.70	0.927	0.929	0.949	0.822
Behavioral Intention to Use	> 0.70	0.970	0.970	0.975	0.847
Perceived Ease of use	> 0.70	0.916	0.919	0.935	0.705
Perceived Risk	> 0.70	0.921	0.924	0.938	0.717
Perceived Usefulness	> 0.70	0.916	0.919	0.935	0.705

Source: Primary data (2024) using SmartPLS (Version 3.3)

Table-3: Fornell-Larker Criterion for All Constructs in the Research Model

	AR	ATT	BIU	PEOU	PR	PU
Administrative Readiness	**0.806**					
Attitude	0.447	**0.907**				
Behavioral Intention to Use	0.381	0.853	**0.920**			
Perceived Ease of use	0.486	0.794	0.746	**0.840**		
Perceived Risk	0.386	0.611	0.556	0.591	**0.847**	
Perceived Usefulness	0.436	0.823	0.717	0.744	0.645	**0.840**

Source: Primary data (2024) using SmartPLS (Version 3.3)

Table- 4: Heterotriat-Monotrait Ratio for All Constructs in the Research Model

	AR	ATT	BIU	PEOU	PR	PU
Administrative Readiness						
Attitude	0.498					
Behavioral Intention to Use	0.415	0.898				
Perceived Ease of use	0.542	0.860	0.790			
Perceived Risk	0.425	0.659	0.585	0.639		
Perceived Usefulness	0.487	0.889	0.760	0.810	0.697	

Source: Primary data (2024) using SmartPLS (Version 3.3)

Table-5: Path Coefficients for the Hypothesized Relationships in the Research Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/ STDEV|)	P Values	Support
Administrative Readiness → Perceived Ease of use	0.304	0.307	0.067	4.535	0.000	Yes
Attitude → Behavioral Intention to Use	0.853	0.852	0.023	37.352	0.000	Yes
Perceived Ease of use → Attitude	0.407	0.408	0.070	5.823	0.000	Yes
Perceived Ease of use → Perceived Usefulness	0.558	0.561	0.060	9.239	0.000	Yes
Perceived Risk → Perceived Ease of use	0.474	0.473	0.054	8.757	0.000	Yes
Perceived Risk → Perceived Usefulness	0.315	0.312	0.065	4.850	0.000	Yes
Perceived Usefulness → Attitude	0.519	0.519	0.072	7.245	0.000	Yes

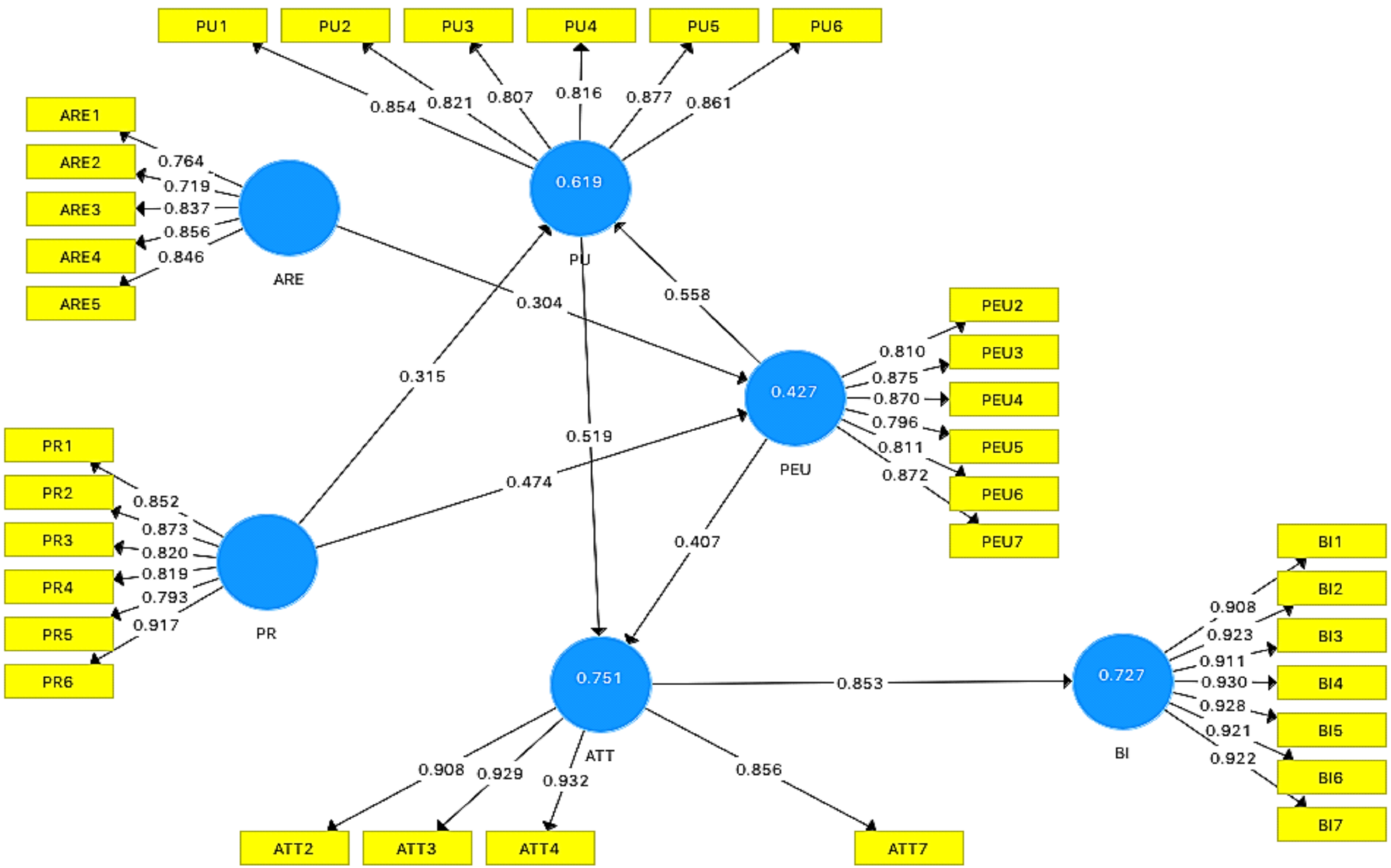
Source: Primary data (2024) using SmartPLS (Version 3.3)

Table - 6: R Squared and Construct Cross-Validated Redundancy for the Endogenous Variables in the Research Model

	R Square	Level of variance influence	Q^2 (=1-SSE/SSO)
Attitude	0.751	Substantial	0.612
Behavioral Intention to Use	0.727	Moderate	0.611
Perceived Ease of use	0.427	Weak	0.295
Perceived Usefulness	0.619	Moderate	0.428

Source: Primary data (2024) using SmartPLS (Version 3.3)

Figure-1: The Research Model Depicting the Proposed Impact of Multiple Variables on the Intention to Use Face-Recognition Attendance Systems in Higher Education



Source: Primary data (2024) using SmartPLS (Version 3.3)