Scientific Journal of Informatics
Vol. 12, No. No. 4, November 2025

p-ISSN 2407-7658 http://journal.unnes.ac.id/nju/index.php/sji e-ISSN 2460-0040

UTAUT-2, HOT-Fit, and PLS-SEM for User Acceptance and Success of the Face Recognition Feature in CAT BKN Application

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Abstract.
Purpose: Face recognition feature was implemented in National Civil Service Agency's Computer Assisted Test in 2021. There has been no evaluation of the system's acceptance and success. This study aims to measure user acceptance and evaluate the feature's success using the R Shiny application.
Methods: The study utilized 337 respondents from a Google Form-based questionnaire distributed throughout the Regional Office VII of the National Civil Service Agency in Palembang. The hybrid model used was UTAUT-2 and HOT-Fit, with PLS-SEM statistical analysis. Acceptance analysis and feature evaluation were conducted using developed R Shiny Dashboard.
Results: The findings indicated that 15 of the 26 hypotheses were accepted. Behavioral intention and use behavior significantly influence hedonic motivation and habit. User behavior significantly influence user satisfaction, system quality, service quality, information quality, system use, and organizational structure and environment. As users become more familiar with the technology, their experience improves and system utilization becomes more effective.
Novelty: The integration of UTAUT-2 and HOT-Fit models within R Shiny Dashboard was applied to analyze user acceptance and evaluate face recognition feature in Computer Assisted Test selection process. The findings provide recommendations for feature development and improving participant face recognition performance. Moreover, R Shiny Dashboard can be adapted for user experience analysis and system evaluation in other contexts.

Keywords: UTAUT-2, HOT-fit, PLS-SEM, Face recognition, R shiny
Received July 2025 / **Revised** September 2025 / **Accepted** November 2025

INTRODUCTION

Digital transformation in government plays a crucial role in ensuring an effective, efficient, and transparent bureaucracy [1]. One example of digital advancement in the government sector is the Civil Service selection system, known as the National Civil Service Agency's Computer-Assisted Test (CAT). The system has been implemented since 2014, and following pandemic, a face recognition feature was introduced as an innovation and security measure to verify participants' identities during registration and login to the examination page.

Face recognition is a technology used to capture human face images and compare them with those stored in a database. However, the selection process using the Computer-Assisted Test (CAT) encountered several challenges, particularly in the implementation of face recognition feature. These challenges included limited infrastructure, technical system constraints, and a lack of understanding of face recognition technology, especially in areas with low internet accessibility [2]. Furthermore, since face recognition feature was added, no specific evaluation has been conducted. Therefore, an analysis of the acceptance of use and evaluation of this face recognition feature was conducted to evaluate user acceptance and success of this feature in Computer Assisted Test. This research aims to examine factors influencing user acceptance and provide recommendations for feature improvements. The user acceptance and success evaluations used UTAUT-2 model, HOT-Fit model, and PLS-SEM statistical analysis.

UTAUT-2 model is known as an effective model in explaining behavioral intention factors in technology adoption [3], [4]. Meanwhile, HOT-Fit model is known as an information system evaluation model that provides perspectives from the human, organizational, and technological aspects [5], [6], [7]. In study [8],

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DOI: [10.15294/sji.v12i4.31229](https://doi.org/10.15294/sji.v12i4.31229)

[9] said HOT-Fit model combines concept of Delone & Mclean's IS Success Model (ISSM) and IT-Organization Fit [8], [9]. These 2 models will be integrated, and the proposed model will be analyzed using PLS-SEM. PLS-SEM is a multivariate statistical technique used to examine the relationships between latent variables and observed variables, which are indirectly measured through multiple indicators [10], [11], [12].

Several studies have specifically integrated UTAUT-2 and HOT-Fit models with PLS-SEM to provide a comprehensive understanding of the factors influencing user acceptance and success of face recognition features in public information systems. Previous research using UTAUT-2 model was conducted as a case study that investigated customer intention factors in adopting facial recognition systems for payment and loyalty account authorization in fast-food restaurants in the United States, involving 558 respondents recruited via Amazon MTurk [13]. Another study employed the UTAUT-2 model to investigate factors influencing behavioral intention and usage behavior of Artificial Intelligence–based products in daily life, covering mobility, household, and healthcare segments with thousands of respondents [14]. UTAUT-2 also explored the factors influencing the adoption of ChatGPT in educational institutions in developing countries, specifically Botswana, with 518 respondents analyzed using SmartPLS 3.0 [4].

In previous studies, HOT-Fit model has often been applied to evaluate information systems in hospitals, such as the hospital information system at Kanujoso Djatiwobowo Regional Hospital with 78 respondents [15]. Another study examined the readiness for implementing e-learning in West Kalimantan's Universities with 298 respondents [16]. Similarly, the HOT-Fit model was used to evaluate the adoption of cloud technology, identifying the factors influencing its use among 76 local councils in Australia [17]. In addition, a combination of UTAUT-2 and HOT-Fit's Human and Technology dimensions was employed to assess satisfaction, net benefits, and effectiveness regarding the surge in e-scooter usage, with 199 respondents in Germany and 184 respondents in Portugal [18]. A statistical approach is necessary to analyze the relationships between variables in these two models. This approach utilizes the PLS-SEM method to assess the relationships between indicators and constructs. One of the PLS-SEM model is analysis of Shopee customer loyalty, conducted with 100 respondents, with the results presented through an interactive R Shiny website [19].

Although numerous studies have examined user factors and information system evaluation, most have been conducted separately [15], [16], [17], [18], [20]. To date, no research has specifically integrated the user acceptance model (UTAUT-2) and the information system success evaluation model (HOT-Fit) into a hybrid model. Moreover, PLS-SEM–based statistical analyses in previous studies were generally conducted using tools such as SmartPLS and have not been optimized for interactive platforms [21]. This study integrates UTAUT-2 and HOT-Fit into a PLS-SEM framework to analyze user acceptance and evaluate the success of face recognition feature using an R Shiny Dashboard.

METHODS

The research uses a combination of Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) and Human-Organization-Technology Fit (HOT-Fit), analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), to measure the level of user acceptance and success of face recognition feature in the Computer Assisted Test application. The research stages, as illustrated in Figure 1, include model design (UTAUT-2 and HOT-Fit), population and sample selection, research instruments, data collection, system development, system testing, data processing and data analysis, and results.

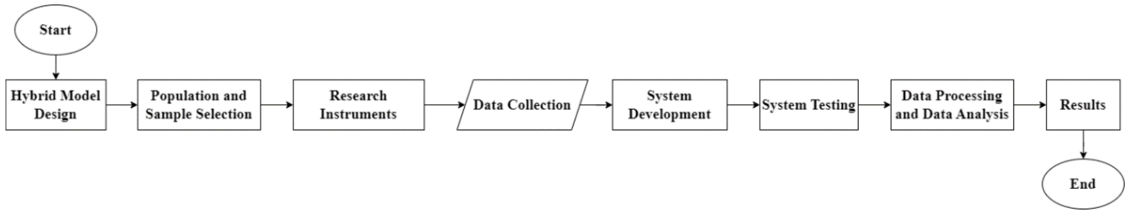

Figure 1. Research Methods for User Acceptance and Evaluation of Face Recognition

The research began with design of UTAUT-2 and HOT-Fit models comprising 17 variables, followed by determining population and sample using Slovin formula with a 5% margin of error. Research instruments were developed using a Likert Scale 1-5, and data were collected from 337 respondents through Google Forms distributed online through Instagram and WhatsApp. Subsequently, an interactive dashboard application was developed using R Shiny, and the system was tested using black-box method. The collected data were analyzed with PLS-SEM method implemented in R Shiny, and the results were interpreted to provide conclusions and give recommendations for future development and improvement of face recognition feature.

Model Hybrid

The combined research model has 9 variables from UTAUT-2 model consisting of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioral Intention, and Use Behavior [14], [22]. Meanwhile, HOT-Fit model has 8 variables consisting of System Quality, Information Quality, Service Quality, System Use, User Satisfaction, Structure, Environment, and Net Benefits [5], [16], [23]. There are 17 variables and consisting 28 hypotheses from hybrid models used to formulate hypotheses in this research. The hypotheses and variable in the research can be seen in Figure 2.

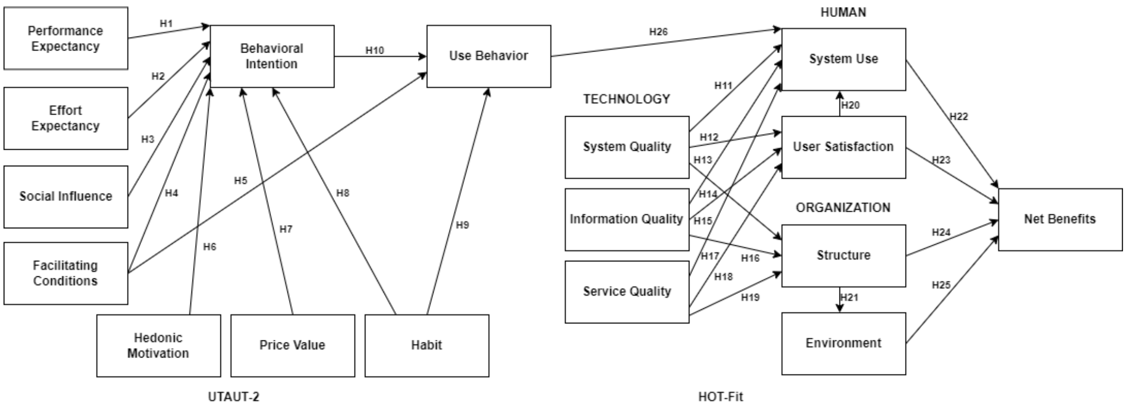

Figure 2. Hybrid Model of UTAUT-2 and HOT-Fit

Research Hypothesis

This research tested 26 hypotheses to examine factors affecting user acceptance and success of face recognition feature in Computer Assisted Test application.

H1: Performance Expectancy has a significant positive influence on Behavioral Intention[18].
H2: Effort Expectancy has a significant positive influence on Behavioral Intention [18].
H3: Social Influence has a significant positive influence on Behavioral Intention [18].
H4: Facilitating Conditions have a significant positive influence on Behavioral Intention [18].
H5: Facilitating Conditions have a significant positive influence on Use Behavior [18].
H6: Hedonic Motivation has a significant positive influence on Behavioral Intention [4], [18], [24].
H7: Price Value has a significant positive influence on Behavioral Intention [18].
H8: Habit has a significant positive influence on Behavioral Intention [4], [18], [24].
H9: Habit has a significant positive influence on Use Behavior [18].
H10: Behavioral Intention has a significant positive influence on Use Behavior [4], [18], [24].
H11: System Quality has a significant positive influence on System Use [19], [24].
H12: System Quality has a significant positive influence on User Satisfaction [19], [25].
H13: System Quality has a significant positive influence on Structure [15].
H14: Information Quality has a significant positive influence on System Use [26], [27], [28].
H15: Information Quality has a significant positive influence on User Satisfaction [19], [24].
H16: Information Quality has a significant positive influence on Structure [29].
H17: Service Quality has a significant positive influence on System Use [26], [27], [28].
H18: Service Quality has a significant positive influence on User Satisfaction [24], [25].
H19: Service Quality has a significant positive influence on Structure [29].
H20: User Satisfaction has a significant positive influence on System Use [15], [26], [28].
H21: Structure has a significant positive influence on Environment [15].
H22: System Use has a significant positive influence on Net Benefits [5], [15], [18].
H23: User Satisfaction has a significant positive influence on Net Benefits [18].
H24: System Use has a significant positive influence on Net Benefits [5], [15], [18].
H25: Environment has a significant positive influence on Net Benefits [15].

H26: Use Behavior has a significant positive influence on System Use [30].

Research Instruments

The research instrument was compiled in questionnaire with a 5-point-Likert Scale [31], [32]. The instrument for this statement was developed using 17 hybrid variables. Each variable has a different number of indicators. Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, Information Quality, System Use, User Satisfaction, Structure, and Environment each have 4 indicators. Facilitation Conditions, System Quality, Service Quality, and Net Benefits each have 5 indicators. Price Value, Behavioral Intention, and Use Behavior each have 3 indicators. The total indicators in the research were 69, which were then used as statements in the questionnaire regarding evaluation of user acceptance and success of face recognition feature.

Respondent Data

The data were collected using a simple random sampling technique. The sample size was determined using the Slovin formula with a margin of error of 0.05 or 5% [34]. In the research, respondents were general public, civil servants, and government contract employee of National Civil Service Agency in Palembang with a total of 440 participants. The data were cleaned using Stats Tools by removing responses with constant answers, ascending scale patterns, and descending scale patterns. After the cleaning process, 337 valid responses were retained for statistical analysis in R. The cleaned dataset, which served as the input for the PLS-SEM analysis, is presented in Figure 3.

pe1;pe2;pe3;pe4;ee1;ee2;ee3;ee4;si1;si2;si3;si4;fc1;fc2;fc3;fc4;fc5;hm1;hm2;hm3;hm4;pv1;pv2;pv3;h1;h2;h3;h4;bi1;bi2;bi3;ub1;ub2;ub3;sq1;sq2;sq3;
sq4;sq5;iq1;iq2;iq3;iq4;seq1;seq2;seq3;seq4;seq5;su1;su2;su3;su4;us1;us2;us3;us4;s1;s2;s3;s4;e1;e2;e3;e4;nb1;nb2;nb3;nb4;nb5
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Figure 3. Respondent Data

R Shiny Dashboard Development

The R Shiny dashboard application was developed using R Studio tools to present results of PLS-SEM statistical analysis. R Shiny was utilized to build the web-based application, utilizing its flexible GUI and reactive output [33]. This simple application consists of a user interface and a offline server [19]. This user interface uses shinydashboard package, while offline server uses SEMinR package for statistical analysis. R Shiny dashboard application consists of Home, Dashboard, Proposed Model, Import Data, PLS-SEM Analysis (Outer Model Analysis and Inner Model Analysis), User Guide, and About menus.

Blackbox Testing

Black-box testing, a behavior-based approach that focuses on evaluating software functionality [34]. The testing examined 4 key aspects: button functionality, user interface, data structure and database access, system performance, and program initialization on R Shiny Dashboard.

PLS-SEM Analysis

The data in this study were analyzed using PLS-SEM, which consists of outer/measurement model analysis and inner/structural model analysis [11]. Table 1 presents the measurement tests conducted at each stage of the analysis, starting with the measurement model and continuing to the structural model.

Table 1. PLS-SEM Statistical Analysis

Measurement Model	1. Convergent Validity (Factor Loading) 2. Discriminant Validity (Cross Loading) 3. Reliability (Cronbach Alpha, AVE, rho_a, dan rho_c)
Structural Model	1. Path Coefficient dan R^2 2. Bootstrapping (Original Sample dan T-Statistic) 3. Q^2 Predict

The analysis begins with the evaluation of the outer model, which consists of convergent validity, discriminant validity, and reliability testing to ensure that indicators accurately represent their respective constructs. Subsequently, the inner model is evaluated by estimating path coefficients to identify relationships among variables, applying bootstrapping for hypothesis testing, calculating the f^2 effect size, and assessing the model's predictive relevance.

RESULT AND DISCUSSION

The R Shiny dashboard-based PLS-SEM analysis application, developed using R Studio, provides several menu features including Home, Respondent Dashboard, Proposed Model, Import Data (CSV format), PLS-SEM Analysis (Outer and Inner Model), User Guide, and About. The respondent data visualization dashboard, as shown in Figure 4, allows customization based on gender, age group, respondent status, educational background, and frequency or experience in participating in the selection process.

Table 2. Demographic Respondent

Criteria	Value	Total	%
Gender	Male	132	39,2
	Female	205	60,8
Age Group	<30	156	46,3
	31-40	160	47,5
	41-50	17	17
	>50	4	4
Status	General Public	81	24
	Civil Servant	176	52,3
	Government Contract Employee	80	23,7
Education Level	High School	20	5,9
	Diploma I/II/III	56	16,6
	Bachelor's	217	64,4
	Master's/Doctoral	44	13,1
Selection Experience	>1	223	66,2
	First Time	114	33,8

The study obtained data from 337 respondents. Based on gender, 39.2% were male and 60.8% female. In terms of age group, 46.3% were under 30 years, 47.5% were 31–40 years, 5% were 41–50 years, and 1.2% were over 50 years. By status, 52.2% were civil servants, 23.7% government employees under work agreements, and 24% represented the general public. Regarding education level, 5.9% had completed high school, 16.6% held a diploma (I/II/III), 64.4% had a bachelor's degree, and 13.1% had a master's/doctoral degree. Meanwhile, based on selection experience, 33.8% were first-time participants, while 66.2% had participated more than once. The respondent demographics are presented in Table 2.

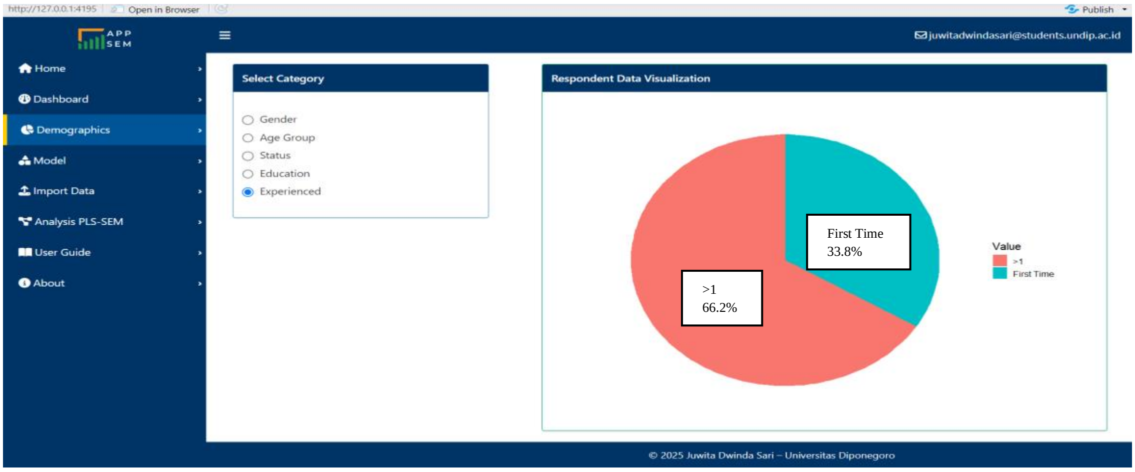
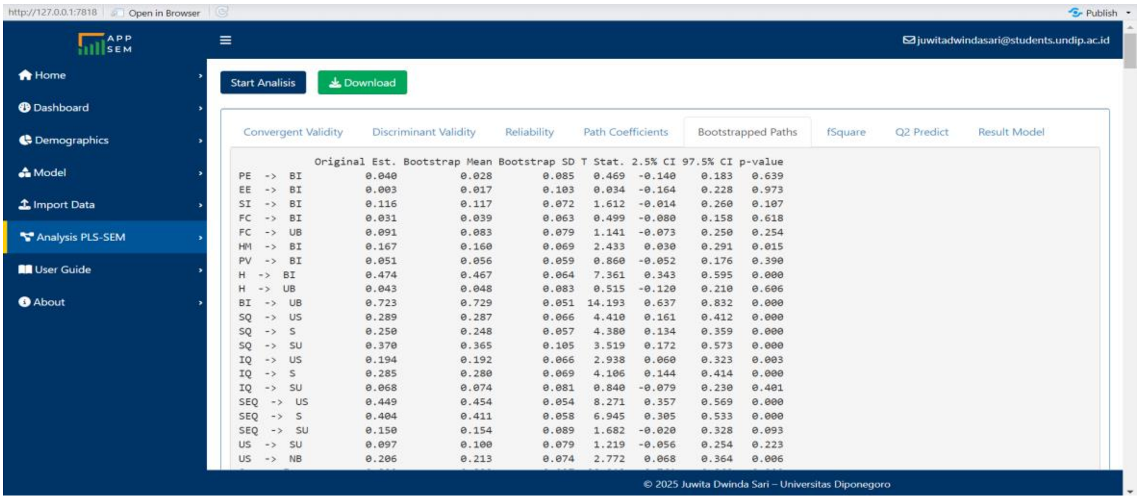


Figure 4. Respondent Dashboard

The PLS-SEM analysis menu provides detailed statistical analysis panels, including Convergent Validity, Discriminant Validity, Reliability, Path Coefficients, Bootstrapped Paths, f Square, Q² prediction, and Analysis Result Model. The analysis process begins by importing respondent data in CSV format through Import Data menu, followed by accessing the PLS-SEM analysis menu and clicking Start Analysis button. Figure 5 illustrates an example of outer model analysis displayed in Bootstrapped Paths panel tab.



	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI	97.5% CI	p-value
PE -> BI	0.040	0.028	0.085	0.469	-0.140	0.183	0.639
EE -> BI	0.003	0.017	0.103	0.034	-0.164	0.228	0.973
SI -> BI	0.116	0.117	0.072	1.612	-0.014	0.260	0.107
FC -> BI	0.031	0.039	0.063	0.499	-0.080	0.158	0.618
FC -> UB	0.091	0.083	0.079	1.141	-0.073	0.250	0.254
HM -> BI	0.167	0.160	0.069	2.433	0.030	0.291	0.015
PV -> BI	0.051	0.056	0.059	0.860	-0.052	0.176	0.390
H -> BI	0.474	0.467	0.064	7.361	0.343	0.595	0.000
H -> UB	0.043	0.048	0.083	0.515	-0.120	0.210	0.606
BI -> UB	0.723	0.729	0.051	14.193	0.637	0.832	0.000
SQ -> US	0.289	0.287	0.066	4.410	0.161	0.412	0.000
SQ -> S	0.250	0.248	0.057	4.380	0.134	0.359	0.000
SQ -> SU	0.370	0.365	0.105	3.519	0.172	0.573	0.000
IQ -> US	0.194	0.192	0.066	2.938	0.060	0.323	0.003
IQ -> S	0.285	0.280	0.069	4.106	0.144	0.414	0.000
IQ -> SU	0.068	0.074	0.081	0.840	-0.079	0.230	0.401
SEQ -> US	0.449	0.454	0.054	8.271	0.357	0.569	0.000
SEQ -> S	0.404	0.411	0.058	6.945	0.305	0.533	0.000
SEQ -> SU	0.150	0.154	0.089	1.682	-0.020	0.328	0.093
US -> SU	0.097	0.100	0.079	1.219	-0.056	0.254	0.223
US -> NB	0.206	0.213	0.074	2.772	0.068	0.364	0.006

Figure 5. PLS-SEM Analysis on R Shiny

Application Testing

Accroding to [34], blackbox testing is conducted to evaluate the suitability of an application for use. In this study, functionality testing covered several aspects, including successful data uploads, error-free application syntax, user-friendly interfaces, proper system execution, and the usability of button function. On the R Shiny Dashboard, respondent data in CSV format was successfully uploaded by clicking Browse button in Import Data menu. Once uploaded, the dashboard generated visualizations of questionnaire results, while the demographics menu displayed respondent group distributions in pie charts. Furthermore, the PLS-SEM analysis menu enabled users to initiate the analysis by clicking the Start Analysis button, with the results appearing directly in the same menu and available for download by Download button. In addition, all 8 tabs panels in the PLS-SEM analysis menu were successfully accessed, confirming that the system interface and navigation functioned as intended.

Measurement Model Analysis

Data analysis using the PLS-SEM model was conducted in two stages. The first stage involved outer or measurement model analysis, which consisted of validity and reliability testing. Validity testing was divided into convergent validity and discriminant validity. Convergent validity is considered acceptable when factor or outer loading value exceeds 0.7 and Average Variance Extracted (AVE) is greater than 0.5. Discriminant validity is established when an indicator's loading on its own construct is higher than its loadings on other constructs. Reliability is confirmed when Cronbach's Alpha, rho_a, and rho_c values all exceed 0.7 [11], [35].

Table 3. Measurement Model Test

Variables	Indicator	Outer Loading	Cronbach Alpha	rho_c	AVE	rho_a
Performance Expentancy (PE)	PE2	0.739	0.728	0.829	0.566	0.832
	PE3	0.906				
	PE4	0.858				
Effort Expentancy (EE)	EE1	0.848	0.865	0.909	0.716	0.878
	EE2	0.729				
	EE3	0.906				
	EE4	0.890				
Social Influence (SI)	SI1	0.734	0.767	0.850	0.590	0.806
	SI3	0.837				
	SI4	0.865				
Facilitating Conditions (FC)	FC2	0.802	0.801	0.862	0.557	0.808
	FC4	0.768				
	FC5	0.787				
Hedonic Motivation (HM)	HM1	0.886	0.890	0.924	0.753	0.892
	HM2	0.870				
	HM3	0.863				
	HM4	0.852				
Price Value (PV)	PV1	0.873	0.829	0.898	0.745	0.835
	PV2	0.845				
	PV3	0.871				
Habit (H)	H2	0.782	0.807	0.875	0.639	0.827
	H3	0.876				
	H4	0.873				
Behavioral Intention (BI)	BI1	0.872	0.811	0.888	0.726	0.811
	BI2	0.847				
	BI3	0.837				
Use Behavior (UB)	UB1	0.922	0.884	0.928	0.812	0.884
	UB2	0.919				
	UB3	0.860				
System Quality (SQ)	SQ1	0.881	0.869	0.905	0.658	0.879
	SQ2	0.858				
	SQ3	0.815				
	SQ4	0.726				
	SQ5	0.763				
Information Quality (IQ)	IQ1	0.873	0.900	0.930	0.769	0.903
	IQ2	0.893				
	IQ3	0.849				
	IQ4	0.892				
Service Quality (SEQ)	SEQ1	0.730	0.920	0.941	0.763	0.922
	SEQ2	0.904				
	SEQ3	0.909				
	SEQ4	0.925				
	SEQ5	0.885				
System Use (SU)	SU1	0.704	0.803	0.870	0.627	0.838
	SU2	0.846				
	SU3	0.857				
	SU4	0.751				
User Satisfaction (US)	US1	0.885	0.827	0.887	0.666	0.860
	US3	0.864				
	US4	0.878				
Structure (S)	S1	0.849	0.888	0.922	0.748	0.890
	S2	0.884				
	S3	0.884				
	S4	0.842				
Environment (E)	E1	0.905	0.929	0.950	0.825	0.929
	E2	0.908				
	E3	0.919				
	E4	0.900				
Net Benefits (NB)	NB1	0.889	0.949	0.961	0.832	0.950
	NB2	0.942				
	NB3	0.937				
	NB4	0.882				
	NB5	0.910				

Table 3 presents the results of measurement model test, which includes Outer Loading, Cronbach's Alpha, rho_c, AVE, and rho_a. All outer loading values are above 0.7, indicating that the latent constructs are well measured. Similarly, Cronbach's Alpha values for all constructs exceed the 0.7 threshold, confirming good internal consistency, with the highest value in the Net Benefit construct 0.949 and the lowest in Performance Expectancy 0.728. The rho_a and rho_c values also surpass the 0.7 minimum requirement, suggesting strong and stable construct relationships. Furthermore, all AVE values are above 0.5, meaning that the latent constructs adequately explain their indicators. The highest AVE value is observed in Net Benefit construct 0.832, while the lowest is in Facilitating Conditions 0.557. Although some values are near the threshold, all remain within acceptable limits, thereby meeting the validity and reliability requirements.

Structural Model Analysis

The structural analysis consists of three stages: bootstrapping, blindfolding, and Q^2 prediction [11], [35]. The bootstrapping test was evaluated by analyzing the relationship between variables through path coefficients and t-statistic value exceeded than 1.96. An R^2 value above 0.67 indicates a strong level of accuracy in explaining the dependent variables. The model's predictive relevance is considered adequate if the Q^2 value is greater than zero, even when the value is relatively small.

Table 4. R^2 Test

Variabel	BI	UB	SU	US	S	E	NB
R^2	0.606	0.666	0.586	0.720	0.734	0.675	0.824
Adjusted R^2	0.598	0.663	0.580	0.717	0.731	0.674	0.821

Table 4 presents the results of the R-Squared test. The R^2 values of the model, ranging from 0.586 to 0.824, indicate that the independent variables explain the dependent variables at a moderate to strong level. Similarly, the Adjusted R^2 values, ranging from 0.580 to 0.821, confirm that the model demonstrates good explanatory power. In this study, an R^2 value above 0.5 is considered satisfactory in explaining user acceptance and the success of the face recognition feature [11].

Table 5. Structural Model Test

Hypotheses Path	Variables	Path Coefficients	T Statistics	Results
H1	PE → BI	0.040	0.476	Rejected
H2	EE → BI	0.003	0.034	Rejected
H3	SI → BI	0.116	1.670	Rejected
H4	FC → BI	0.031	0.492	Rejected
H5	FC → UB	0.091	1.180	Rejected
H6	HM → BI	0.167	2.498	Accepted
H7	PV → BI	0.051	0.897	Rejected
H8	H → BI	0.474	7.268	Accepted
H9	H → UB	0.043	0.532	Rejected
H10	BI → UB	0.723	15.415	Accepted
H11	SQ → SU	0.370	3.581	Accepted
H12	SQ → US	0.289	4.645	Accepted
H13	SQ → S	0.250	4.363	Accepted
H14	IQ → SU	0.068	0.817	Rejected
H15	IQ → US	0.194	3.076	Accepted
H16	IQ → S	0.285	4.173	Accepted
H17	SEQ → SU	0.150	1.696	Rejected
H18	SEQ → US	0.449	8.481	Accepted
H19	SEQ → S	0.404	7.086	Accepted
H20	US → SU	0.097	1.196	Rejected
H21	S → E	0.822	30.228	Accepted
H22	SU → NB	-0.082	-2.491	Accepted
H23	US → NB	0.206	2.750	Accepted
H24	S → NB	0.032	0.511	Rejected
H25	E → NB	0.763	14.523	Accepted
H26	UB → SU	0.194	2.786	Accepted

Table 5 shows the results of the structural model test, which consist of Path Coefficients/Original Sample and T-Statistics. A hypothesis is considered accepted if the T-statistic value exceeds 1.96. Based on the analysis, 15 hypotheses were accepted, indicating positive and significant relationships between constructs.

The accepted hypotheses include: (H6)HM has a significant positive effect on BI, (H8)H has a significant positive effect BI, (H10)BI has a significant positive effect UB, (H11)SQ has a significant positive effect SU, (H12)SQ has a significant positive effect US, (H13)SQ has a significant positive effect S, (H15)IQ has a significant positive effect US, (H16)IQ has a significant positive effect S, (H18)SEQ has a significant positive effect US, (H19)SEQ has a significant positive effect S, (H21)S has a significant positive effect E, (H22)SU has a significant positive effect NB, (H23)US has a significant positive effect NB, (H25)E has a significant positive effect NB, and (H26)UB has a significant positive effect SU. These findings confirm that the relationships between constructs in the research model are statistically significant and align with the theoretical expectations.

The PLS-SEM model was further tested for predictive capability using error metrics, namely Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), for latent indicators. The results showed that the highest RMSE value was found in the SU1 indicator 0.93, while the lowest was in the NB4 indicator 0.371. A smaller RMSE value, closer to 0, indicates higher prediction accuracy of the model. Similarly, MAE results showed the SU1 indicator with the highest value 0.683 and the NB4 indicator with the lowest value. MAE value below 0.35 suggests a very small difference between the average actual and predicted values, which reflects good predictive accuracy.

Evaluation Model

The evaluation of the integrated research model is presented in the results model panel tab. In this display, each construct is represented by its indicators, which are interconnected through directional arrows. These arrows are accompanied by path coefficient values that illustrate the strength and direction of the relationships between variables. The overall evaluation model is shown in Figure 6.

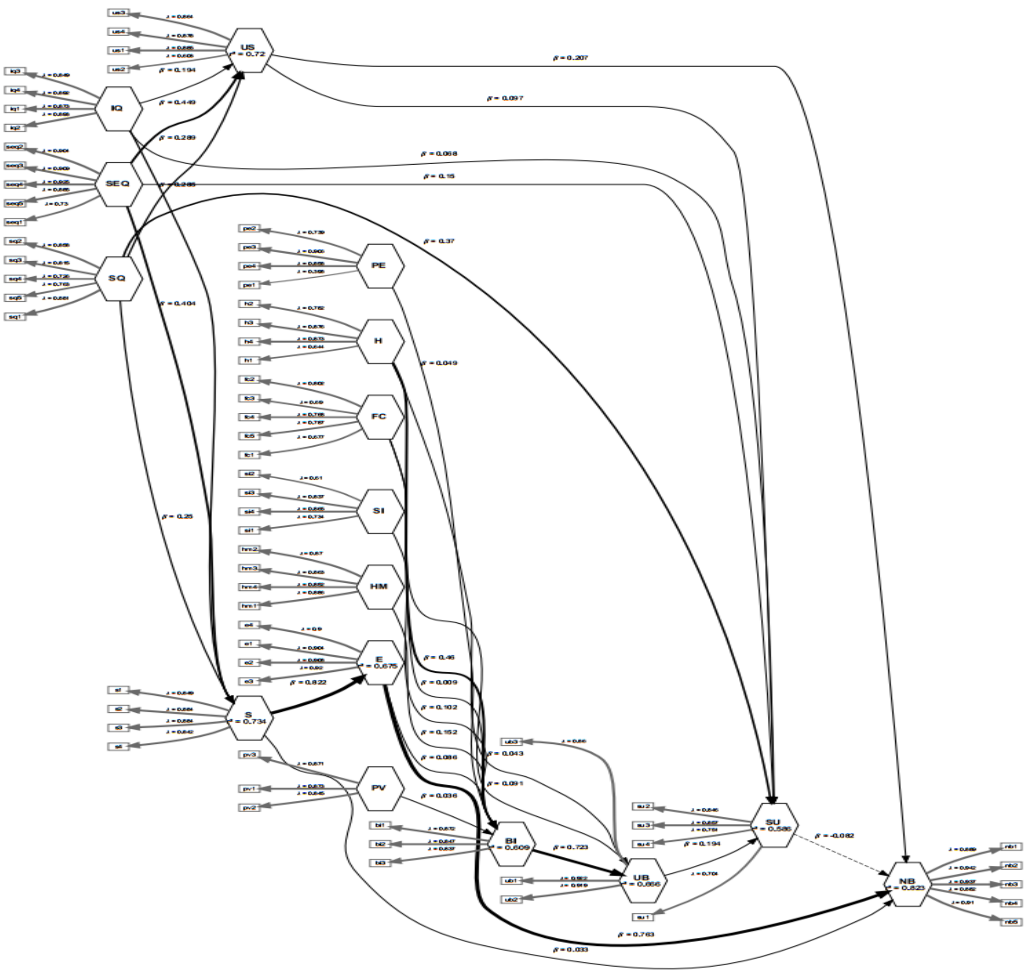


Figure 6. Evaluation Model

Model Results and Recommendations

The analysis of user acceptance and the success of face recognition feature in Computer Assisted Test was conducted using UTAUT-2 and HOT-Fit. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to examine user acceptance, technology usage, and system success. PLS-SEM is a statistical approach designed to measure and test hypotheses as well as the relationships among variable constructs in a research model. In this study, statistical analysis was performed using R Studio tools to test the hypotheses and to illustrate the resulting model.

To facilitate hypothesis testing, a simple interactive website was developed using R Shiny dashboard. This dashboard enables statistical analysis by importing data in Comma Separated Values (CSV) format and generating results for the measurement model, structural model, and evaluation model, including values for each indicator and path. The application was built using R user interface and offline server. The statistical analysis results displayed on R Shiny Dashboard indicated that not all indicators and construct variables were accepted. Specifically, the measurement and structural model tests showed that 15 hypotheses were accepted, while 11 hypotheses were rejected.

Figure 7 presents the research model, illustrating the variables and paths of the accepted hypotheses were positive and significant. The model indicates that user acceptance and the success of the face recognition feature are influenced by user habits, hedonic motivation, behavioral intention, use behavior, feature quality, information quality, service quality, system use, user satisfaction, environment and organization strcuture, and net benefits.

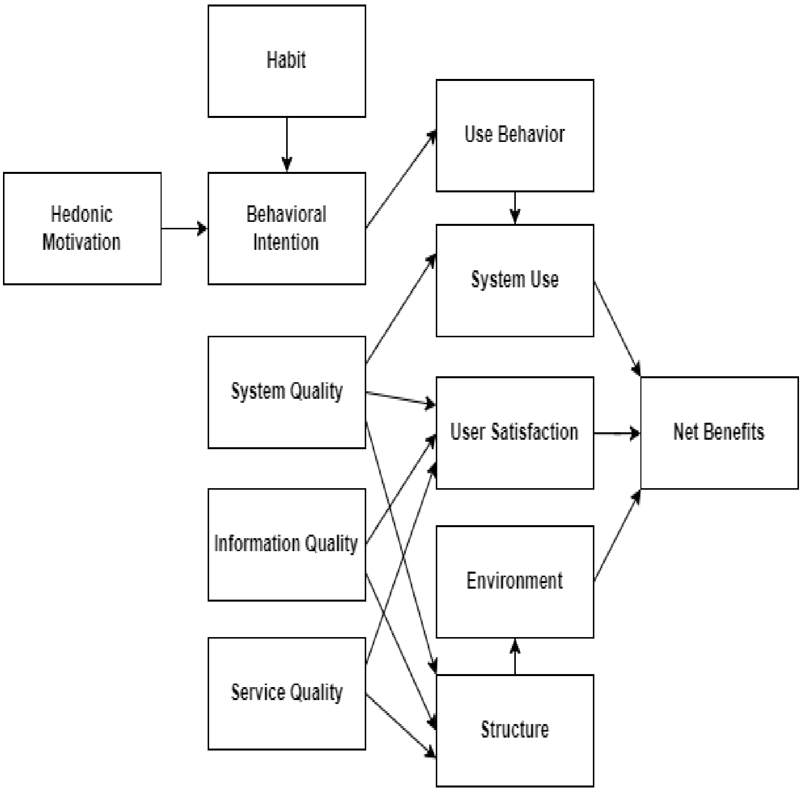


Figure 7. Research Result Model

This research, which using hybrid UTAUT-2 and HOT-Fit model analyzed via PLS-SEM, not only identified the factors influencing user acceptance and the success of the face recognition feature in the Computer Assisted Test application but also resulted in the development of an interactive website using R Shiny Dashboard. The R Shiny Dashboard created in this study offers a convenient platform for conducting PLS-SEM analyses in future research and can be adapted or customized to meet specific research needs.

Furthermore, this research successfully identified variables influencing acceptance and success of feature in Computer Assisted Test application. The findings revealed 12 positive variables that significantly influenced the use and success of the face recognition feature. Through these variables, it was revealed that user habit and hedonic motivation had a positive and significant influence on feature use. The quality of system information and services provided by the examination team influenced user satisfaction in accessing the face recognition feature during registration and accessing examination page. Ease of use and user satisfaction in accessing face recognition feature in Computer Assisted Test selection process benefited by increasing security and transparency of selection process. This research is expected to further contribute to the adoption and evaluation of information systems, as well as provide recommendations for improvements in digital technology in public service sector. Table 6 summarizes the study's findings, supported hypotheses, and the alignments with previous studies.

Table 6. Summary of Findings and Related Literature

Hypothesis	Findings	Previous Research
H6: HM→ BI	Hedonic motivation has a positive and significant effect on behavioral intention; enjoyment and satisfaction increase intention to use feature.	[4], [24]
H8: H → BI	Habit has a positive and significant effect on behavioral intention; users who are accustomed to face recognition adopt the feature more easily.	[4], [24]
H10: BI → UB	Behavioral intention has a positive and significant effect on use behavior; stronger intention encourages actual use.	[4], [24]
H11: SQ → SU	System quality has a positive and significant effect on system use; a fast, stable, and user-friendly system increases usage.	[26], [27]
H12: SQ → US	System quality has a positive and significant effect on user satisfaction; higher system quality leads to greater satisfaction.	[26], [28]
H13: SQ → S	System quality has a positive and significant effect on organizational structure; high-quality systems support organizational coordination.	[15]
H15: IQ → US	Information quality has a positive and significant effect on user satisfaction; accurate information improves satisfaction.	[26], [27]
H16: IQ → S	Information quality has a positive and significant effect on organizational structure; coordination is strengthened through high-quality information.	[29]
H18: SQ → US	Service quality has a positive and significant effect on user satisfaction; fast and responsive services enhance the user experience.	[27], [28]
H19: SQ → S	Service quality has a positive and significant effect on organizational structure; better services strengthen organizational capacity.	[29]
H21: S → E	Organizational structure has a positive and significant effect on organizational environment; an effective structure creates a supportive environment.	[15]
H22: SU → NB	System use has a negative significant effect on net benefit; high usage reduces net benefit due to technical issues.	[5], [15], [18]
H23: US → NB	User satisfaction has a positive and significant effect on net benefit; satisfied users perceive the system as more beneficial.	[18]
H25: E → NB	Organizational environment has a positive and significant effect on net benefit; external support enhances transparency and effectiveness.	[15]
H26: UB → SU	Use behavior has a positive and significant effect on system use; previous experience facilitates system utilization.	[30]

CONCLUSION

The research developed a hybrid model combining UTAUT-2 and HOT-Fit to analyze factors influencing user acceptance and evaluation of face recognition feature in Computer Assisted Test, using PLS-SEM statistical analysis method within development of an R Shiny Dashboard. A total of 337 respondents participated in the study through online questionnaires distributed through social media platforms. The findings indicate that behavioral intention and use behavior are influenced by hedonic motivation, habit, and system use, while user satisfaction is determined by system quality, service quality, information quality, system use, and organizational structural environment. The implementation of face recognition feature provides benefits such as transparency, improved public services, and enhanced security in the selection process. The findings revealed that 15 hypotheses were accepted and 11 were rejected, out of 26 hypotheses. The limitation of this study lies in its respondents being restricted to the regional office VII of National Civil Service Agency and relying solely on quantitative data collection. Future research with a similar focus is expected to involve more diverse and larger samples across different regions, include additional variables to enrich user satisfaction and system evaluation factors, and employ complementary data collection methods such as interviews.

ACKNOWLEDGMENT
The authors would like to extend my sincere gratitude to the Lembaga Pengelola Dana Pendidikan (LPDP) of the Ministry of Finance of the Republic of Indonesia for their invaluable support in funding this research.

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