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Unfolding factors affecting e-learning services: Gender perspectives

Factores en desarrollo que afectan los servicios de aprendizaje electrónico: Perspectivas de género

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Abstract

Esta investigación investigó las variables que afectan la intención de utilizar servicios de aprendizaje electrónico en las universidades abiertas de Indonesia (IOU). Modificamos el modelo de aceptación de tecnología con seis variables: normas subjetivas, facilidad de uso percibida, utilidad, actitudes e intención de uso; Se compararon los datos de los encuestados masculinos y femeninos para comprender el análisis del modelo estructural. Inicialmente, hicimos una prueba piloto del cuestionario para evaluar la confiabilidad de los datos. Los datos principales se obtuvieron de 419 hombres y 782 mujeres encuestados. Utilizamos modelos de ecuaciones estructurales de mínimos cuadrados parciales (PLS-SEM) para el análisis de datos. Los hallazgos informan que existe una ligera diferencia en los resultados del análisis de ruta estadística entre hombres y mujeres encuestados, en el que se rechazaron dos hipótesis de los datos de los hombres encuestados. Mientras tanto, todas las hipótesis fueron confirmadas a partir de datos femeninos. La actitud es el factor que más influye en la intención de utilizar los servicios de aprendizaje electrónico percibido por los estudiantes tanto hombres como mujeres. Los hallazgos benefician a las partes interesadas en la implementación de políticas relativas al uso de la tecnología en línea en la educación.

Keywords: e-learning, gender, online learning, path analysis, TAM

Resumen

This research investigated variables affecting the intention to use e-learning services in Indonesian open universities (IOU). We modified the technology acceptance model with six variables: subjective norms, perceived ease of use, usefulness, attitudes, and intention to use; the data from male and female respondents were compared to understand the analysis of the structural model. Initially, we piloted the questionnaire to assess the data's reliability. Main data were obtained from 419 male and 782 female respondents. We utilized partial least square structural equation modeling (PLS-SEM) for the data analysis. Findings inform that there is a slight difference in the statistical path analysis results between male and female respondents, in which two hypotheses were rejected from male respondents' data. Meanwhile, all hypotheses were confirmed from female data. In general, attitude is the strongest factor affecting intention to use e-learning services perceived by male and female students. The findings benefit stakeholders in implementing the policies regarding online technology use in education.

***Palabras clave**: e-learning, género, aprendizaje en línea, análisis de ruta, TAM*

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1. INTRODUCTION

The Internet, which includes cross-platform apps, benefits the educational sector. Electronic learning (e-learning), as part of Internet advancement, facilitates learning chances for students worldwide. E-learning applications like Duolingo, Google Classroom, Khan Academy, and EdX can offer knowledge and instruction sharing through computers and smartphones via the Internet. Within e-learning, teachers can improve students' participation, curiosity, and simulation through experiential e-learning (Elshareif & Mohamed, 2021; Şahin et al., 2022). The systems benefit users by facilitating effective and efficient communication and collaboration. Google Classroom, for instance, can streamline assignments, boost collaboration, and foster communication on the website and mobile applications. Google Classroom is linked to many tools, such as Gmail, Google Docs, and Google Calendar, easing users in teaching and learning activities.

To improve the quality use of e-learning, perceptions of users on factors affecting the use and intention are important (Baby & Kannammal, 2020; Balaman & Baş, 2023; Mailizar et al., 2021; Tawafak et al., 2023). Limited research investigated determinants of students' behavioral intention to use e-learning in the setting of open universities (Jovanka et al., 2023; Kuliya & Usman, 2021; Madhubhashini, 2021). In addition, fewer studies reported demographic data as a basis for investigating e-learning. Regarding the limitations, the current work hypothesizes relationships among factors based on the technology acceptance model (TAM) to understand factors affecting IOU male and female students' intention to use e-learning services that include digital library, online tutorial, dry lab, self-training portal, and Indonesia cyber education (ICE) institute.

IOU and e-learning services

Every advancement in technology catalyzes the progression of online learning. With the advent of radio and television, the dissemination of knowledge was revolutionized, broadcasting educational content to a broader audience. However, these media primarily facilitated a unidirectional flow of information, lacking the interactive essence of contemporary education. The pivotal transformation occurred with the emergence of the internet and digital technologies (Zhang et al., 2022). This fusion of educational methodologies with technological innovations gave rise to the e-learning sector, which has become an integral component of the educational fabric. Online platforms, virtual learning environments, and digital resources now offer learners a dynamic and adaptable educational space tailored to individual learning styles and speeds (Eynon & Malmberg, 2021). The widespread availability of high-speed internet and mobile technology has further expanded access to education, enabling learners to engage with educational content anytime, anywhere, thereby making higher education more accessible and adaptable to a diverse student population, including working adults, caregivers, and those with disabilities who may find traditional classroom attendance challenging.

Open universities have used distance learning for a long time and have grown and changed. In the early period, education was delivered through mail, radio, and TV broadcasts. In the subsequent time, it was through teleconferences. Currently of technology, the Internet is a very popular and useful resource for open universities. For the IOU context where this research was conducted, technology development must be followed by improvements in e-learning services

(Jovanka et al., 2023). Five e-learning services are facilitated in IOU: digital library, online tutorial, dry labs, self-learning portal, and ICE institute (Table 1).

Table 1

Service and facility

Services	Facility
Digital library https://www.pustaka.ut.ac.id/lib/	The library includes Books and articles on many topics, especially those related to the study plans. It has over 33,000 titles, including books, magazines, modules, documents, reports, and theses, print and digital formats. Archived audio and video files are also kept in the digital library
Online tutorial https://elearning.ut.ac.id/	Online tutorial adds platforms for users to facilitate learning for online activities, e-learning, and educational materials. It operates as a self-directed service that efficiently gathers and distributes educational materials.
Dry labs https://www.ut.ac.id/tags/dry-lab/	Dry labs enable the completion of practicum by utilizing mobile and computers for simulation purposes. Self-learning initiatives and motivation are supported by a web learning facility accessible.
Self-learning portal https://lm.ut.ac.id/	Self-learning initiatives and motivation are supported by a web-based training facility accessible
ICE http://icei.ac.id/tracks/about.	ICE Institute offers extensive online providers across Indonesia, guaranteeing the integrity of distance education and online learning services. Individuals can select appropriate training via the ICE.

Technology acceptance model (TAM)

TAM has drawn a lot of criticism, leading its initial proponents to make several attempts at reinterpreting it. The questionable value, poor explanatory and predictive capacity, triviality, and lack of usefulness in real-world situations have all been critiqued (Shachak et al., 2019). Although TAM has created the appearance of progress in knowledge acquisition and diverted attention from other important research questions, individual efforts to expand TAM to account for constantly changing technological environments have led to theoretical uncertainty and disarray. TAM is a useful paradigm based on several studies on the elements influencing the intention to use technology in education. Extensive research on TAM in 2023 shows that TAM is still one of the important frameworks in academia (Al-Adwan et al., 2023; Alsyouf et al., 2023; Chen et al., 2023; Muflih, 2023; Thomas-Francois & Somogyi, 2023; C. Wang et al., 2023). This research used the seminal TAM model within the variables of perceived ease of use, perceived usefulness, attitudes, intention to use, and subjective norm as an extended factor.

Perceived Ease of Use (PEoU), Perceived Usefulness (PU), and Attitudes (AT)

PEoU is the level to which people believe that the use of a certain system will be effort-free. Academically, PEoU hypothetically gets a strong bond with PU, AT, and IU. Some research has reported that PEoU is significantly linked with PU and AT (Chen et al., 2023; Hanham et al., 2021; He et al., 2023; C. Wang et al., 2023; Zardari et al., 2021). Baber (2021b) explored PEoU's role in affecting students' intention to use (IU) technology (Mutambara & Bayaga, 2021) and emphasized the significant role of PEoU in predicting PU and AT regarding m-learning application in science technology, engineering, and math education. Sukendro et al. (2020)

reported the same result that PEoU was a significant predictor of PU and AT. On the other hand, Hanham et al. (2021) PEoU was correlated to PU. Three hypotheses (H1, H2, and H3) are listed within the role of PEoU in affecting PU, AT, and IU as perceived by male and female IOU students.

H1: PEoU is a significant predictor of PU.
H2: PEoU significantly determines AT.
H3: PEoU significantly affects IU.

PU is the degree to which people believe using a certain system would improve their job performance (Davis, 1989). In the current study, PU is hypothesized to play important roles in predicting AT (H4) and IU (H5) IOT e-learning services perceived by male and female students. Prior studies inform that PU in educational settings produces impactful roles in determining technology use in teaching and learning activities (Al-Adwan et al., 2023; He et al., 2023; Mutambara & Bayaga, 2021; Tawafak et al., 2023). For example, Mutambara and Bayaga (2021), who investigated e-learning among students in rural areas, reported that both AT and IU were affected by PU.

H4: PU is a significant determinant of AT.
H5: PU significantly affects IU.

AT is defined as users' behavior on the use of a system (Davis, 1989). Within the original TAM, AT is hypothesized to influence IU. In this study, AT toward IOU e-learning services use perceived by male and female students is hypothesized to affect IU (H6). Some research has explored the relationship between AT and IU (Alsyouf et al., 2023; Chen et al., 2023; He et al., 2023; Muflih, 2023; Rizun & Strzelecki, 2020; Sukendro et al., 2020; Syahruddin et al., 2021; C. Wang et al., 2023). For example, Rizun and Strzelecki (2020) investigated whether AT significantly influenced IU of distance learning; the samples were obtained from Polish students at Katowice University, School of Education. Further, Syahruddin et al. (2021) and Sukendro et al. (2020) reported the significant impact of AT on IU in sport education of two Indonesian provinces, South Sulawesi and Jambi, respectively. Therefore, one hypothesis was proposed regarding the role of AT on IU.

H6: AT is a significant predictor of IU.

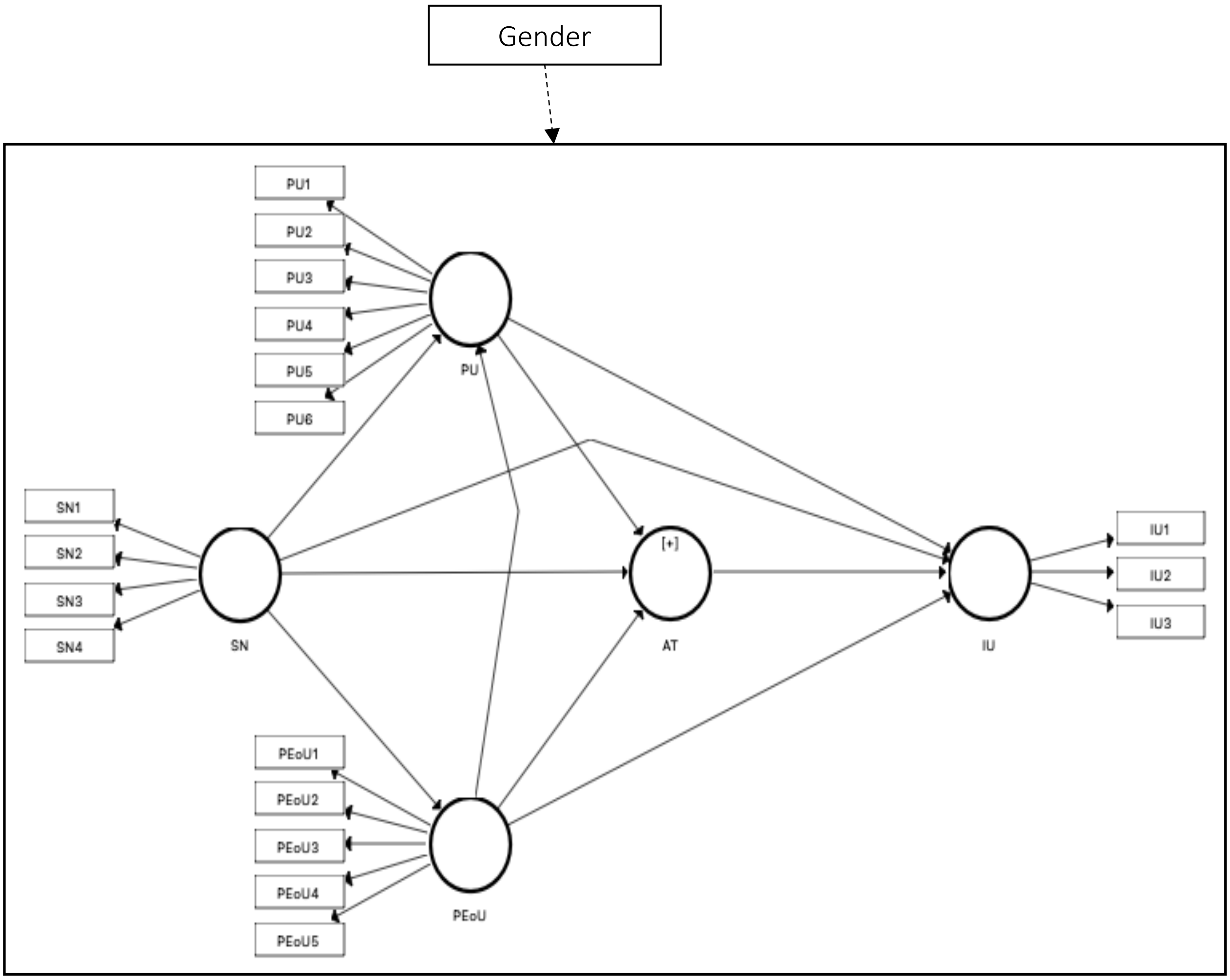
Subjective Norms (SN) as an External Variable

SN believes that an important person or group will approve and encourage a particular behavior. SN is the perceived social pressure from others for an individual to behave in a certain manner and their motivation to comply with those people's views (Ajzen, 1991). The SN in this study is an IOU male and female user whose beliefs and perspectives regarding people close to them would motivate the use of e-learning services. The reports of previous research encouraged that SN possessed a robust relationship with PEoU, PU, and IU, which resulted in the important role of SN on the three variables of TAM (Kumar et al., 2020; Pannen et al., 2023; Rejón-Guardia et al., 2020; Rokhmawati & Nugraha, 2021). Three hypothetical statements (H7, H8, H9) were included regarding the important role of SN on PU, PEoU, and IU.

H7: SN will be significant in affecting PU.
H8: SN will significantly predict PEoU.
H9: SN will significantly influence IU.

Figure 1

Proposed model



2. METHODS

A survey in this research was used to get information for a wide range of opinions and data that can be used in other situations (Dong et al., 2020; Wang et al., 2023). Quantitative data for statistical analysis is a proper option to protect privacy and identity. Previous research aids in defining and analyzing concepts and ideas related to the ground theory basis and indicators used in the current instrumentation procedure. The tool was developed to meet the goals of the study. In this study, a customized questionnaire was used to evaluate the factors that influence IOU male and female students' behavioral intention to use the digital library, online tutorial, dry lab, self-training portal, and ICE institute (Jovanka et al., 2023; Rizun & Strzelecki, 2020; Venkatesh et al., 2008). In the initial process, we listed 22 indicators for content validity with educational experts (Habibi et al., 2020) to validate the indicators for the suitability of the survey. After the discussion, seven indicators were revised, and one (SN5) was dropped.

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2.1. Data collection

We piloted the indicators to assess their reliability through the test of Cronbach's alpha in the statistical program for social science (Teresi et al., 2022). All variables were reliable, with all alpha values of more than .700. The final indicators were distributed through Google Form within quota sampling as a non-probability technique and selection of a predefined response (Iliyasu & Etikan, 2021; Zhang et al., 2020). We predefined the samples of > 1000 responses since the survey was sent to more than 1000 students' emails aided by IOU staff. In total, responses were gathered from 1021 students of IOU students. 419 male respondents filled in the survey, spread between 305 students from cities and 114 from village areas. Meanwhile, female respondents almost doubled the number (n.782), with ages ranging from <20 years old (n. 141) to >23 years old (n.498). Table 1 displays a comprehensive compilation of the respondents' demography.

Table 1

Demographic information

	Male (n. 419)			Female (n. 782)		
	Type	n	%	Type	n	%
Location	Cities	305	72.79	Cities	528	67.52
	Villages	114	27.21	Villages	254	32.48
Age	<20	65	15.51	18-20	141	18.03
	20-23	80	19.09	20-23	143	18.29
	>23	266	63.48	>23	498	63.68
Semester	1	172	41.05	1	282	36.06
	2	53	12.65	2	71	9.08
	3	70	16.71	3	102	13.04
	>4	124	25.59	>4	327	41.82

3. DATA ANALYSIS AND FINDINGS

3.1. Measurement model

Every factor, which consisted of univariate data, had a normal distribution. The skewness and kurtosis values were between -2 and +2. The skewness of the data from this study is from -.985 to -.101, whereas the range of kurtosis values is between -.253 and .665. The measurement model was calculated when the data had a normal distribution (Singh & Masuku, 2014; Xiao & Hau, 2023). The values of loadings should be >.500, Cronbach's alpha, Rho_A, Composite reliability (CR) (>.700) for the reliability. Average variance extraction or AVE values must exceed .500 for discriminant validity (Habibi et al., 2022, 2023; Ogbeibu et al., 2021).

For male respondents, the lowest loading is SN1 (.869), while the most robust is IU2 (.964). Cronbach's alpha (α) perceived by male students ranged from .868 to .959, and Rho_A values from .880 (AT) to .959 (PU), resulting in good loading values. CR values were between .918 (AT) and .972 (IU). AVE values were higher than .500 between .891 (AT) and .963 (IU). The least robust loading for female respondents is AT3, with a value of .819, while the greatest loading is IU2, with a value of .950. The female students' perceived values of α ranged from .820 to .951, while the Rho_A values ranged from .789 (AT) to .920 (IU). Similarly, the CR values ranged from .891(AT) to .963 (IU). The AVE values ranged from .731 (AT) to .896 (IU), higher than .500. Figure 2 extends the loading values of the data, while Table 2 explores the complete computation of the reliability test of the proposed model.

Table 2

Reliability test

	Male				Female			
Variable	Alpha	rho_A	CR	AVE	Alpha	rho_A	CR	AVE
AT	0.868	0.880	0.918	0.789	0.820	0.853	0.891	0.731
IU	0.956	0.956	0.972	0.920	0.942	0.942	0.963	0.896
PEoU	0.942	0.944	0.955	0.811	0.938	0.940	0.953	0.802
PU	0.959	0.959	0.967	0.829	0.951	0.952	0.961	0.805
SN	0.927	0.929	0.948	0.821	0.923	0.924	0.946	0.813

Table 3 displays data utilizing the HTMT (Heterotrait-Monotrait) ratio approach. This approach is commonly employed in statistics and research to evaluate the soundness of constructs in a model (Becker et al., 2023; Hair et al., 2022). The table compares different variables, including AT, IU, PEoU, PU, and SN, between male and female groups. Each characteristic is associated with distinct HTMT ratio values for both genders. These values represent the extent of similarity or dissimilarity between conceptions, which is essential for comprehending the discriminant validity in the dataset. The data presented. For example, IU to AT has the HTMT ratio for males of 0.840, whilst females have a slightly lower value of 0.784. This indicates a greater resemblance between constructs among males compared to females. The HTMT for PEoU of males is 0.779 with IU and 0.770 with PU. The figures for females are 0.794 and 0.761, respectively. This suggests a comparable level of discriminant validity amongst different genders. Perceived Usefulness (PU) is measured by three ratios for males: 0.785 with IU, 0.756 with PEoU, and 0.893 with SN. The results for females are 0.769, 0.736, and 0.885, respectively, indicating a consistent trend that aligns with the male statistics. In general, HTMT results suggest a little lower similarity between constructs in females than in males. The HTMT ratios indicate a consistently high level of discriminant validity among the constructs, with slight differences observed between male and female groups.

Table 3

HTMT (Heterotrait-Monotrait)

Variable	Male					Female			
	AT	IU	PEoU	PU		AT	IU	PEoU	PU
IU	0.840				IU	0.784			
PEoU	0.779	0.770			PEoU	0.794	0.761		
PU	0.785	0.756	0.893		PU	0.769	0.736	0.885	
SN	0.866	0.793	0.849	0.821	SN	0.851	0.773	0.801	0.775

The cross-loading data obtained from the PLS-SEM study indicates that each indicator demonstrates a strong association with its respective construct, as evidenced by high loadings. Additionally, the indicators exhibit good discriminant validity for both genders. As an illustration, AT1 exhibits the highest level of influence on AT (0.887 for males, 0.874 for females), suggesting that it is a reliable indicator of Attitude for both genders. Similarly, IU1 exhibits a high level of Intention to Use, with loadings of 0.961 for males and 0.948 for females. PEoU measure, namely PEoU1, exhibits strong loadings of 0.859 for males and 0.873 for females. The Perceived Usefulness (PU1) score is significantly higher for males (0.908) compared to females (0.865). Lastly, the SN1 factor, which is believed to assess Social Norms, exhibits consistently high loadings for both males (0.869) and females (0.881). The observed patterns demonstrate that each construct is effectively represented by its indicators, with consistent perceptions throughout genders. This indicates that the constructs are globally relevant and similarly comprehended by both males and females in the setting of the study.

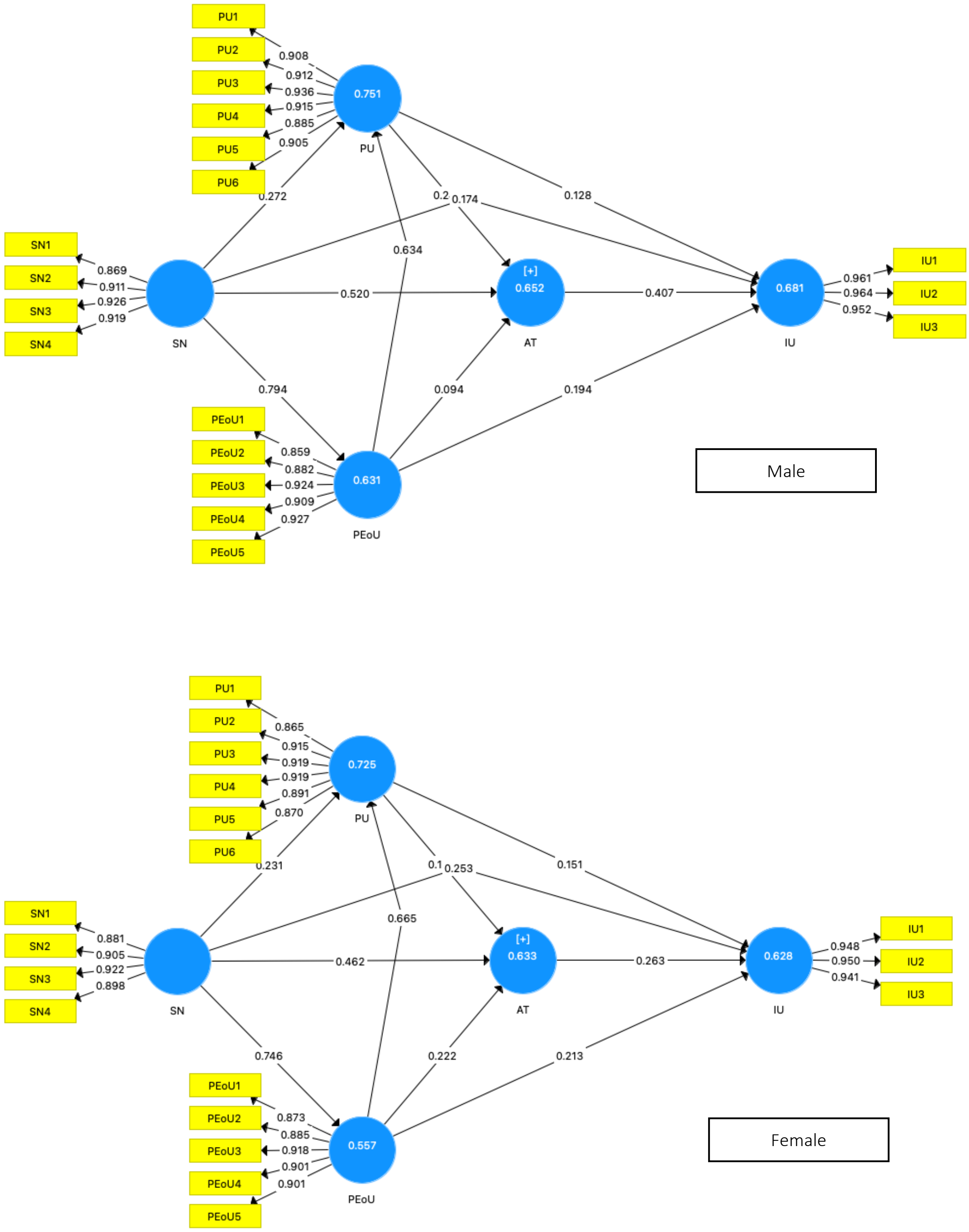
Table 4

Loading and cross-load

	Male					Female				
	AT	IU	PEoU	PU	SN	AT	IU	PEoU	PU	SN
AT1	0.887	0.797	0.728	0.746	0.763	0.874	0.754	0.725	0.724	0.749
AT2	0.901	0.623	0.591	0.599	0.676	0.872	0.549	0.569	0.538	0.613
AT3	0.878	0.621	0.563	0.569	0.633	0.819	0.470	0.500	0.488	0.543
IU1	0.749	0.961	0.697	0.688	0.715	0.653	0.948	0.665	0.634	0.674
IU2	0.752	0.964	0.696	0.695	0.729	0.705	0.950	0.686	0.678	0.699
IU3	0.730	0.952	0.714	0.701	0.705	0.664	0.941	0.683	0.668	0.674
PEoU1	0.613	0.584	0.859	0.677	0.660	0.585	0.595	0.873	0.675	0.628
PEoU2	0.678	0.647	0.882	0.802	0.730	0.668	0.638	0.885	0.741	0.664
PEoU3	0.680	0.697	0.924	0.796	0.750	0.662	0.650	0.918	0.781	0.684
PEoU4	0.586	0.654	0.909	0.771	0.687	0.646	0.660	0.901	0.775	0.677
PEoU5	0.657	0.707	0.927	0.774	0.743	0.642	0.664	0.901	0.772	0.686
PU1	0.628	0.622	0.761	0.908	0.661	0.593	0.603	0.728	0.865	0.629
PU2	0.620	0.651	0.769	0.912	0.675	0.647	0.661	0.756	0.915	0.662
PU3	0.649	0.663	0.787	0.936	0.718	0.622	0.622	0.751	0.919	0.650
PU4	0.647	0.659	0.770	0.915	0.695	0.657	0.628	0.760	0.919	0.663
PU5	0.683	0.651	0.776	0.885	0.728	0.619	0.600	0.757	0.891	0.627
PU6	0.737	0.705	0.779	0.905	0.754	0.625	0.638	0.753	0.870	0.680
SN1	0.686	0.666	0.709	0.670	0.869	0.686	0.654	0.694	0.671	0.881
SN2	0.686	0.657	0.693	0.672	0.911	0.674	0.638	0.656	0.640	0.905
SN3	0.721	0.700	0.736	0.726	0.926	0.705	0.654	0.682	0.672	0.922
SN4	0.747	0.683	0.740	0.742	0.919	0.665	0.654	0.659	0.639	0.898

Figure 2

Measurement model of male and female participants



3.2. Structural model

Before presenting the structural model of the study, we developed the model foot to enhance the clarity of the suggested model evaluation (Hu & Bentler, 1998; Schuberth et al., 2022). This study established three criteria for evaluating ft indices: standardized root means square residual (SRMR), d_ULS, and d_G. The SRMR was primarily employed to assess the model's fit by quantifying the discrepancy between the observed connection and the model's correlation matrix. The quantitative indicator assesses the degree to which a model accurately fits the data by calculating the average magnitude of the differences between observed and expected correlations. The SRMR cutoff is below 0.08. The criteria d_ULS and d_G were utilized as additional benchmarks for the ft evaluation; no specific thresholds exist for d_ULS and d_G. Table 4 displays the adequate measurement data for the model feet, including an SRMR of 0.062, d_ULS of 0.985, and d_G of 0.396.

Table 5

Model fit

	Male Saturated Model	Female Saturated Model
SRMR	0.049	0.052
d_ULS	0.557	0.615
d_G	0.382	0.314
Chi-Square	950.114	1476.937
NFI	0.908	0.914

The path coefficients in the structural model outlined in Table 6 unveil intriguing disparities across genders. When comparing the significant relationship between AT and IU, males exhibit a coefficient of 0.407, greater than 0.263 observed in females. The path from PEoU AT has a much greater influence on females (0.222) with strong relationships of p-value less than .001 than on males (0.094), showing insignificant correlations with a p-value of .094. The index of PEoU is somewhat higher for females (0.213) than males (0.194), indicating significant relationships. However, the index of PEoU to PU is practically similar, with 0.634 for males and 0.665 for females, showing robust roles of the determinants to the dependent variables. The PU to AT path coefficient for males is 0.244 (significant), but the PU to IU coefficient is 0.128 (insignificant). The corresponding ratios for females are significant, showing values of 0.178 (PU ->AT) and 0.151 (PU -> IU), respectively. The association between SN and AT is stronger for males (0.520; $p < .001$) compared to females (0.462; $p < .001$), whereas the link between SN and IU exhibits an opposite pattern, with higher values for females (0.253) than males (0.174). The SN -> PEoU is marginally greater for males (0.794) than for females (0.746). Similarly, SN -> PU follows a comparable trend, with males at 0.272 and females at 0.231. The coefficients in the model capture the subtle ways in which gender impacts the interactions between variables. Table 6 and Figure 3 present the results of the assessment. Of significant level within the current work.

Table 6

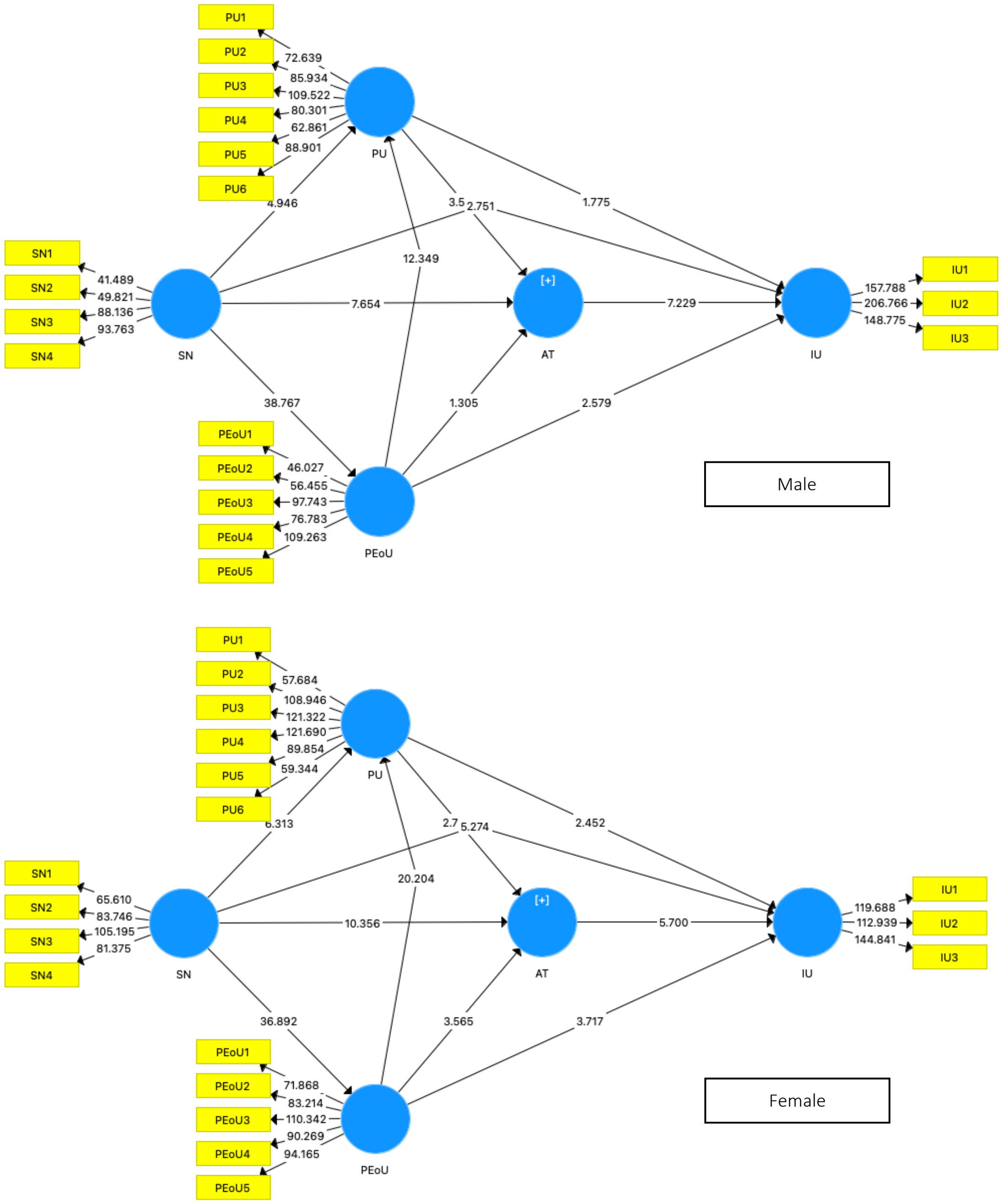
Significance level

Path	Male Path	 T value	 P values	Female Path	 T value	 P values
AT -> IU	0.407	7.229	0.000	0.263	5.700	0.000
PEoU -> AT	0.094	1.305	0.192	0.222	3.565	0.000
PEoU -> IU	0.194	2.579	0.010	0.213	3.717	0.000
PEoU -> PU	0.634	12.349	0.000	0.665	20.204	0.000
PU -> AT	0.244	3.561	0.000	0.178	2.708	0.007
PU -> IU	0.128	1.775	0.076	0.151	2.452	0.014

	Male			Female		
Path	Path	T value	P values	Path	T value	P values
SN -> AT	0.520	7.654	0.000	0.462	10.356	0.000
SN -> IU	0.174	2.751	0.006	0.253	5.274	0.000
SN -> PEoU	0.794	38.767	0.000	0.746	36.892	0.000
SN -> PU	0.272	4.946	0.000	0.231	6.313	0.000

Figure 3

Final model of the study



4. DISCUSSION

The proposed model in this study utilizes an extended technology acceptance model (TAM) to effectively explain the intention of Indonesian Open University students to use e-learning services. The assessment was achieved through rigorous content validity and measurement model processes. Additionally, comparable validation procedures were conducted, yielding a valid and trustworthy model for each study (Fornell & Larcker, 1981; Jarvis et al., 2003; Scherer et al., 2017). The present study centers around a program that aims to optimize research on the relevant subject of study inside a single institution, the Indonesian Open University. Future researchers are anticipated to utilize this study's trustworthy and dependable data to research in different contexts and settings. Accurate and dependable data greatly enhance academic research, particularly in the survey methodology and PLS-SEM as a statistical analysis technique.

The distinct path coefficients are revealed in our structural model (Table 6). The illustration in Figure 3 highlights subtle gender differences in the acceptance and utilization of e-learning services among male and female students. These differences emphasize variations in behavior and beliefs among genders and can offer valuable insights for customizing technology and marketing strategies. The correlation between attitude (AT) and intention to use (IU) is larger among males, indicating that enhancing their view of technology can significantly influence their plans. Conversely, the greater coefficient for perceived ease of use (PEoU) with AT among females suggests that enhancing the user-friendliness of technology is more likely to significantly influence their positive attitudes towards technology. Furthermore, the comparable impact of PEoU on perceived usefulness (PU) for both genders indicates that the ease of use continues to be a basic factor in how individuals evaluate the usefulness of technology, irrespective of gender, as previously documented in other studies. (Chen et al., 2023; Hanham et al., 2021; He et al., 2023; Wang et al., 2023; Zardari et al., 2021). However, the findings contrast with Hanham et al.'s (2021) study, which offers valuable insights for designers striving for universal appeal that can be gained from the data. The gender-specific variations in the PU to AT and IU paths, however, indicate that although males may value e-learning services' functionality more (as indicated by the significant PU to AT path coefficient), female students are more interested in the e-learning services usefulness in their intended uses (as indicated by the PU to IU path coefficient).

The strong association between social norm (SN) and AT for males indicates the significant influence of societal expectations and peer influence on their attitudes towards technology. For females, though the relationship between SN and AT is slightly weaker, the stronger link between SN and IU suggests that social factors can be more effective in the decision to use technology. The differences in the SN to PEoU and SN to PU path coefficients across genders in this study imply that while males and females are influenced by SN, the impact is slightly more reported for male students. The results present a trend where males' e-learning services use in open universities is more heavily influenced by peer acceptance; other studies in TAM also revealed similar results (Kumar et al., 2020; Pannen et al., 2023; Rejón-Guardia et al., 2020; Rokhmawati & Nugraha, 2021). For practitioners, a deep understanding of the factors specific to gender in TAM is important. Initiatives aimed at increasing the use of technology should take gender as a demographic element into consideration, with an emphasis on improving PEoU to influence AT. The evaluation will certainly encourage a more equal technology use rate among genders. Along with adding to the larger discussion about gender and technology, our results shed light on the small but important ways that gender roles play out in technological areas. In the future, researchers might investigate the cultural, economic, and psychological factors that affect how men and women react differently to technology. In this way, it would be possible to investigate the causes of these differences in more detail.

The gender disparities in the acceptance and utilization of e-learning services at Indonesian Open Universities are clarified within this study. More context, nevertheless, is needed to comprehend these differences completely. Indonesian Open Universities provide services to a wide range of students, including non-traditional ones who might have full-time jobs, live in distant places, or have family responsibilities. Students' interactions with e-learning may be influenced by gender roles in Indonesian society. Women may face subtle biases that hinder their participation and success in online learning environments, whereas men may have greater social support for pursuing education in technology subjects. We agree that further investigation into this context is necessary. Consequently, a thorough demographic analysis outlining the students' age distribution, socioeconomic position, and previous educational exposure should be a part of future research. Comprehending these characteristics can shed light on the reasons behind specific gender disparities and their expression in the online learning environments of Indonesian Open Universities.

5. CONCLUSIONS

The paths in our structural model strongly suggest that men and women have different thoughts and plans about using technology. Female students are more interested in technology that is easy to use and has practical uses. Male students, on the other hand, seem to be more affected by technology's inherent qualities, such as how useful they think it is and how it fits in with society's norms. The p-values show how strong the connections are, which stresses how true these gender-specific patterns are. Based on these results, marketers and product designers must develop gender-specific tactics. Men who use e-learning services might be more interested in practical benefits and recommendations from their peers, while women might be more interested in how easy the service is. These data show that gender is important when academics and policymakers study how people adopt new technologies, especially regarding e-learning services in an open university setting. It suggests a shift toward study designs that are more gender-inclusive and take differences in gender into account. This could lead to more fair technological solutions in the long run. This study fills in some gaps in our understanding of how men and women adopt technology differently and suggests new research areas that could improve these early results. As technology continues to spread into every part of life, it is becoming more important to understand these processes to promote a digital society that is open to everyone.

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