APTISI Transactions on Technopreneurship (ATT)
Vol. 6, No. 3, November 2024, pp. 404–417
E-ISSN: 2656-8888 | P-ISSN: 2655-8807, DOI:10.34306

Technopreneurship in Healthcare: Evaluating User Satisfaction and Trust in AI-Driven Safe Entry Stations

Untung Rahardja[1*], Po Abas Sunarya[2], Qurotul Aini[3], Shofiyul Millah[4], Sabda Maulana[5]
[1]Dept. of Engineering, Universiti Teknologi Malaysia, Malaysia
[2]Dept. of Retail Management, University of Raharja, Indonesia
[3,4,5]Dept. of Digital Business, University of Raharja, Indonesia
[1]rahardjauntung@graduate.utm.my, [2]abas@raharja.info, [3]aini@raharja.info, [4]shofiyul@raharja.info [5]sabda@raharja.info
***Corresponding Author**

Article Info

Article history:

Submission June 27, 2024
Revised August 12, 2024
Accepted September 10, 2024
Published September 13, 2024

Keywords:

Technopreneurship
Healthcare
Satisfaction
Trust
Safe Entry Stations

ABSTRACT

The development of technology in the health sector has encouraged the adoption of technopreneurship, especially in the application of artificial intelligence (AI) to support the safety and efficiency of health services. One of the innovations that has emerged is the AI-driven Safe Entry Station, which is designed to improve the safety and comfort of patients and medical personnel. However, the success of implementing this technology is highly dependent on the level of user satisfaction and trust. **This study aims** to evaluate the level of user satisfaction and trust in Safe Entry Stations in the health care environment and also explore the variables that influence the acceptance of this technology among users. **This research method** uses a quantitative approach with a survey involving 673 respondents from various health institutions that have used Safe Entry Stations. Data were analyzed using Structural Equation Modeling (SEM) with SmartPLS 4.0 software to identify the relationship between User Satisfaction (US), trust (TR), behaviour intention (BI), usage behaviour (SB) and technopreneurial impac (TI). **The results** showed that US and TR significantly influences BI and UB. Additionally, BI strongly impacts TI, suggesting that stronger intentions lead to a greater perceived impact on technopreneurship. **This study found** that AI-driven Safe Entry Stations has great potential for widespread adoption in the healthcare sector. These findings provide important insights for further development of this technology as well as technopreneurship strategies in the healthcare sector.

DOI: https://doi.org/10.34306/att.v6i3.489

1. INTRODUCTION

Technological developments have driven a revolution in various sectors, including the health sector [1]. One of the latest innovations that has received attention is the application of artificial intelligence to the Safe Entry Stations system in health facilities [2]. This technology is not only designed to improve operational efficiency, but also to strengthen the safety and comfort of patients and medical personnel. Amid the global pandemic and the need for stricter precautions, AI-driven Safe Entry Stations are a very relevant solution [3]. This technology can automatically monitor and screen individuals entering health facilities, detect body temperature, check mask use, and monitor other health conditions in a short time, so that it can significantly reduce the risk of spreading infectious diseses in highly vulnerable places such as hospitals and clinics [4].

However, although AI-driven Safe Entry Stations technology offers many benefits, there are several major **challenges** that need to be overcome regarding the acceptance of this technology by users, both patients and health workers [5]. Experience from the implementation of new technologies in the health sector shows that the application of advanced technology is often faced with psychological and social barriers from users [6]. Factors such as distrust of new technologies, concerns about data privacy, and doubts about the accuracy of the system are major barriers that can hinder the adoption of this technology [7]. This distrust is often triggered by users' lack of understanding of how the technology works or concerns about the potential risks it poses [8]. On the other hand, low user satisfaction can affect the sustainability of the use of this technology in the long term [9]. If users feel that the technology does not meet their expectations or is not reliable enough, they are likely to stop using the technology, which can ultimately hinder the achievement of the main goal of implementing the technology, namely improving the quality of health services [10].

Research on AI-driven Safe Entry Stations is still in its early stages [11]. Most of the existing literature focuses more on the technical aspects of this technology, such as the AI algorithm used, sensor accuracy, and the effectiveness of the system in detecting certain health conditions [12]. Meanwhile, research that explores the perspective of users, especially regarding their satisfaction and trust in this technology, is still very limited [13]. Factors such as user perceptions of data security, system reliability, and ease of use are often overlooked in previous studies, even though these factors have a significant influence on determining the success of adopting new technologies [14]. For example, perceptions of data security can influence the extent to which users are willing to provide their personal information to the system [15]. In addition, system reliability is also a key factor influencing user trust, where users are more likely to accept technology that is perceived to deliver consistent and reliable results [16]. Furthermore, little attention has been paid to how these variables interact with each other and influence users intention to continue using AI-driven Safe Entry Stations in the future.

Although this study attempts to address the existing **research gap**, there are several limitations that need to be considered. First, this study used a quantitative approach with a survey involving only respondents from a select few healthcare institutions. This selection of respondents may not fully reflect the broader user population across contexts and geographic regions [17]. This may affect the generalizability of the study findings, especially if there are significant differences in organizational culture, institutional policies, or local customs that influence technology acceptance [18]. Second, the data collected in this study was cross-sectional, meaning that data was only collected at a single point in time. This approach limits the study's ability to capture changes in user perceptions over time, or to identify long-term trends in the use of AI-driven Safe Entry Stations [19]. The dynamics of technology use may change over time, especially with technological updates or changes in public perceptions of AI technology. Third, this study focused more on aspects of user satisfaction and trust without considering other external factors that may play an important role, such as institutional policies, government regulations, or socio-economic conditions that may influence the adoption of this technology. These external factors can be very important, especially in the context of how this technology is implemented and accepted across different healthcare settings. **Limitations** in the data collection method also need to be considered, as survey results may be influenced by respondent bias or limitations in the interpretation of survey questions [20]. For example, respondents may provide answers that are considered most desirable rather than those that truly reflect their experiences, or they may misinterpret questions due to a lack of understanding of the technology in question. With these limitations in mind, this study aims to make a meaningful contribution to the literature by further exploring user perspectives on AI-driven Safe Entry Stations in the healthcare context. This study will not only enrich the understanding of the factors influencing the adoption of this technology but also provide practical recommendations for technology developers and policymakers in designing more effective implementation strategies in the future.

2. LITERATURE REVIEW

2.1. Artificial Intelligence in Healthcare

Artificial intelligence (AI) has become an integral component in the transformation of the healthcare sector, with applications ranging from medical diagnostics and patient management to security systems [18]. AI plays a critical role in advancing Sustainable Development Goals (SDGs) [21], which aims to "ensure healthy lives and promote well-being for all at all ages". By automating previously manual processes and improving operational efficiency, AI-driven technologies, such as Safe Entry Stations, contribute to enhancing the quality, accessibility, and safety of healthcare services. Recent studies highlight how AI has improved healthcare outcomes, particularly in response to global health crises like COVID-19, by facilitating rapid health screenings, real-time diagnostics, and contactless monitoring, directly supporting the targets under SDGs, especially those related to reducing mortality and improving healthcare system efficiency [22].

Furthermore, while AI-driven Safe Entry Stations have proven effective in detecting health conditions, current literature highlights a significant gap in understanding how these technologies impact user experience and perception. This is particularly relevant to SDGs reduced inequalities, which emphasizes the need to reduce inequality within and among countries. As AI-driven healthcare technologies become more prevalent, it is essential to ensure that they are accessible and equitable, providing the same level of care and safety to all individuals, regardless of socioeconomic status, geographic location, or technical literacy. Further research is needed to explore how AI technologies, such as Safe Entry Stations, influence user trust, acceptance, and satisfaction across diverse populations to ensure that AI does not exacerbate existing healthcare disparities. By addressing these challenges, AI in healthcare can significantly contribute to achieving the SDGs, particularly by promoting innovation, improving health outcomes, and ensuring equitable access to advanced healthcare technologies [23].

2.2. AI-driven Safe Entry Stations

AI-driven Safe Entry Stations represent a key innovation aimed at improving safety and security in healthcare environments. These systems utilize advanced AI algorithms to conduct screenings that monitor various health indicators, such as body temperature, heart rate, and respiratory conditions [24]. According to recent studies, these technologies have proven crucial in addressing the heightened healthcare needs brought about by the COVID-19 pandemic, as they enable rapid and accurate screenings necessary to mitigate the spread of infectious diseases. Comparisons between AI-driven Safe Entry Stations and traditional manual screening methods show that AI is capable of delivering faster, more consistent, and reliable results, particularly in high-traffic environments. Despite these benefits, challenges such as the need for frequent system updates, potential technical malfunctions, and concerns surrounding data privacy continue to impact user trust in these technologies. Comparisons between AI-driven Safe Entry Stations and traditional manual screening methods reveal that AI can deliver faster and more consistent results, which is particularly important in high-traffic healthcare environments where delays can lead to crowding and increased risk of disease transmission. Manual methods, while still widely used, are prone to human error, fatigue, and inconsistency, especially when conducted over long periods. In contrast, AI systems can operate continuously with the same level of accuracy, providing a more reliable solution for health screening. However, these advantages come with challenges, such as the need for regular system updates, the potential for technical malfunctions, and concerns about data privacy and security, which can all affect user trust.

2.3. User Satisfaction and Trust in Health Technology Adoption

User satisfaction is a key factor in the successful adoption of new technologies, including in the health sector [25]. Existing literature suggests that ease of use, system reliability, and perception of the benefits of the technology are key determinants of user satisfaction. In the context of health technology, several studies have evaluated user satisfaction with systems such as telemedicine and electronic medical records, but few have examined AI-driven Safe Entry Stations. The factors that influence user satisfaction with this technology need to be further explored to ensure wider and sustainable adoption [26]. User trust is a critical element influencing the adoption of AI technology, especially in sensitive sectors such as healthcare. Research shows that data security, algorithm transparency, and prediction accuracy are key factors that shape user trust in AI technology [27]. However, the existing literature has not discussed much about how this trust develops in the context of AI-driven Safe Entry Stations. Given the important role of trust in determining the success of technology adoption, there is a need for more research that on how users perceive this technology and what can be done to improve this trust.

2.4. Technopreneurship in the Healthcare Sector

Technology adoption in the healthcare sector refers to the process by which healthcare organizations, professionals, and patients begin to use new technologies to improve the quality, efficiency, and accessibility of healthcare services. This adoption process encompases a wide range of technologies, including electronic health records (EHRs), telemedicine, mobile health applications, AI, and medical devices like wearable sensors [28]. The adoption of these technologies is driven by several factors, including the potential for improved patient outcomes, enhanced operational efficiency, regulatory compliance, and cost reduction [29]. Technologies like AI-driven diagnostics, telemedicine, and EHRs contribute to better patient care, faster diagnosis, and more personalized treatment plans. Automation and digital tools streamline administrative tasks, reduce errors, and improve resource management. Regulatory bodies often mandate the use of certain technologies to ensure compliance with healthcare standards, while the long-term reduction in healthcare costs through technologies like remote monitoring also motivates adoption [30]. However, the adoption of technology in healthcare is not without challenges. High initial costs, the need for training, and usability issues can create barriers, especially for smaller providers. Concerns over data privacy and security, particularly in the face of cybersecurity threats, can slow the adoption process.

3. METHODS

This study employs a quantitative approach with a cross-sectional survey design to evaluate user satisfaction and trust in AI-driven Safe Entry Stations within healthcare facilities. The survey method was selected to directly capture user perceptions through data collection from a large sample of respondents, ensuring that a wide variety of experiences and opinions were represented [31]. However, one limitation of the cross-sectional design is that it collects data at a single point in time, which can prevent the capture of dynamic changes in user satisfaction, trust, and usage behavior over time. To mitigate this limitation, efforts were made to ensure that the sample was diverse and representative of different demographic and usage backgrounds, allowing for a broader perspective of the population. Additionally, the survey was carefully designed to capture retrospective data, where respondents were asked to reflect on their experience over time, thus offering some insight into potential changes in behavior and perceptions. Although longitudinal studies could provide deeper insights into temporal changes, the cross-sectional approach was deemed appropriate for providing a snapshot of current user attitudes, with plans for future studies to explore these dynamics over an extended period [32].

3.1. Population and Sample

The population of this study included users of AI-driven Safe Entry Stations in a range of healthcare institutions, such as hospitals, clinics, and community health centers located in urban areas. A purposive sampling method was employed, specifically selecting respondents who had direct experience using this technology. This sampling method was chosen because it allows for a more targeted approach, ensuring that the respondents are relevant to the research objectives and have firsthand experience with the technology being studied. By focusing on users who interact directly with the system, we aim to obtain more accurate and relevant insights into their perceptions of satisfaction, trust, and usage behavior. The purposive sampling method also allows for better control over sample characteristics, improving the relevance of the results to the study's context.

The sample size consisted of 673 respondents, which was considered sufficient to yield representative results and facilitate robust statistical analysis. Data were collected using a structured questionnaire that captured demographic details such as age, gender, and education level [33]. The questionnaire employed a 5-point Likert scale, where respondents indicated their level of agreement with various statements related to user satisfaction, trust, behavioral intention, usage behavior, and technopreneurial impact [34]. Before implementation, the instrument was tested for validity and reliability to ensure accuracy. The data collection spanned three months, during which online questionnaires were distributed via email and social media platforms to ensure quick and efficient dissemination. Respondents were given two weeks to complete the questionnaires, with periodic reminders sent to encourage a higher response rate. All data were kept confidential and used exclusively for this study [32].

3.2. Hypothesis Development

Based on the outlined research model, this study carefully formulates six hypothesis Safe Entry Stations, each of which is intricately designed to explore and explain the relationships between key variables that play a significant role in the adoption and subsequent impact of technopreneurship in the context of AI-driven technologies [35]. The conceptual model, as shown in Figure 1. allows for statistical analysis of the relationships between key variables, including user satisfaction, trust, behavioral intention, usage behavior, and the technopreneurial impact of AI-driven technologies.

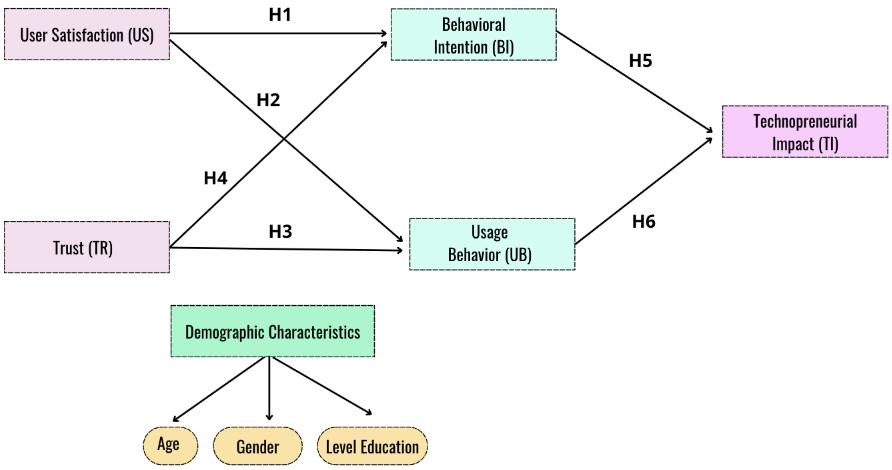

Figure 1. Research Model

- ***H1*** : User Satisfaction (US) has a positive impact on Behavioral Intention (BI).
- ***H2*** : User Satisfaction (US) has a positive impact on Usage Behavior Intention (SB).
- ***H3*** : Trust (TR) has a positive impact on Behavioral Intention (BI).
- ***H4***: Trust (TR) has a positive impact on Usage Behavior Intention (SB).
- ***H5***: Behavioral Intention (BI) has a positive impact on Technopreneurial Impact TI
- ***H6***: Usage Behavior Intention (SB). has a positive impact on Technopreneurial Impact TI

These hypothesis Safe Entry Stations are not only designed to the direct influence of one particular variable on another, but also aim to identify and highlight critical success factors in the complex process of technology adoption [36]. By systematically testing these hypothesis Safe Entry Stations, this study seeks to provide a deeper understanding of the underlying mechanisms that drive successful technopreneurship and to offer insights into how various psychological and behavioral factors interact to shape the adoption and effectiveness of new technological innovations in the healthcare sector [15].

3.3. Measurement Model

The collected data were analyzed using descriptive statistical methods to describe the distribution of respondents answers and to provide an overview of demographic characteristics and user perceptions of AI-driven Safe Entry Stations [37]. Additionally, the data were further examined using Structural Equation Modeling (SEM) with the SmartPLS 4.0 tool, chosen for its robust ability to handle complex relationships between various variables, including latent variables that cannot be measured directly but are instead represented by multiple observed indicators. Utilizing SEM with SmartPLS 4.0, this study was able to explore the intricate interactions between various factors, offering a deeper understanding of how these variables collectively contribute to the adoption of Safe Entry Stations technology [38]. This advanced modeling approach also facilitated more precise hypothesis testing by considering both direct and indirect effects of each variable, ultimately helping to identify the most significant pathways of influence that impact user decisions to adopt and continue using this innovative technology.

Measurement Model Analysis is a crucial stage in Structural Equation Modeling (SEM) which aims to assess the validity and reliability of the constructs measured in the model [39]. This analysis involves several important steps, including convergent and discriminant validity testing. Convergent validity ensures that indicators in one construct are highly correlated with each other, which is usually tested through factor loadings and Average Variance Extracted (AVE) [40]. Discriminant validity tests whether the measured construct is significantly different from other constructs in the model, which can be assessed by comparing AVE with the correlation between constructs [41]. In addition to validity, construct reliability is also evaluated using Cronbach's Alpha and Composite Reliability (CR). These two measurements ensure the internal consistency of indicators in one construct, with values above 0.7 indicating good reliability. After validity and reliability are tested, the measurement model is evaluated as a whole to ensure a good fit with the data collected. Various model fit indicators, such as R-Square, Goodness of Fit Index (GFI) are used to assess the extent to which the measurement model fits the data. By ensuring a valid and reliable measurement model, this study can be more confident that the results of the structural analysis will be accurate and reliable [42].

4. RESULT AND DISCUSSION

4.1. Demographic Profile

Descriptive analysis was conducted on 673 valid data covering gender, age and education level variables. This descriptive analysis provides an initial overview of the demographic profile of respondents, which will be used as a basis for further analysis in understanding the factors influencing user satisfaction and trust in AI-driven Safe Entry Stations.

Table 1. Examining of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	340	50.52%
	Female	333	49.48%
Age	<20 years	120	17.83%
	20 - 30 years	325	48.29%
	31 - 40 years	150	22.28%
	>40 years	78	11.6%
Education Level	High School	150	22.28%
	Bachelor's Degree	350	52%
	Master's Degree	130	19.31%
	Doctorate	43	6.39%

Based on table 1. it can be seen that the distribution of data driven on gender shows an almost balanced distribution, with 50.52% of respondents being male and 49.48% being female. This shows that this study has a fairly even gender representation, which can provide a balanced view in further analysis. In terms of age, the majority of respondents are in the 20-30 year age range, which covers 48.29% of the total respondents. This age group is likely to be the most active segment of the population in using AI-driven healthcare technology and services, making it a relevant group for this study. Respondents aged under 20 and over 40 years showed lower frequencies, at 17.83% and 11.60%, respectively. Meanwhile, the 31-40 year age group covers 22.28% of the total respondents. For education level, the majority of respondents have a Bachelor's Degree, which covers 52.00% of the total respondents. This is followed by respondents with a high school education level (22.28%), Master's degree (19.31%), and Doctoral degree (6.39%). This level of education reflects that the majority of respondents have a fairly high educational background, which may affect their perception of technology and innovation in the health sector [43].

4.2. Realibity and Validity

To ensure the reliability and validity of the constructs in table 2. several statistical indicators have been used, including Cronbach's Alpha, Composite Reliability (rho_a and rho_c), and Average Variance Extracted (AVE) [44]. The results of the analysis show that all constructs have Cronbach's Alpha values above 0.7, which indicates a good level of internal consistency. In particular, the US construct shows the highest reliability with a Cronbach's Alpha value of 0.924, while the TR construct has the lowest value of 0.832, but remains within the acceptable range.

In addition, Composite Reliability, both rho_a and rho_c, also showed strong internal consistency for all constructs with values exceeding 0.7. These results indicate that the indicators in each construct consistently measure the same concept. US again showed the highest reliability with a Composite Reliability (rho_a) value of 0.925 and a Composite Reliability (rho_c) of 0.924. On the other hand, the Average Variance Extracted (AVE) analysis indicated that most constructs had adequate ability to explain the variability of their indicators, with AVE values above 0.5. However, there was an exception in the SB construct which had an AVE value of 0.486, slightly below the threshold of 0.5 [45].

Table 2. Realibity and Validaty Testing

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
BI	0.895	0.898	0.896	0.633
TI	0.914	0.916	0.914	0.681
TR	0.832	0.851	0.836	0.512
SB	0.82	0.837	0.823	0.486
UB	0.924	0.925	0.924	0.709

This suggests that the indicators in the Usage Behavior construct may be less powerful in explaining the variability of the construct, and therefore require further attention in the analysis or interpretation of the results. Furthermore, the relatively lower AVE value for SB also highlights the need for careful interpretation in subsequent analyses. Researchers should consider that while the construct demonstrates adequate reliability, the lower convergent validity may impact the precision with which usage behavior is measured. Future studies should investigate alternative measurement approaches or consider revising the existing indicators to enhance the construct's ability to explain variability more effectively.

Overall, the results of this analysis indicate that the constructs in this study have good reliability and validity, supporting the appropriateness of the measurement model used. However, it is necessary to be aware of the explanatory power of the Usage Behavior construct, which shows a slight weakness in terms of convergent validity.

4.3. Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was used to assess the measurement model in this study and ensure that the indicators used validly and reliably measure the intended construct. In this study, the measurement model was evaluated using several criteria, including Discriminant Validity tested with the Fornell-Larcker Criterion [46].

Table 3. Discriminant Validity Tested with the Fornell-Larcker Criterion

Construct	BI	TI	TR	SB	US
BI	0.795	-	-	-	-
TI	0.939	0.825	-	-	-
TR	0.991	0.898	0.715	-	-
SB	0.959	0.93	0.697	0.842	-
US	0.913	0.873	0.856	0.842	0.709

The results presented in table 3. demonstrate that the discriminant validity of the constructs in the model has been successfully tested using the Fornell-Larcker Criterion. The diagonal values, which represent the square root of the Average Variance Extracted (AVE) for each construct, are higher than the correlation values between each construct and other constructs in the model. For example, the AVE value for Behavioral Intention (BI) is 0.795, which is greater than its correlations with TI (0.939), TR (0.991), Usage Behavior (SB) (0.959), and User Satisfaction (US) (0.913). This pattern holds for all constructs, including TI, TR, SB, and US, where their AVE values exceed the correlations with other constructs.

This result indicates that each construct in the model explains more variance in its own indicators than it shares with other constructs, which is a key indicator of good discriminant validity. Despite some high correlations between constructs, such as between BI and TR, or SB and TI, the AVE values consistently remain higher, confirming that the constructs are distinct and measure unique aspects of the model. The strong discriminant validity ensures that the constructs do not overlap significantly and can stand alone in explaining their respective indicators. Overall, the measurement model has been validated, making it suitable for further structural analysis

Fornell-Larcker Criterion table given, we can see that the diagonal (which is the square root of AVE for each construct) has a higher value compared to the correlation value between other constructs in the same row and column. For example, for the Behavioral Intention (BI) construct, the AVE value is 0.795, which is greater than the correlation with Technopreneurial Impact (TI) of 0.939 and with other constructs. This shows that each construct has good discriminant validity, namely each construct is better able to explain the variability of its own indicators compared to the variability explained by other constructs.

The results of the Confirmatory Factor Analysis (CFA) show that the measurement model in this study has strong discriminant validity, which supports the feasibility of the model for further analysis. This shows that the constructs in this model are able to stand alone and do not overlap significantly in explaining the indicators being measured.

4.4. Structural Equation Modelling (SEM)

Structural Equation Modeling (SEM) was employed study to evaluate the structural relationships between the measured constructs and test the proposed hypothesis [47]. SEM is a powerful statistical technique that allows for the examination of complex relationships between latent variables, which are variables that cannot be directly measured but are instead represented by multiple observable indicators. By using SEM, we are able to simultaneously assess multiple relationships within the research model, providing a comprehensive understanding of how different factors interact.

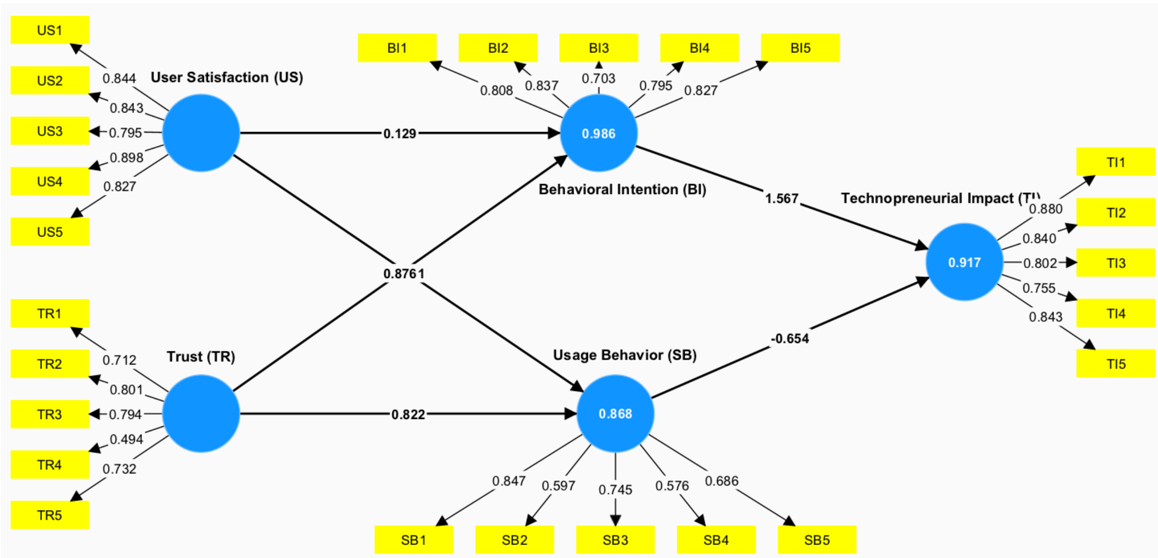

Figure 2. Visualization of PLS-SEM

In SEM, path coefficients represent the strength and direction of the relationships between variables in the model, ranging from -1 to 1. A positive path coefficient indicates a direct positive relationship, while a negative coefficient indicates an inverse relationship. The closer the coefficient is to 1 or -1, the stronger the relationship. As shown in Figure 2, the path coefficient between User Satisfaction (US) and Behavioral Intention (BI) is 0.129, indicating a small but positive relationship. This suggests that an increase in user satisfaction leads to a slight increase in the intention to use the AI-driven Safe Entry Stations. However, this effect is relatively weak compared to other relationships in the model. The path coefficient between Trust (TR) and Behavioral Intention (BI) is significantly stronger, at 0.876. This indicates that trust in the AI-driven technology plays a crucial role in shaping users behavioral intention, implying that users who trust the technology are much more likely to intend to use it. The relationship between Behavioral Intention (BI) and Technopreneurial Impact (TI) is particularly strong, with a path coefficient of 1.567. This suggests that the perceived impact of technopreneurship greatly enhances users intention to adopt the technology. It implies that the higher the perceived value and benefits of technopreneurship from AI-driven solutions, the more motivated users are to engage with the technology. Meanwhile, the path coefficient between Trust (TR) and Usage Behavior (SB) is 0.822, reflecting a strong positive influence. This highlights that users who trust the system are more likely to translate their intentions into actual usage behavior. Similarly, the coefficient between User Satisfaction (US) and Usage Behavior (SB) is 0.876, further confirming that satisfaction with the technology strongly drives actual usage. In contrast, the path between Usage Behavior (SB) and Technopreneurial Impact (TI) is negative, with a coefficient of -0.654. This inverse relationship suggests that frequent usage does not necessarily correlate with a higher perception of technopreneurial impact. This might indicate that users who are already familiar with the technology may not always perceive its broader impact as significantly as those who are newly introduced to it. Lastly, the measurement model demonstrates high levels of reliability and validity, with factor loadings ranging from 0.712 to 0.898 across the observed variables. These loadings indicate strong correlations between the observed indicators and their respective latent constructs, ensuring that the measurement model effectively captures the underlying factors in the study.

The results in the table 4. revealed that Technopreneurial Impact (TI) has a very strong positive influence on Behavioral Intention (BI), with a path coefficient of 1.567. This suggests that the more significant the perceived impact of technopreneurship, the stronger the user's intention to adopt the technology. Additionally, Behavioral Intention (BI) was found to have a strong positive effect on Trust (TR), with a path coefficient of 0.876. This indicates that a stronger intention to use the technology correlates with increased user trust in the technology.

Table 4. Path Coefficients

Construct	**BI**	**TI**	**TR**	**SB**	**US**
BI	-	1.567	-	-	-
TI	-	-	0.876	-	-
TR	-	-	-0.654		-
SB	-	-	-	–0.822	-
US	-	-	-	0.121	0.129

However, there is a fairly strong negative relationship between TR and SB, indicated by a path coefficient of -0.654. This may indicate that although users may trust the technology, this is not always directly proportional to an increase in technology use. In contrast, the relationship between BI and US is positive with a path coefficient of 0.129, although the effect is relatively weak. This shows that although the intention to use technology exists, its effect on user satisfaction is not too great. In addition, SB also has a positive influence on US with a path coefficient of 0.121. Although this effect is also weak, it shows that the use of technology can slightly increase user satisfaction. Finally, IT has a strong positive effect on US with a path coefficient of 0.822, indicating that the influence of technopreneurship directly contributes to user satisfaction.

Overall, the SEM results indicate that the proposed theoretical model is largely supported by the collected data, with some relationships showing very strong effects, while others show weaker or even negative effects. These findings provide important insights into understanding how different factors interact to influence technology adoption and use in the context of this study.

4.5. Hyphotesis Development

The results in table 5. hypothesis testing show several significant relationships in the proposed model. First, BI behavioral intention is proven to have a very significant positive effect on IT, with a coefficient of 0.760. This indicates that the stronger the user's intention to behave in accordance with the technology, the greater the perceived impact of technopreneurship. This influence is supported by the T-Statistics value of 9.071 and P-Values of 0.000, indicating high significance.

Table 5. Hyphotesis Result

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (O/STDEV)**	**P Values**
BI $\rightarrow$ TI	0.76	0.753	0.084	9.071	0.000
TR $\rightarrow$ BI	0.557	0.562	0.09	6.219	0.000
TR $\rightarrow$ SB	0.505	0.507	0.099	5.11	0.000
SB $\rightarrow$ TI	0.111	0.121	0.103	1.079	0.281
US $\rightarrow$ BI	0.39	0.385	0.093	4.183	0.000
US $\rightarrow$ SB	0.353	0.349	0.116	3.053	0.002

Furthermore, user trust in TR is also proven to have a significant effect on BI, with a coefficient of 0.557. This means that increasing trust significantly increases user intention to use technology. This result is supported by the T-Statistics of 6.219 and P-Values of 0.000, indicating the consistency and significance of this influence. In addition, TR also significantly influences SB technology usage behavior, with a coefficient of 0.505, T-Statistics of 5.110, and P-Values of 0.000. However, the influence of SB technology usage behavior on IT impact does not show high significance. With a coefficient of 0.111, T-Statistics of 1.079, and P-Values of 0.281, these results indicate that technology usage behavior does not have a significant direct influence on the impact of technopreneurship in this model. On the other hand, US shows a significant influence on BI and SB. With coefficients of 0.390 and 0.353, respectively, and T-Statistics of 4.183 and 3.053, and very low P-Values (0.000 and 0.002), these results confirm that user satisfaction plays an important role in driving technology usage intentions and behavior.

Overall, the results of this hypothesis test indicate that user trust and satisfaction play a key role in driving technology adoption and use, which in turn can affect the impact of technopreneurship. However, the direct relationship between usage behavior and technopreneurship impact is not significant, indicating the need for further research to understand these dynamics in more depth.

5. MANAGERIAL IMPLICATIONS

From a practical perspective, the findings of this study offer several important insights for healthcare institutions and technopreneurs developing AI-based solutions. The significant influence of User Satisfaction (US) on Behavioral Intention (BI) and Usage Behavior (SB) highlights that improving user satisfaction should be a top priority for healthcare developers and providers aiming to integrate AI-based systems, such as Safe Entry Stations. Practical steps that can be taken include improving the user interface, increasing system reliability, and providing adequate training for users. The weak but positive relationship between BI and US (path coefficient = 0.129) highlights that while the intention to use the technology exists, user satisfaction needs to be continuously improved to ensure continued use. The strong positive relationship between Trust (TR) and Behavioral Intention (BI) also suggests the importance of building trust through measures such as algorithmic transparency, data security, and reliable system performance. For healthcare institutions, addressing concerns related to data privacy and system reliability is critical to enhancing user trust and promoting adoption of AI-based technologies. Regular system updates, clear communication about how data is managed, and assurances about the security and accuracy of the system are practical steps that can increase user trust.

The findings in this study suggest several important directions for future research. First, the negative relationship between Usage Behavior (SB) and Technopreneurial Impact (TI) suggests the need for further research to understand how and why increased usage does not necessarily translate into greater technopreneurship success. Future research could explore whether mediating factors such as user experience, system scalability, or contextual factors (e.g., health policy) play a role in moderating this relationship. Additionally, the lower AVE value for the Usage Behavior (SB) construct suggests that this variable requires a more comprehensive indicator or alternative measure to more fully capture user behavior. Future research should also delve deeper into the role of trust in the adoption of AI technologies, especially in sensitive environments such as healthcare. Given the importance of trust in driving behavioral intentions, understanding how trust evolves over time and identifying specific strategies to enhance it could provide valuable insights for technopreneurs and healthcare providers. Longitudinal studies could be particularly useful in exploring how trust evolves as users become more familiar with AI-based systems. Send feedback Side panels History Saved

6. CONCLUSION

This study **aimed** to explore the relationships between user satisfaction, trust, behavioral intention, usage behavior, and their impact on technopreneurship within the context of AI-driven technology in the healthcare sector. The analysis revealed that both user satisfaction and trust play a crucial role in driving behavioral intention and usage behavior. Specifically, **user satisfaction significantly** influences both the intention to use the technology and the actual usage behavior, with path coefficients of 0.390 (H1) and 0.353 (H2), respectively. Similarly, **TR has a significant** positive effect on both behavioral intention and usage behavior, with path coefficients of 0.557 (H3) and 0.505 (H4), respectively. Additionally, behavioral intention was found to have a strong positive impact on technopreneurial impact, with a path coefficient of 0.760 (H5), indicating that the stronger the intention to use the technology, the greater the perceived impact on technopreneurship.

These findings support the hypotheses that user satisfaction and trust significantly influence behavioral intention and usage behavior (H1, H2, H3, H4) and that behavioral intention significantly impacts technopreneurial impact (H5). However, the study also found that the direct relationship between usage behavior and technopreneurial impact was not significant, as indicated by a path coefficient of 0.111 (H6). This suggests that merely using the technology does not directly lead to a measurable impact on technopreneurship in this context. These findings underscore the importance of fostering user satisfaction and trust to drive successful technology adoption and enhance technopreneurial outcomes.

The **future research** should delve deeper into understanding the factors that might mediate or moderate the relationship between usage behavior and technopreneurial impact. Additionally, exploring external factors such as institutional policies and socio-economic conditions that may influence technology adoption would provide a more comprehensive understanding. While this study has touched on these factors, further analysis is needed to explore how institutional policies, such as regulatory frameworks, data protection laws, and healthcare standards, may either hinder or facilitate the adoption of AI-driven Safe Entry Stations technology. For instance, stringent regulations around data privacy could slow down adoption, while supportive policies could accelerate its use. Similarly, socio-economic conditions, including access to technology, income levels, and digital literacy, play a significant role in shaping user acceptance and usage of such systems. In low-income regions or areas with limited technological infrastructure, adoption may be slower, whereas in economically advantaged settings, the uptake might be faster. Thus, understanding these external influences is crucial for creating tailored strategies that foster the successful integration of AI in healthcare settings. Longitudinal studies could also offer valuable insights into how user perceptions and behaviors evolve over time, further informing strategies for successful technopreneurship. The study contributes to the literature on AI adoption in healthcare by highlighting the importance of trust and user satisfaction in shaping technology usage. Practically, healthcare providers and technopreneurs should prioritize building trust and improving user experience to encourage broader adoption.

Overall, this study provides important insights into the factors influencing the adoption of AI-driven Safe Entry Stations in the healthcare sector. The findings emphasize the importance of user trust and satisfaction, while also highlighting the complexity of the relationship between usage behavior and technopreneurial impact. Both theoretical and practical implications have been identified, contributing to a broader understanding of the adoption of AI technologies in the healthcare context. Future research should continue to explore these relationships, focusing on trust, usage behavior, and technopreneurship, to further advance the field.

7. DECLARATIONS

7.1. About Authors

Untung Rahardja (UR) https:///orcid.org/0000-0002-2166-2412

Po Abas Sunarya (AS) https://orcid.org/0000-0002-3869-2837

Qurotul Aini (QA) https://orcid.org/0000-0002-7546-5721

Shofiyul Millah (SM) https://orcid.org/0000-0002-6696-94506

Sabda Maulana (SB) https://orcid.org/0000-0002-0871-6463

7.2. Author Contributions

Conceptualization: UR; Methodology: AS; Software: SB; Validation: SM and QA; Formal Analysis: SM and QA; Investigation: SB; Resources: UR; Data Curation: QA; Writing Original Draft Preparation: QA and UR; Writing Review and Editing: UR and AS; Visualization: QA; All authors, UR, AS, QA, SM, and SB, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.4. Funding

We would like to express our deepest gratitude to the Ministry of Education, Culture, Research, and Technology for supporting this research through the Applied Research Program with decree number 0459/E5/PG.02.00/2024. Thanks to their assistance, this research can be carried out. We would also like to thank University of Raharja, especially Alphabet Incubator, for their invaluable assistance in completing this research. Finally, we would like to thank our strategic partner, PredictMedix, for their excellent cooperation throughout this research journey. All contributions and support provided by these parties are very meaningful for the progress of this research. Thank you for all your help.

7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] S. M. Williamson and V. Prybutok, "Balancing privacy and progress: a review of privacy challenges, systemic oversight, and patient perceptions in ai-driven healthcare," *Applied Sciences*, vol. 14, no. 2, p. 675, 2024.

[2] B. Y. Kasula, "Advancements in ai-driven healthcare: A comprehensive review of diagnostics, treatment, and patient care integration," *International Journal of Machine Learning for Sustainable Development*, vol. 6, no. 1, pp. 1–5, 2024.

[3] P. N. K. Sarella and V. T. Mangam, "Ai-driven natural language processing in healthcare: transforming patient-provider communication," *Indian Journal of Pharmacy Practice*, vol. 17, no. 1, 2024.

[4] B. Y. Kasula, "Ethical implications and future prospects of artificial intelligence in healthcare: A research synthesis," *International Meridian Journal*, vol. 6, no. 6, pp. 1–7, 2024.

[5] S. Maleki Varnosfaderani and M. Forouzanfar, "The role of ai in hospitals and clinics: transforming healthcare in the 21st century," *Bioengineering*, vol. 11, no. 4, p. 337, 2024.

[6] J. Chen, Y. Shi, C. Yi, H. Du, J. Kang, and D. Niyato, "Generative ai-driven human digital twin in iot-healthcare: A comprehensive survey," *arXiv preprint arXiv:2401.13699*, 2024.

[7] M. Elhaddad and S. Hamam, "Ai-driven clinical decision support systems: an ongoing pursuit of potential," *Cureus*, vol. 16, no. 4, 2024.

[8] I.-H. Chang, P.-C. Hsu, and R.-S. Chen, "The effects of trust on user satisfaction with parenting apps for taiwanese parents: The mediating roles of social ties and perceived value," *Education and Information Technologies*, pp. 1–19, 2024.

[9] A. Choudhury and H. Shamszare, "The impact of performance expectancy, workload, risk, and satisfaction on trust in chatgpt: Cross-sectional survey analysis," *JMIR Human Factors*, vol. 11, p. e55399, 2024.

[10] C. Gunawan, E. Febriani, and A. Kusumah, "Trust and user satisfaction in digital application: An analysis of gopay e-money service," *JASS (Journal of Accounting for Sustainable Society)*, vol. 6, no. 1, pp. 15–24, 2024.

[11] Ş. Altay and T. Ş. Yaprakli, "The relationship among u-constructs, trust and satisfaction: Evidence from mobile banking users," *International Journal of Management Studies (IJMS)*, vol. 31, no. 1, pp. 171–208, 2024.

[12] R. Hanif, W. Astuti, and S. Sunardi, "The mediating role of customer satisfaction in the effect of perceived enjoyment on customer trust in online investment application," *Innovation Business Management and Accounting Journal*, vol. 3, no. 1, pp. 18–29, 2024.

[13] A. A. Soren and S. Chakraborty, "Adoption, satisfaction, trust, and commitment of over-the-top platforms: An integrated approach," *Journal of Retailing and Consumer Services*, vol. 76, p. 103574, 2024.

[14] R. S. Hamid, I. Ukkas, G. Goso, A. Abror, S. M. Anwar, and A. R. Munir, "The role of social media in building trust, self-perceived creativity and satisfaction for millennial entrepreneurs," *Journal of Small Business and Enterprise Development*, vol. 31, no. 2, pp. 377–394, 2024.

[15] M. M. DHARSHANA and S. SUMATHI, "Exploring the challenges and business opportunities in technopreneurship," *Journal of Emerging Technologies and Innovative Research (JETIR)*, vol. 11, no. 4, pp. 669–677, 2024.

[16] E. E. Djajasasana and J. R. K. Bokau, "Utilization of micro influencers and engagement in social media to gain cadet candidates," *ADI Journal on Recent Innovation*, vol. 6, no. 1, pp. 1–7, 2024.

[17] T. Phuthong, "Defining technopreneurs' commercialization research process in the emerging thai economy: Research for constructing grounded theory," *TEM Journal*, vol. 12, no. 2, pp. 1142–1155, 2023.

[18] G. Ikhwanudin, H. D. Wahyudi, and W. A. Andriyani, "Health of indonesian soe banking in facing the

society 5.0 era to support the technopreneur intention program," in *Proceeding Medan International Conference on Economic and Business*, vol. 1, 2023, pp. 1206–1221.

[19] D. S. S. Wuisan, R. A. Sunardjo, Q. Aini, N. A. Yusuf, and U. Rahardja, "Integrating artificial intelligence in human resource management: A smartpls approach for entrepreneurial success," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 5, no. 3, pp. 334–345, 2023.

[20] B. Hasan, N. P. Ardianysah *et al.*, "Development of technopreneur training models using internet of things (iot)-based smart healthcare system for upi students," in *2021 3rd International Symposium on Material and Electrical Engineering Conference (ISMEE)*. IEEE, 2021, pp. 119–123.

[21] P. L. Lau, M. Nandy, and S. Chakraborty, "Accelerating un sustainable development goals with ai-driven technologies: A systematic literature review of women's healthcare," in *Healthcare*, vol. 11, no. 3. MDPI, 2023, p. 401.

[22] Z. Fan, Z. Yan, and S. Wen, "Deep learning and artificial intelligence in sustainability: a review of sdgs, renewable energy, and environmental health," *Sustainability*, vol. 15, no. 18, p. 13493, 2023.

[23] G. Alandjani, "Integrating ai with green internet of things in healthcare for achieving un's sdgs," *Tuijin Jishu/Journal of Propulsion Technology*, vol. 44, no. 3, pp. 513–521, 2023.

[24] E. S. Ariestiningsih, G. Genoveva, D. F. S. Has, and D. F. N. Hasan, "Popularize healthy food by millennials based on technopreneurship," *Journal of Technology Management and Technopreneurship (JTMT)*, vol. 10, no. 2, pp. 11–23, 2022.

[25] M. A. Oladejo, S. Wahyuni, and D. Avrillianda, "Technopreneurship engagement: The behavioral intentions of nigerian and indonesian undergraduates in an emerging society 5.0," *Journal of Nonformal Education*, vol. 8, no. 2, pp. 151–161, 2022.

[26] A. Isma, N. Halim, A. A. Kemalasari, M. Rakib, and H. Dewantara, "The influence of entrepreneurship education and technopreneurship literacy on entrepreneurial intention with self-efficacy as an intervening variable in generation z," *International Journal of Health, Economics, and Social Sciences (IJHESS)*, vol. 6, no. 3, 2024.

[27] D. M. Rathnayake and T. Roca, "The emergence of technopreneurship for sustainable and ethical economic growth: Theory, research and practice," in *Integrated business models in the digital age: Principles and practices of technology empowered strategies*. Springer, 2022, pp. 467–535.

[28] S. Wahyuningsih, A. Sutarman, I. N. Hikam *et al.*, "Understanding purposeful leadership in entrepreneurial contexts: A bibliometric analysis," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 2, pp. 213–230, 2024.

[29] I. N. Aieni, C. Taurusta *et al.*, "Rancang bangun game adventure 3d edukasi sampah organik dan non-organik: Design and build an educational 3d adventure game on organic and non-organic waste," *Technomedia Journal*, vol. 9, no. 1, pp. 61–75, 2024.

[30] D. Nugroho and P. Angela, "The impact of social media analytics on sme strategic decision making," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 169–178, 2024.

[31] J. Gopinath, *Techpreneurship: Navigating the IT Sector Landscape*. Academic Guru Publishing House, 2024.

[32] L. Sanbella, I. Van Versie, and S. Audiah, "Online marketing strategy optimization to increase sales and e-commerce development: An integrated approach in the digital age," *Startupreneur Business Digital (SABDA Journal)*, vol. 3, no. 1, pp. 54–66, 2024.

[33] M. Sarstedt, S. J. Adler, C. M. Ringle, G. Cho, A. Diamantopoulos, H. Hwang, and B. D. Liengaard, "Same model, same data, but different outcomes: Evaluating the impact of method choices in structural equation modeling," *Journal of Product Innovation Management*, 2024.

[34] A. Pambudi, N. Lutfiani, M. Hardini, A. R. A. Zahra, and U. Rahardja, "The digital revolution of startup matchmaking: Ai and computer science synergies," in *2023 Eighth International Conference on Informatics and Computing (ICIC)*. IEEE, 2023, pp. 1–6.

[35] M. A. Bakar, A. A. Bakar, A. M. Noor, and N. M. Mohamad, "Islamic technopreneurship in the midst of covid-19 pandemic: A malaysia review," *PalArch's Journal of Archaeology of Egypt/Egyptology*, vol. 17, no. 9, pp. 746–765, 2020.

[36] C. Paramasivan and S. Muthusamy, "Emerging trends in new start-up technopreneurs," *Journal of Business Management*, vol. 2, no. 7, 2016.

[37] N. Ani, S. Millah, and P. A. Sunarya, "Optimizing online business security with blockchain technology," *Startupreneur Business Digital (SABDA Journal)*, vol. 3, no. 1, pp. 67–80, 2024.

[38] S. Muthusamy, “Evolution of technopreneurial entreprneurs in the covid-19 pandemic situation,” *Research Explorer*, vol. 8, no. 29, pp. 23–28, 2020.

[39] A. S. K. Kukah, D.-G. Owusu-Manu, E. Badu, and E. Asamoah, “Structural equation model (sem) for evaluating interrelationships among risks inherent in ghanaian public–private partnership (ppp) power projects,” *Engineering, Construction and Architectural Management*, vol. 31, no. 6, pp. 2327–2352, 2024.

[40] H. Hashemi, S. V. Salekfard, N. Khodadadi, M. Bonyadi, F. Jalayer, F. Nemati, and M. Kordbagheri, “The mediating role of rumination in the relationship between pathological personality traits and self- and other-blame among parents of children with autism spectrum disorder: Structural equation modeling (sem),” *Current Psychology*, vol. 43, no. 12, pp. 11 013–11 022, 2024.

[41] M. F. Nur and A. Siregar, “Exploring the use of cluster analysis in market segmentation for targeted advertising,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 158–168, 2024.

[42] M. J. Zyphur, C. V. Bonner, and L. Tay, “Structural equation modeling in organizational research: The state of our science and some proposals for its future,” *Annual Review of Organizational Psychology and Organizational Behavior*, vol. 10, no. 1, pp. 495–517, 2023.

[43] R. Sivaraman, M.-H. Lin, M. I. C. Vargas, S. I. S. Al-Hawary, U. Rahardja, F. A. H. Al-Khafaji, E. V. Golubtsova, and L. Li, “Multi-objective hybrid system development: To increase the performance of diesel/photovoltaic/wind/battery system.” *Mathematical Modelling of Engineering Problems*, vol. 11, no. 3, 2024.

[44] M. D. Wani, Z. A. Dada, and S. A. Shah, “The impact of community empowerment on sustainable tourism development and the mediation effect of local support: a structural equation modeling approach,” *Community Development*, vol. 55, no. 1, pp. 50–66, 2024.

[45] P. N. Perdana, D. Armeliza, H. Khairunnisa, and H. Nasution, “Research data processing through structural equation model-partial least square (sem-pls) method,” *Jurnal Pemberdayaan Masyarakat Madani (JPMM)*, vol. 7, no. 1, pp. 44–50, 2023.

[46] L. Wang, X. Li, H. Zhu, and Y. Zhao, “Influencing factors of livestream selling of fresh food based on a push-pull model: A two-stage approach combining structural equation modeling (sem) and artificial neural network (ann),” *Expert Systems with Applications*, vol. 212, p. 118799, 2023.

[47] B. Any, S. Four, and C. Tariazela, “Technology integration in tourism management: Enhancing the visitor experience,” *Startupreneur Business Digital (SABDA Journal)*, vol. 3, no. 1, pp. 81–88, 2024.