JDM (Jurnal Dinamika Manajemen), 15 (1) 2024, 125-143

http://jdm.unnes.ac.id

Nationally Accredited based on the Decree of the Minister of Research and Technology/ National Agency of Research and Innovation Number 85/M/KPT/2020

Examining The Interplay of Technology Readiness and Behavioural Intentions in Health Detection Safe Entry Station

Untung Rahardja ✉[1], Qurotul Aini[2], Ankur Singh Bist[3], Sabda Maulana[4], Shofiyul Millah[5]
University of Technology Malaysia, Malaysia[1]
University of Raharja, Tangerang, Indonesia[2,4,5]
Graphic Era Hill University, India[3]

Info Article

History Article:
Submitted 23 November 2023
Revised 14 January 2024
Accepted 20 January 2024

Keywords:
Artificial Intelligence, Behavioural Intention, Health Detection, Safe Entry Station, Technology Readiness

Abstract

This research aims to determine the factors that influence the adoption of safe entry station (SES) as a health detection technology. There are six main constructs that will be studied, namely Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Technology Readiness, towards Behavioural Intention. Data collection was carried out using a survey distributed to 824 participants by analysis was carried out using the Structural Equation Model. The research findings show a significant relationship between technology readiness and behavioral intention regarding the use of safe entry station. The results of this research specifically show that the application of artificial intelligence in safe entry station health detection technology has a significant positive impact on increasing accuracy in the health examination process. Furthermore, this research provides insight into substantial practical implications in various business sectors, highlighting the importance of integrating safe entry station with organizational systems. The academic implications contained in this research will make a positive contribution to the development of knowledge and theory in the field of safe entry station technology adoption and can provide a strong basis for further research, while the managerial implications of this research lie in the ability to further design effective implementation strategies in various sectors.

Menguji Interaksi dari Kesiapan Teknologi dan Niat Perilaku Penggunaan Sistem Deteksi Kesehatan

Abstrak

Penelitian ini bertujuan untuk mengetahui faktor-faktor yang mempengaruhi adopsi Safe Entry Station (SES) sebagai teknologi deteksi kesehatan. Terdapat enam konstruk utama yang akan dikaji yaitu ekspektasi kinerja, ekspektasi usaha, pengaruh sosial, kondisi fasilitas, dan kesiapan teknologi terhadap intensitas perilaku. Pengumpulan data dilakukan melalui survei kepada 824 responden dengan menggunakan analisis Structural Equation Model. Temuan penelitian menunjukkan adanya hubungan signifikan antara kesiapan teknologi dan intensitas perilaku terkait penggunaan safe entry station. Hasil penelitian ini secara khusus menunjukkan bahwa penerapan kecerdasan buatan pada teknologi deteksi kesehatan safe entry station memberikan dampak positif yang signifikan terhadap peningkatan akurasi proses pemeriksaan kesehatan. Selain itu, penelitian ini memberikan wawasan mengenai implikasi praktis yang substansial di berbagai sektor bisnis, menyoroti pentingnya mengintegrasikan safe entry station dengan sistem organisasi. Implikasi akademis yang terkandung dalam penelitian ini akan memberikan kontribusi positif bagi pengembangan ilmu pengetahuan dan teori di bidang adopsi teknologi safe entry station serta dapat memberikan landasan yang kuat untuk penelitian selanjutnya, sedangkan implikasi manajerial dari penelitian ini terletak pada kemampuan mendesain lebih lanjut strategi implementasi yang efektif di berbagai sektor.

JEL Classification: D8, I1, O3

How to Cite: Rahardja, U., Aini, Q., Bist, A. S., Maulana, S., & Millah, S. (2024). Examining The Interplay of Technology Readiness and Behavioural Intentions in Health Detection Safe Entry Station. *JDM (Jurnal Dinamika Manajemen), 15*(2), 125-143.

✉Correspondence Address
Institutional address: Johor, Malaysia
Email: rahardjauntung@graduate.utm.my

ISSN
2337-5434 (online)

INTRODUCTION

Rapid developments in health detection technology reflect a significant evolution in the approach to health care (Komalasari, 2023). This phenomenon creates a strong foundation for research and development in the health sector, bringing about profound changes in the way we approach the diagnosis, treatment, and monitoring of health conditions (Văduva et al., 2023). Despite rapid progress, current health detection still has several limitations. A screening process that is not optimal can hamper the health system's ability to provide fast and accurate services (Proal et al., 2023). Therefore, it is necessary to adopt the latest technology to increase the efficiency and effectiveness of health detection (Mustafa et al., 2023). Basically, the success of health detection technology supported by Artificial Intelligence (AI) illustrates a new paradigm in health services. Leveraging this technology is not only changing the way healthcare professionals operate, but is also having a positive impact on the patient experience (Limna, 2023). With AI in health detection, disease diagnosis can be done more accurately and quickly.

The presence of the Safe Entry Station (SES) opens up great opportunities to increase effectiveness by detecting a number of health indicators, such as body temperature, heart rate, fatigue level and breathing (Maroju et al., 2023). By utilizing AI technology and infrared sensors, SES offers sophisticated solutions to obtain screening results quickly and accurately (Manickam et al., 2022). The system is capable of exploring medical data on a scale that is impossible for humans, identifying complex patterns that may not be visible to the ordinary human eye. As a result, patients can receive an earlier diagnosis, allowing for more effective intervention and faster recovery (Naik et al., 2022). The application of health detection technology supported by AI is not only limited to hospitals or health facilities, but has penetrated the business sector in innovative and varied ways. In the business world, this transformation opens up new opportunities to utilize health data to provide significant positive impacts in various industries. A number of companies are integrating health detection technology into employee wellness programs to improve well-being and productivity. By leveraging wearable devices and health sensors, companies can provide real-time information about employee health, enabling monitoring of stress levels, fatigue and physical activity (Siala & Wang, 2022). Although the development of health technology continues to advance, background health detection still faces a number of challenges that limit its optimization.

The problem faced in this research is a significant lack of understanding of the dynamics of the interaction between individuals' technology readiness and their behavioral intentions (Sun et al., 2022). Although developments in health detection technology have shown great potential in improving public safety and health, it is not yet fully known how a person's technology readiness factors may influence their willingness to adopt and use these stations effectively (Feng et al., 2022). A number of previous studies have consistently highlighted the increasingly important role of AI in detecting and preventing health problems. In this context, the main focus of the research is to apply this technology into the public sector being the main point of emphasis.

Most previous studies indicate that the public sector is considered a priority for the development of AI-based health detection technologies (Celi et al., 2022). This is caused by an imbalance of information in society and the potential risk of misuse of data or information needed for health detection (Putri & Meria, 2023). The researchers note that the adoption of AI technology, with its ability to improve data security and privacy, is a key element to increase public confidence in adopting health detection. While the growth of discussions around AI in health detection shows a significant increase, several studies highlight the deep need to understand people's adoption behavior (Ayuna, 2023). Within this framework, this research becomes relevant by presenting the current understanding of health detection adoption and considering potential modifications to behavioral models of technology adoption. Understanding the extent to which society understands and responds to AI technologies, especially in the context of health detection, is investigated by exploring user perceptions and intentions.

An academic study of AI in health detection extends to the development of the technology and its application in business systems. Furthermore, several researchers have estimated the potential adoption of AI if applied in many sectors, especially in the public sector. So far, the public sector has been considered a priority for developing this technology because of asymmetric information and the potential for misuse of data or information (Rahardja, 2022a). Although the growth of discussions of health detection AI has shown a significant increase over the past few years, these studies emphasize the benefits of AI adoption for society ignoring adoption behavior (Anggara, 2020). Stakeholders need this situation to demonstrate current understanding of health detection adoption.

This research fills the empirical gap in previous literature by providing strong and contextual empirical evidence regarding the impact of implementing health detection in overcoming health detection challenges in society (Amany & Desire, 2020). Although research has involved initial testing and design verification in the laboratory, There is empirical data obtained through systematic data collection and analysis. Through this approach, this research is able to provide more concrete and measurable information regarding effectiveness in improving the health screening process (Watini, 2023).

This research aims to explore the theoretical foundations that form the basis of the concept and implementation of health detection as a health scanning device. The primary focus of this research is to build a solid theoretical understanding of the acceptability of the technology, the effectiveness of health interventions, and the ethical aspects involved in the use of health detection (Hariguna et al., 2021).

The urgency of this research lies in the urgent need to overcome the limitations and obstacles still faced by the current health detection system. The importance of understanding the intention to use SES is a focal point, which emphasizes the need for an in-depth understanding of the factors that influence the acceptance of this technology. By aligning advanced technology with the real needs of society, this research is committed to making a substantial contribution to the development of health screening that is more effective, responsive and accessible to all levels of society (Rouidi et al., 2022).

Unified Theory of Acceptance and Use of Technology (UTAUT) is a model Venkatesh which developed to explain how users behave toward information technology (F. A. Rahardja et al., 2022). This model has become a central theoretical framework in understanding technology acceptance by users. By identifying factors such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, this model provides a solid theoretical foundation for evaluating how users may receive and adopt health technologies such as SES (Venkatesh, 2022a). Through analysis of these factors, this study aims to understand the dynamics of technology acceptance in the context of health screening. This research makes a significant contribution to the scientific realm of health technology by focusing on the development of SES as an AI-based health scanning device and infrared sensors.

The novelty of this research covers several important aspects, such as bringing innovation by integrating AI technology in health screening, offering effective and efficient solutions for detecting various health indicators. This reflects significant progress in the application of digital technology in the health sector, with the potential to improve the quality of services. Then, this research places special emphasis on aspects of technology acceptance by including the UTAUT Model as a theoretical framework. Through this approach, the study highlights the importance of understanding SES usage intentions, contributing to the user behavior literature regarding the adoption of technological innovations in health contexts.

Analysis of factors that influence public acceptance of health technology adds in-depth understanding of user behavior. The results of this research will serve as a basis for practitioners to develop a deeper understanding of the adoption of health detection technologies, with the potential to provide a foundation for more effective implementation initiatives in the community.

The Relationship between Effort Expectancy and Behavioral Intentions toward SES.

Effort Expectancy (EE) refers to the extent to which the user believes that level ease associated with using a system or technology. This includes perceived ease of use and the user's assessment of how easy it is to interact with the technology. For technologies such as SES, which may involve complex interactions or new usage paradigms, perceived ease of use becomes an important factor in determining whether users are willing to adopt them. For organizations implementing SES understanding these relationships can guide change management strategies, emphasizing ease of user transition to the new system (Huang, 2023). Based on the description above, the following research hypothesis is proposed (Rahmad et al., 2022).

H1: Effort Expectancy (EE) has a significant effect on user Behavioral Intention (BI) toward SES.

The Relationship between Performance Expectancy and Behavioral Intentions toward SES.

Performance Expectancy (PE) is a measure of someone's trust in a PE refers to the extent to which an individual believes that using a system will help him or her to achieve benefits in achieving increased daily performance or productivity (Miraz et al., 2022). This relationship highlights the importance of perceived benefits in adopting new technology (Figueroa-Armijos et al., 2023). If users see real benefits in using SES, they will be more motivated to adopt it. In designing an SES, it is important to ensure that the system provides clear and measurable performance benefits to its users. Given the relevance of this research, exploring the relationship between PE and BI is critical, especially within SES. Therefore, in our effort to evaluate the ease of use of SES, we formulated the following hypothesis for careful assessment:

H2: Performance Expectancy (PE) has a significant effect on user Behavioral Intention (BI) towards SES.

The Relationship between Social Influence and Behavioral Intentions toward SES.

Social Influence (SI) is the level or benchmark of the environment in influencing people around them to encourage them to use a new technological system (Gumz et al., 2022). In the context of SES, the influence of reference groups or social networks can be a key factor in deciding to adopt these technologies, especially if the technology is perceived as a status symbol or innovation (Kano et al., 2022). These relationships suggest that social perceptions and norms related to SES play an important role in shaping individuals' attitudes and intentions toward technology adoption. Understanding these influences can help in designing marketing strategies that target social groups and leverage advocacy from early adopters or influencers to promote adoption. With that, the following hypothesis is proposed:

H3: Social Influence (SI) has a significant effect on user Behavioral Intention (BI) towards SES.

The Relationship between Facilitating Conditions and Behavioral Intentions toward SES.

Facilitating Conditions (FC) is the extent to which a person believes that the existing infrastructure and available support are adequate to support the use of the technology. In SES, the intention to adopt and use this technology can be influenced by how easy and comfortable the user feels in using the system. This hypothesis suggests that if users feel they have sufficient supporting conditions to use SES, they are more likely to have a higher intention to adopt it. SES developers need to ensure that their technology is supported with sufficient resources and infrastructure to encourage use. So, the following hypothesis is proposed:

H4: Facilitating Conditions (FC) have a significant effect on user Behavioral Intention (BI) towards SES.

The Relationship between Technology Readiness and Behavioral Intentions toward SES.

Technology Readiness (TR) is the level at which an individual or organization is ready to adopt and integrate with new technology. In the context of SES, this includes infrastructure readiness, human resource readiness, and acceptance of technology at the psychological level. BI can be greatly influenced by how ready users and their organizations are to accept and use the technology (Gao et al., 2022). This hypothesis states that the higher the technology readiness of an individual or organization, the more likely they are to have strong intentions to adopt and use SES. Understanding these influences can help SES designers and developers prepare strategies that take into account their users' level of technology readiness. With that, the following hypothesis is proposed:

H5: Technology Readiness (TR) has a positive influence on Behavioral Intention (BI) on SES.

The aim of this research is to thoroughly investigate the acceptance of SES technology (Marina et al., 2023). Which serves as a foundational theoretical framework for the study is a UTAUT, which is a strong framework in the field of information technology adoption (Venkatesh, 2022b). The UTAUT model shown in Figure 1, illustrates the model suggested by Venkatesh et al. The model has six key constructs : EE, PE, SI, FC, BI, and TR, which are moderated by G, A, and E. The validation of these six constructs along with the three moderated will be executed through a questionnaire (Lin & Huang, 2023; Roh et al., 2023).

The PE factor is used to measure the level of benefit or advantage obtained by user in using technology to carry out their daily activities. Meanwhile, EE is used to measure a person's level of ease in using information technology, which will directly influence the ease of carrying out daily work. Furthermore, SI is defined as the extent to which an individual feels that his contribution is important to the surrounding environment. On the other hand, FC

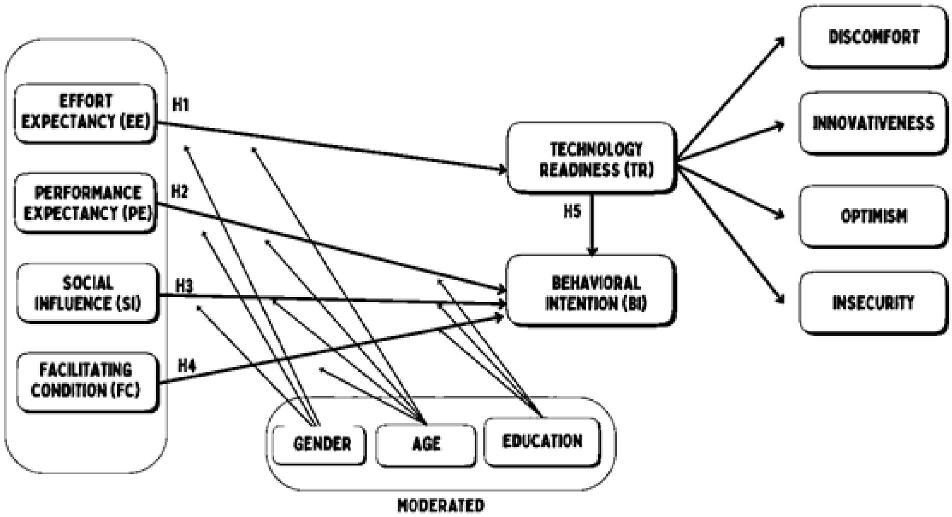

Figure. 1 UTAUT Framework Proposed
Source: Data Processed (2023)

is used to measure the level of confidence that organizational resources and support as well as technical infrastructure are available to support system use. TR refers to the extent to which a person or group is ready and able to adopt technology. Meanwhile, BI refers to a person's tendency or desire to act or use technology (Maulani et al., 2020). The indicators given in the UTAUT model are clear and easy to understand, so they have flexibility in their implementation in various areas of life that apply information technology. The flexibility of the UTAUT model can also add more specific indicators regarding the information technology used that do not have to be based on the initial model.

METHOD

This research developed a survey instrument to collect data, incorporating measurement scales adapted from previous related research (Basuki & Anugrah, 2019; Qadri et al., 2020). To ensure the content validity and relevance of the questions, ten experts carefully reviewed the methodology and measurement scales used. We applied a 5-point Likert scale to measure various construct elements (Zulkarnain & Andini, 2020), with response options ranging from "strongly disagree" to "strongly agree". To avoid bias due to question order, we applied two-stage randomization. First, the order of construct pages and measurement items within each construct page was randomized (Apriani et al., 2023). Second, the next section of the survey includes questions about demographic data such as age, gender, and education level (Rahardja, 2022b; Hardini et al., 2023).

The data collected from the questionnaires is used to analyse the SES, distributed to 824 participant including the general public, health workers, students and lecturers. Data was collected through an online survey using Google Forms for 3 months, from March 22 to Mei 14, 2023. Total data 824 obtained and 773 were considered valid because they were complete without missing questions. The remaining 51 respondents needed to meet specific criteria, such as being under 15 years old or having an education level of less than one month. A total of 773 participants voluntarily filled out the survey independently. The selected and collected data will be processed using SmartPLS version 4.0 software, applying the SEM Structural Equation Modelling Variance Based (VB) and bootstrapping analysis.

RESULT AND DISCUSSION

The details of demographic data is shown through Figure 2, which breakdown includes three categories: Gender, Age, and Education. These selected demographics have proven invaluable for research because they provide valuable insight into how different groups in the population may interact with and respond to technology (Hardjosubroto et al., 2020). This allows researchers and developers to design more customized and practical solutions, ultimately increasing the acceptance and effectiveness of the technology in various demographic groups (Rahardja & Triyono, 2020). The table above shows that 57% of respondents are women, while 42% are men. Regarding age, the majority are in the 15-20 year category (28%), and most respondents' education level is SES-UR S3 (32%). Therefore, the subjects in this study were carefully selected to explore demographic segments that show a high level of interest in air quality monitoring applications and to examining the dynamics of user loyalty towards SES.

SES is a human health detection system that can measure body temperature, heart rate, fatigue level and breathing using AI technology and infrared sensors. This system is handy for overcoming the risk of transmitting virus SES such as COVID-19, which can occur due to human interaction. During the project trial period of 8 months from February 10 to September 22, 2023, 4,202 tests were carried out. This figure reflects a firm commitment to ensuring the safety and quality of health products currently in the development stage.

In the development of SES-UR, a more comprehensive approach was adopted by utilizing two essential technologies to develop an effective and efficient body temperature, heart rate and breathing detection system. In addition, to train the AI model from SES-UR, a unique AI development tool is used, namely NVIDIA TAO Toolkit (Kam et al., 2022).

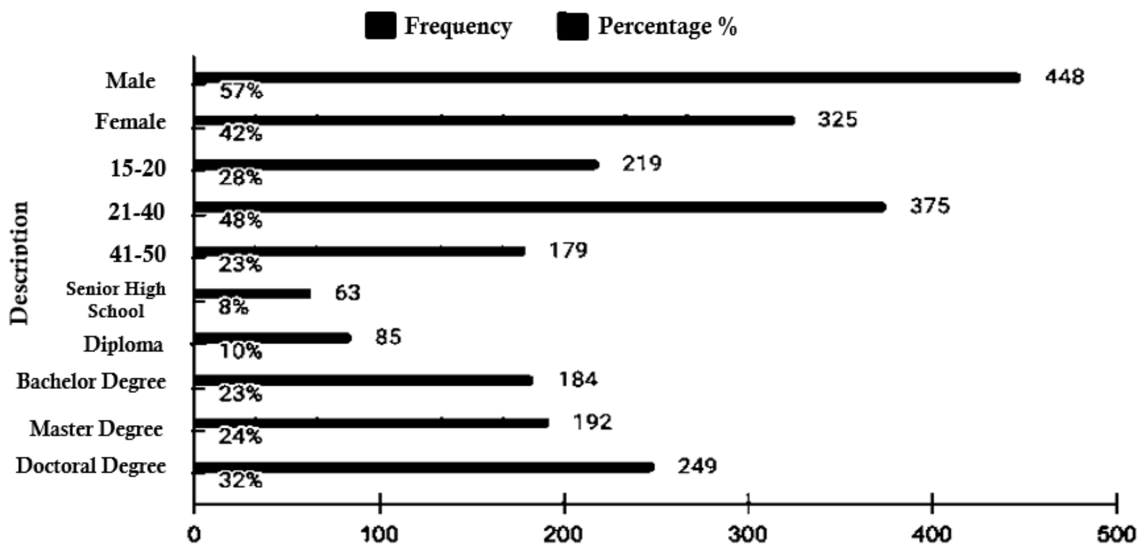

Figure. 2 Demographic Data of Respondents (n = 773)
Source: Data Processed (2023)

Table 1. Data Reliability

Variable	Item	Range of Factor Loading	AVE	CR	a	Status
Performance Expectancy (PE)	5	.786 - .867	.509	.763	.763	Reliable
Effort Expectancy (EE)	5	.822 - .867	.626	.874	.874	Reliable
Social Influence (SI)	5	.748 - .769	.522	.799	.799	Reliable
Facilitating Condition (FC)	5	.713 - .798	.689	.891	.891	Reliable
Behavioral Intention (BI)	5	.734 - .799	.501	.751	.751	Reliable
Technology Readiness (TR)	4	.767 - .809	.539	.794	.794	Reliable

Source: Data Processed (2023)

NVIDIA TAO Toolkit was developed using TensorFlow and PyTorch, software for building and training artificial intelligence models (Li et al., 2023). Using transfer learning technology, this Toolkit can simplify the model training process and optimize model performance to run on specific platforms (Liang et al., 2022). The result is a highly efficient workflow, making it easy to use existing models or create your models with original or custom data, then optimize their performance to run on specific platforms. The advantage of using this Toolkit is that you do not need special knowledge in artificial intelligence or large training datasets to utilize this NVIDIA TAO Toolkit

Measurement Model's Analysis

The research measurement analysis reveals that all the metrics used are reliable, consistently exceeding the threshold of 0.60 in their loadings. This high level of loading indicates a strong and dependable measure for each variable under consideration, ensuring that the data collected is robust and dependable for analysis.

Table 1, presents detailed information about various variables measured in a study, including their reliability and validity statistics. Each variable is associated with a set of items (presumably survey items or measurement indicators), and the table provides data on factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) for each variable it includes such as PE, EE, SI, FC, BI, and TR.

The table also details the range of factor loadings for each variable, which indicates how much of a variable's variance is explained by a factor in factor analysis. The TR had factor loadings ranging from 0.767 to 0.808, indicating a strong relationship between the items and the underlying factors. AVE is another critical measure presented, assessing the amount of variance captured by a construct versus the variance due to measurement error. The AVE values for all variables show good convergent validity >0.5, with TR having an AVE of 0.539.

In addition, Composite Reliability (CR) for each variable is also provided, thereby providing insight into the reliability of the composite score derived from the scale or index used. The CR value for TR is 0.794, indicating a high level of reliability. Interestingly, the table also includes a column labeled 'a'a,' which replicates the value of column CR, possibly indicating a measure of reliability or error involved in the table.

Finally, the status of each variable was marked as "Reliable," confirming the statistical robustness and reliability of the

Table 2. Fornell Lacker

	BI	EE	FC	PE	SI	TR
BI	.713					
EE	.591	.791				
FC	.689	0.59	.723			
PE	.413	.503	.449	0.83		
SI	.594	.651	.799	.456	.708	
TR	.639	.547	.475	.451	0.49	.734

Source: Data Processed (2023)

construct for research purposes. Overall, this table demonstrates a thorough and careful approach to ensuring the reliability and validity of the constructs measured in research, which is essential for drawing accurate and meaningful conclusions from the data.

From Table 2, analysis using the Fornell-Larcker criteria, we can conclude that the constructs in this study show good discriminant validity. This can be seen from the fact that the square root value of the Average Variance Extracted (AVE) for each construct, which is located on the diagonal of the table, is greater than the correlation with other constructs. The diagonal value for BI is 0.713, which is higher than the correlation with other constructs such as EE with a value of 0.591, FC with a value of 0.689, and so on. This indicates that each construct is sufficiently unique and significantly different from the other constructs in the model, meeting the Fornell Larcker criterion for discriminant validity. This conclusion is important to ensure that the constructs in the Structural Equation Modelling (SEM) model being studied accurately reflect different variables and do not overlap with each other.

The essence of the Fornell Larcker criteria is a comparison between the Average Variance Extracted (AVE) for each construct and the correlation of that construct with other constructs in the model. AVE, a measure of convergent validity, represents the average amount of variance in an observed variable explained by a construct. According to the Fornell-Larcker criteria, for a model to demonstrate adequate discriminant validity, the square root of the AVE for each construct must exceed the correlation of that construct with the other constructs in the model. Table 4 provides information regarding the R-square and adjusted R-square values for a particular variable, in a statistical model, in this case BI.

Table 3. R-Square

Variable	R-square	R-square adjusted
BI	0.612	0.610

Source: Data Processed (2023)

This suggests that BI is likely the dependent variable in the regression model, and the analysis aims to understand how well other independent variables predict or explain variance in BI. The R-square value for BI is 0.612 or 61.2%, which is generally considered significant. The R-squared value (R^2), also known as the coefficient of determination, is an essential statistical metric used in regression analysis to evaluate Goodness of Fit (GOF).

After evaluating the R-squared, the next step is to calculate the model's Goodness of Fit (GOF). GOF is an additional measure that helps assess how well the

Table 4. GOF Index

Average Communality Variable	Average R2	GOF
.565	.612	.588

Source: Data Processed (2023)

model fits the observed data. In this context, GOF is calculated using the formula .

In the context of the statistical analysis presented in Table 4, observing the relatively high R-squared (R^2) values provides essential insight into the effectiveness of the regression model used. The R-squared value in this table shows how well the model's independent variables can explain the dependent variable's variability. A high R-squared value in this context indicates that most of the change in the dependent variable can be explained by the independent variables included in the model. This Table 6, presents the results of statistical analysis to test a number of hypotheses in research related to the influence of various constructs EE, FC, PE, SI, TR on BI.

Hypothesis Evaluation

Table 5, presents the results of statistical analysis to test a number of hypotheses in research related to the influence of various constructs EE, FC, PE, SI, TR on BI.

The data provided suggests a statistical analysis was conducted to explore the influence of various factors on BI (Ogbeide & EJ, 2016; Ali et al., 2021). H1, H2, and H5 were supported, indicating that EE, FC, and TR have a statistically significant positive impact on BI (Chauhan et al., 2022) This is evidenced by their high t-statistics and p-values of 0.000, strongly suggesting these relationships are not due to chance (Gashaw et al., 2020). On the other hand, H3 and H4 shows that PE of SES performance do not have a significant impact on SI. This could be due to a lack of evidence or the respondent's belief that the use of SES will bring significant benefits or increase the effectiveness of health checks. Furthermore, the finding that H3 and H4, which tried to identify the impact of PE and SI on BI, did not receive statistical support. The t-statistics for these were lower, and the p-values did not indicate statistical significance (p-value for H3 being 0.593 and for H4 being 0.205). This analysis demonstrates that while EE, FC, and TR are likely important factors driving BI, PE and SI may not be as influential within the context of this study. The findings from such an SES can be crucial for developing strategies that effectively enhance or predict BI in the related domain.

The research Figure 3, results show that H1 has a positive influence, with

Table 5. Result of Hypothesis Evaluation

Hypothesis	Path	Original Sample	Sample Mean (M)	Standard Deviation (STDEV)	t-value	p-values	Result
H1	EE ->BI	.16	.158	.037	4.327	.000	Supported
H2	FC ->BI	.482	.483	.049	9.905	.000	Supported
H3	PE ->BI	-.018	-.018	.033	.535	.593	Not Supported
H4	SI ->BI	-.065	-.064	.051	1.268	.205	Not Supported
H5	TR ->BI	.362	.363	.037	9.837	.000	Supported

Source: Data Processed (2023)

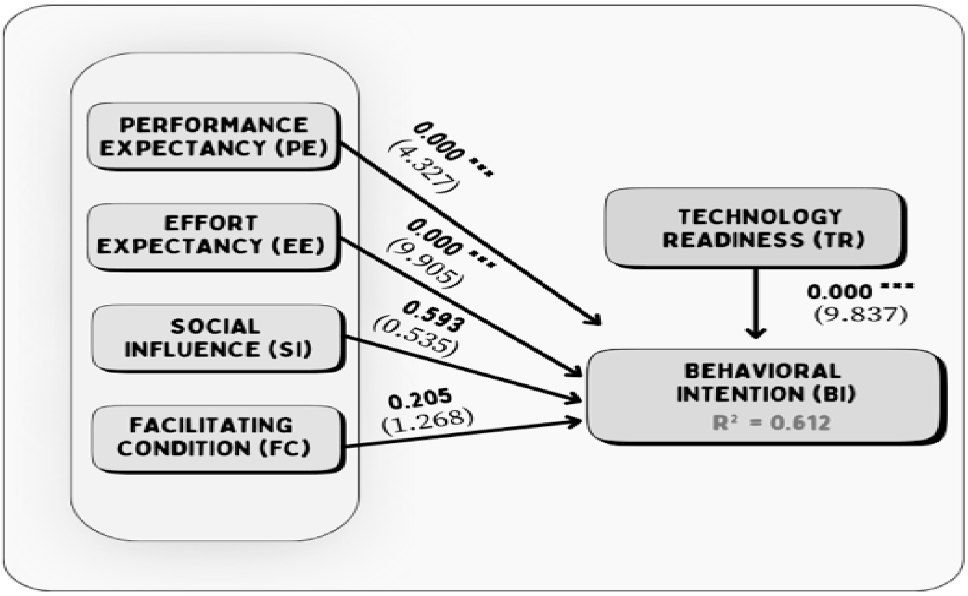

Figure 3. Hypothesis Result
Source: Data Processed (2023)

a coefficient value of 0.16, a t-value of 4.327, and a p-value of 0.000 which shows support for the hypothesis. H2 shows a greater influence with a coefficient of 0.482, a t-value of 9.905, and a p-value of 0.000, thus supporting the hypothesis. However, H3 and H4 do not maintain the hypothesis, showing a negative coefficient of -0.018 and SI -0.065, with a p-value higher than 0.05. Finally, H5 shows a significant positive effect on BI with a coefficient of 0.362, a t-value of 9.837, and a p-value of 0.000, thus supporting the hypothesis.

Based on Table 6, it can be concluded that each of these indicators has high significance in the context of technological readiness. The P-value of 0.000 in the context of SES technology readiness indicates a highly statistically significant relationship or influence, providing strong evidence to support the hypothesis or assumption tested in the research.

In this context, Multi-Group Analysis (MGA) might have been used to examining how demographic characteristics and organizational size influence adaptation and response to technology. Table 7, Table 8, and Table 9 provide details about the MGA results, including statistical comparisons and interpretations of how these variables influence technology readiness across groups.

Table 6. Technology Readiness Result

Indicator	Standard Deviation (STDEV)	t-value (|O/STDEV|)	p-value
Discomfort	.020	39.152	.0000
Innovativeness	.016	51.813	.0000
Optimism	.015	53.414	.0000
Insecurity	.038	16.591	.0000

Source: Data Processed (2023)

Table 7. Gender Examination

Indicators	Standard Deviation (STDEV)	Sample	t-value (|O/STDEV|)	p-values
EE ->BI	Male	488	.049	.001
	Female	325	.057	.003
FC ->BI	Male	488	.064	.000
	Female	325	325	.000
PE ->BI	Male	488	.052	.662
	Female	325	.074	.806
SI ->BI	Male	488	.065	.505
	Female	325	.041	.175
TR ->BI	Male	488	.052	.000
	Female	325	.074	.000

Source: Data Processed (2023)

Taking into account Table 7, we seek to assess the impact of gender on various constructs regarding BI users in the context of SES [87]. To investigate this influence, we performed bootstrap analysis, grouping the data by gender, and distinguishing between women and men [88]. The results in table show that only EE ($p < 0.001$), FC ($p < 0.001$), and TR ($p < 0.01$), are susceptible to the influence of gender. These findings reveal that the interactions between gender and certain factors that influence users' behavioral intentions in SES vary significantly. This suggests that strategies and approaches in adopting and using technology in SES environments may need to be adapted or managed to take gender differences into account.

The data within Table 8 is divided into age groups: 15-20, 21-40, and 41-45 years. This approach allows researchers to compare and evaluate how age influences

Table 8. Age Examination

Path	Age	Sample	Standard Deviation (STDEV)	p-values
EE ->BI	15-20	219	.066	.094
	21-40	375	.053	.000
	41-50	179	.062	.182
FC ->BI	15-20	219	.087	.000
	21-40	375	.064	.000
	41-50	179	.110	.000
PE ->BI	15-20	219	.057	.615
	21-40	375	.051	.408
	41-45	179	.065	.522
SI ->BI	15-20	219	.082	.278
	21-40	375	.073	.768
	41-50	179	.101	.123
TR ->BI	31-35	219	.065	.000
	36-40	375	.054	.000
	41-45	179	.079	.000

Source: Data Processed (2023)

different constructs related to BI in SES. The results show that age has a significant influence on constructs such as EE, FC, and TR. This indicates that perceptions and responses to these factors change with age. These findings highlight that the dynamics between age demographics and factors influencing user engagement by SES are complex and diverse. This shows the importance of considering age in designing, implementing, and communicating technology in the context of SES.

In Table 9, provides insight into examining the influence of users' education levels on the various constructs that make up users' BI on SES. This analysis was carried out through bootstrapping, which grouped the data into different experience groups, starting from senior high school, diploma, bachelor's, master's, and doctoral degrees. The results in Table 10 clearly illustrate that users' education level significantly impacts constructs such as EE, FC and TR, which collectively shape their behavioural intentions regarding SES. These findings explain the complex dynamics between education level and specific factors that influence their engagement with SES.

Table 9. Education Examination

Path	Education	Sample	Standard Deviation (STDEV)	p-values
EE ->BI	Senior High School	63	.133	.695
	Diploma	85	.093	.684
	Bachelor Degree	184	.084	.151
	Master Degree	192	.089	.003
	Doctoral Degree	249	.058	.007
FC ->BI	Senior High School	63	.243	.002
	Diploma	85	.180	.002
	Bachelor Degree	184	.076	.000
	Master Degree	192	.097	.000
	Doctoral Degree	249	.110	.000
PE ->BI	Senior High School	63	.131	.793
	Diploma	85	.074	.296
	Bachelor Degree	184	.068	.886
	Master Degree	192	.081	.548
	Doctoral Degree	249	.060	.164
SI ->BI	Senior High School	63	.208	.160
	Diploma	85	.165	.998
	Bachelor Degree	184	.101	.717
	Master Degree	192	.100	.914
	Doctoral Degree	249	.076	.103
TR ->BI	Senior High School	63	.267	.954
	Diploma	85	.107	.001
	Bachelor Degree	184	.068	.000
	Master Degree	192	.095	.003
	Doctoral Degree	249	.088	.000

Source: Data Processed (2023)

Discussion

The theoretical model proposed in this research has revealed several key factors influencing Behavioral intentions to use SES. In-depth analysis produces exciting findings about how various aspects affect users' decisions to adopt and use this system, including EE, FC, and TR as very influential factors. EE indicates that users' perceived ease of use influences their decision to use SES. FC suggested that the infrastructure support and resources available for users to use SES greatly influenced their decisions. TR indicates that users' general readiness and comfort with technology play a vital role in their acceptance of SES.

On the other hand, PE and SI were barriers to BI to use SES. PE indicates that users may not see immediate benefits from increased performance, or the system does not emphasize enough the performance benefits that can be gained. SI suggests that adopting this technology is based more on the user's internal factors rather than external influences.

The path coefficients of EE ->BI, FC ->BI, and TR ->BI adopting SES have a positive influence which are consistent with previous research. These findings imply that when users feel at ease in using SES (Effort Expectancy), feel supported by facilitating conditions, and have high technology readiness; they tend to have higher intentions. It is vital to adopt and use the system. EE findings are consistent with literature showing that users are more likely to adopt technology they find easy and comfortable to use.

TR's findings support research showing that individuals' attitudes toward technology, including their confidence in using technology and their openness to innovation, influence technology acceptance. These findings emphasize the importance of understanding and addressing the factors influencing user acceptance of new technologies such as SES. By focusing efforts on improving ease of use, providing adequate infrastructure support, and increasing users' technology readiness, organizations can increase the likelihood of adoption and effective use of systems such as SES. The TR path coefficient in this study shows a p-value of 0.000, indicating a significant influence on BI to adopt the technology. This research explores the impact of demographic factors such as G, A, and E on BI. By incorporating these demographic factors into the analysis, this research can provide more prosperous and differentiated insights into how SES is received and used across different population segments. This allows SES developers and implementors to better understand the needs and preferences of diverse users, enabling them to adapt their implementation and communication strategies to increase acceptance and effective use of the system. Additionally, the results of this demographic analysis can help in identifying groups that may require additional support or unique resources to maximize the acceptability and utility of SES.

In line with previous research findings, this study also recognizes that the public sector is considered a priority for the development of health detection technology. However, this study provides an additional dimension by introducing SES as a specific tool to improve health screening by looking at body temperature, heart rate, fatigue level, and respiration. The importance of data security and privacy, as emphasized by previous research, is also reflected in the implementation of SES and ensures that the integration of AI in SES not only provides fast and accurate screening results but also prioritizes the security and privacy of personal data. This research brings new contributions by considering society's understanding regarding the adoption of health detection. Not only providing technological solutions, but also exploring user perceptions and intentions towards AI technology in the context of health detection. This reflects a deep need to understand people's adoption behavior, as recognized by previous research. Overall, this research can provide a useful basis for stakeholders to make informed decisions and guide the development of better health detection technologies in the future.

CONCLUSION AND RECOMMENDATION

This paper aims to examining investigate the acceptance of SES technology by exploring the UTAUT conceptual framework. Based on the results of SEM analysis, the proposed model is proven to fit effectively with the constructs used in this research. With the integration of TR, this research succeeded in expanding and deepening analytical capabilities that are more detailed and comprehensive toward technology acceptance behavior and the intensity of intention to use SES. Our findings further reveal the significant impact of various dimensions, including EE, FC, and TR, on BI in the context of health screening using SES.

The research results shows that the four main factors in TR, namely discomfort, innovativeness, optimism, and insecurity positively influence the intention to use SES. These three factors collectively highlight the dynamic nature of technology readiness. They show that willingness to adopt new technologies is driven not only by comfort with the innovation but also by dissatisfaction with old methods and concerns about security and risk. These results provide important insights into how healthcare organizations and SES developers can target and adapt their strategies to increase technology acceptance and use among users. The findings from this study provide substantial and in-depth support for the developed model, explicitly highlighting how users' technology readiness influences SES acceptance and adoption. Through careful analysis, this research revealed vital aspects that affect how users respond and interact with SES technology. This study offers invaluable insights and has broad practical implications for developing and implementing SES. By deeply understanding the factors that influence the acceptance of these technologies, developers and practitioners in the technology and healthcare fields can take strategic steps to design and implement more effective SES systems with long-term impact and healthcare effectiveness.

Integrating the UTAUT, BI, and TR frameworks in the context of SES is a significant theoretical contribution. In the context of SES, UTAUT helps identify factors such as PE, EE, SI, and FC that may influence how individuals and organizations adopt and use SES. The UTAUT framework in our research is the primary analytical tool for understanding the factors influencing technology acceptance. These include PE, EE, SI, and FC. This framework provides insight into how these factors contribute to individuals' decisions to adopt technology. Additionally, we integrate the TR framework to explore how individuals' tendencies, beliefs, and attitudes toward technology influence their decisions to adopt and use it. This allows us to understand the psychological and behavioral aspects underlying technology acceptance. By using UTAUT frameworks, our research successfully addresses gaps in the existing literature and presents a more holistic approach. We consider external factors that influence technology acceptance and pay attention to individual internal factors. The result is a comprehensive framework that enables a deeper understanding of how various aspects influence user behavior in the context of health screening, providing important insights for policymakers, practitioners and researchers in this field. This approach is particularly relevant in the context of health screening, where the acceptance and use of technology can significantly impact the effectiveness and efficiency of health services.

This study contributes to existing knowledge by highlighting factors influencing user behaviour in the context of health screening. The identified significant impacts of EE, FC, and TR on BI add valuable insights to the literature. Researchers can leverage these findings to deepen their understanding of user engagement with SES technology. Additionally, our identification of areas such as PE and SI as insignificant factors provides a basis for future investigations to explore and address these challenges. Our research offers practical implications for users by providing insight into factors that may increase their interest and engagement in air quality monitoring solutions. Examining the positive impact of support TR on a user's BI allows individuals to make informed decisions regarding the adoption and continued use of the technology. For SES technology developers, this study is a practical guide to improving application design and functionality. By recognizing the key aspects influencing BI, developers can strategically improve features to align with user expectations, fostering intrinsic motivation and habitual usage patterns. By increasing awareness and engagement, this research contributes to forming a more informed and environmentally conscious society. This is important to ensure that the public understands the importance of health checks and actively participates in related efforts. These findings can help design programs and initiatives to change public health behavior, encourage the adoption of better health practices, and improve overall health.

Overall, this research offers important insights that can assist government agencies and related organizations in designing and implementing effective strategies to improve health and environmental sustainability at the community level.

ACKNOWLEDGEMENT

We want to extend our heartfelt gratitude to the Ministry of Education, Culture, Research, and Technology for supporting this research through the Applied Research Program with reference number 180/E5/PG.02.00.PL/2023. With their help, this research came to fruition. We also thank the University of Raharja, especially the Alphabet Incubator, for their invaluable assistance in completing this study. Finally, we thank our strategic partner, PredictMedix, for their outstanding collaboration throughout this research journey. All contributions and support provided by these parties have been significant for the progress of this research. Thank you for all your assistance.

REFERENCES

Ali, M. A., Hassan, M. S., Mohamed, B. D., & Ali, A. H. (2021). Evaluation and Path-Coefficient Analysis of Some Sugarcane Clones under Upper Egypt Region Conditions. *SVU-International Journal of Agricultural Sciences*, *3*(4), 159–171.

Amany, D., & Desire, A. (2020). Pembelajaran Interaktif Berbasis Gamifikasi Guna Mendukung Program WFH pada Saat Pandemic Covid-19. *ADI Bisnis Digital Interdisiplin Jurnal*, *1*(1), 48–55.

Anggara, Y. (2020). Cegah COVID-19 di Era New Normal pada KP. Sambengan. *ADI Pengabdian Kepada Masyarakat*, *1*(1), 59–68.

Apriani, D., Devana, V. T., Sagala, A. P., Sunarya, P. A., Rahardja, U., & Harahap, E. P. (2023). Security Using Blockchain-Based OTP with The Concept of IOT Publish/Subscribe. *AIP Conference Proceedings*, *2808*(1).

Ayuna, N. E. (2023). Peran Komunikasi

dalam Proses Akulturasi Sistem Sosial Lokal. *Technomedia Journal*, *8*(1), 1–17.

Basuki, S., & Anugrah, R. (2019). Transaction Document Security Protection in the Form of Image File, JPG or TIF Interbank Transfer Using Steganography and Cryptography. *IAIC Transactions on Sustainable Digital Innovation*, *1*(1), 42–48.

Celi, L. A., Cellini, J., Charpignon, M.-L., Dee, E. C., Dernoncourt, F., Eber, R., Mitchell, W. G., Moukheiber, L., Schirmer, J., & Situ, J. (2022). Sources of Bias in Artificial Intelligence that Perpetuate Healthcare Disparities—A Global Review. *PLOS Digital Health*, *1*(3), e0000022.

Chauhan, S., Tyagi, S. D., Gupta, A., & Singh, S. (2022). Genetic Variability, Correlation, Path Coefficient and Cluster Analysis in Bread Wheat (Triticum Aestivum L.) Under Rainfed Conditions. *The Pharma Innovation Journal, 11*(11) 818-823.

Feng, J., Phillips, R. V, Malenica, I., Bishara, A., Hubbard, A. E., Celi, L. A., & Pirracchio, R. (2022). Clinical Artificial Intelligence Quality Improvement: Towards Continual Monitoring and Updating of AI Algorithms in Healthcare. *NPJ Digital Medicine*, *5*(1), 66.

Figueroa-Armijos, M., Clark, B. B., & Da Motta Veiga, S. P. (2023). Ethical Perceptions of AI in Hiring and Organizational Trust: The Role of Performance Expectancy and Social Influence. *Journal Of Business Ethics*, *186*(1), 179–197.

Gao, J., Ren, L., Yang, Y., Zhang, D., & Li, L. (2022). The Impact of Artificial Intelligence Technology Stimuli on Smart Customer Experience and the Moderating Effect of Technology Readiness. *International Journal of Emerging Markets*, *17*(4), 1123-1142.

Gashaw, Z., Gebreselassie, W., & Hailemichael, G. (2020). Correlation and Path Coefficient Analysis in Yield and Yield-Related Components of Black Cumin (Nigella Sativa L.) Accessions, at Jimma, Southwest Ethiopia. *International Journal of Agronomy*, *2020*, 1–9.

Gumz, J., Fettermann, D. C., Sant'Anna, Â. M. O., & Tortorella, G. L. (2022). Social Influence as a Major Factor in Smart Meters' Acceptance: Findings from Brazil. *Results in Engineering*, *15*, 100510.

Hardini, M., Sunarjo, R. A., Asfi, M., Chakim, M. H. R., & Sanjaya, Y. P. A. (2023). Predicting Air Quality Index Using Ensemble Machine Learning. *ADI Journal on Recent Innovation*, *5*(1), 78–86.

Hardjosubroto, R., Raharja, U., Anggraini, N., & Yestina, W. (2020). Penggalangan Dana Digital untuk Yayasan Disabilitas Melalui Produk UMKM Di Era 4.0. *ADI Pengabdian Kepada Masyarakat*, *1*(1), 1-14.

Huang, Y.-C. (2023). Integrated Concepts of The UTAUT and TPB In Virtual Reality Behavioural Intention. *Journal of Retailing and Consumer Services*, *70*, 103127.

Kam, H. C., Lui, N. C. K., Du, E. Y. C., Lui, M. N. K., Chan, C. S., Cheung, Y. T., Cheung, K. C., & Leung, M. S. M. (2022). Effective Real-Time Face Mask Detection on NVIDIA Edge Devices. *HKIE Transactions Hong Kong Institution Of Engineers*, *29*(2), 120–128.

Kano, K., Choi, L. K., & Subhan Riza, B. (2022). Implications of Digital Marketing Strategy the Competitive Advantages of Small Businesses in Indonesia. *Startupreneur Bisnis Digital*, *1*(1), 44–62.

Komalasari, R. (2023). Telemedicine in Pandemic Times in Indonesia: Healthcare Professional's Perspective. *In Health Informatics and Patient Safety in Times of Crisis* (138–153). IGI Global.

Li, X., Tao, S., Huang, Z., Chen, S., Zeng, Z., Ni, L., Huang, Z., Zhuang, C., Wu, H., & Li, W. (2023). IEDA: An Open-Source Intelligent Physical Implementation Toolkit and Library. *Arxiv Preprint Arxiv:2308.01857*.

Liang, B., Wei, R., Zhang, J., Li, Y., Yang, T., Xu, S., Zhang, K., Xia, W., Guo, B., & Liu, B. (2022). Applying Pytorch Toolkit to Plan Optimization for Circular Cone based Robotic Radiotherapy. *Radiation Oncology*, *17*(1), 82.

Limna, P. (2023). The Digital Transformation of Healthcare in The Digital Economy:

A Systematic Review. *International Journal of Advanced Health Science and Technology*, *3*(2), 127–132.

Lin, M., & Huang, Y. (2023). Research on User Experience Design Strategy of Digital Aquarium Based on UTAUT2 Model. *International Conference on Human-Computer Interaction*, 167–188.

Manickam, P., Mariappan, S. A., Murugesan, S. M., Hansda, S., Kaushik, A., Shinde, R., & Thipperudraswamy, S. P. (2022). Artificial Intelligence (AI) And Internet of Medical Things (IOMT) Assisted Biomedical Systems for Intelligent Healthcare. *Biosensors*, *12*(8), 562.

Marina, D., Pandjaitan, N. K., Hasanah, N., & Cesna, G. P. (2023). Analysis of Lifestyle and Consumer Attitude towards Intention to Purchase a Personal Car during Pandemic. *APTISI Transactions on Management (ATM)*, *7*(1), 15–34.

Maroju, R. G., Choudhari, S. G., Shaikh, M. K., Borkar, S. K., Mendhe, H., Maroju Jr, R. G., & Borkar, S. (2023). Role of Telemedicine and Digital Technology in Public Health in India: A Narrative Review. *Cureus*, *15*(3) e35986..

Maulani, G., Rahardja, U., Hardini, M., I'zzaty, R. D., Aini, Q., & Santoso, N. P. L. (2020). Educating Farmers Using Participatory Rural Appraisal Construct. *2020 Fifth International Conference on Informatics and Computing (ICIC)*, 1–8.

Miraz, M. H., Hasan, M. T., Rekabder, M. S., & Akhter, R. (2022). Trust, Transaction Transparency, Volatility, Facilitating Condition, Performance Expectancy towards Cryptocurrency Adoption Through Intention to Use. *Journal of Management Information and Decision Sciences*, *25*(1S), 1–20.

Mustafa, U., Kreppel, K. S., Brinkel, J., & Sauli, E. (2023). Digital Technologies to Enhance Infectious Disease Surveillance in Tanzania: A Scoping Review. *Healthcare*, *11*(4), 470.

Naik, N., Hameed, B. M., Shetty, D. K., Swain, D., Shah, M., Paul, R., Aggarwal, K., Ibrahim, S., Patil, V., & Smriti, K. (2022). Legal and Ethical Consideration in Artificial Intelligence in Healthcare: Who Takes Responsibility? *Frontiers in Surgery*, *9*, 266.

Ogbeide, K. O., & EJ, E. M. (2016). Path-Loss Prediction for UHF/VHF Signal Propagation in Edo State: Neural Network Approach. *Aptikom Journal on Computer Science and Information Technologies*, *1*(2), 77–84.

Proal, A. D., Vanelzakker, M. B., Aleman, S., Bach, K., Boribong, B. P., Buggert, M., Cherry, S., Chertow, D. S., Davies, H. E., & Dupont, C. L. (2023). SARS-Cov-2 Reservoir in Post-Acute Sequelae of COVID-19 (PASC). *Nature Immunology*, *24*(10), 1616-1627.

Putri, S. Y., & Meria, L. (2023). Pengaruh Persepsi Nilai dan Kepercayaan terhadap Keputusan Pembelian yang di Mediasi oleh Minat Beli. *Technomedia Journal*, *8*(1), 92–107.

Qadri, Y. A., Nauman, A., Zikria, Y. Bin, Vasilakos, A. V, & Kim, S. W. (2020). The Future of Healthcare Internet of Things: A Survey of Emerging Technologies. *IEEE Communications Surveys & Tutorials*, *22*(2), 1121–1167.

Rahardja, F. A., Chen, S.-C., & Rahardja, U. (2022). Review of Behavioral Psychology in Transition to Solar Photovoltaics for Low-Income Individuals. *Sustainability*, *14*(3), 1537.

Rahardja, U. (2022a). Masalah Etis dalam Penerapan Sistem Kecerdasan Buatan. *Technomedia Journal*, *7*(2), 45–52.

Rahardja, U. (2022b). Social Media Analysis as a Marketing Strategy in Online Marketing Business. *Startupreneur Bisnis Digital (SABDA Journal)*, *1*(2), 176–182.

Rahardja, U., & Triyono, T. (2020). Model Scheduling Optimization Workforce Management Marketing. *Aptisi Transactions on Management (ATM)*, *4*(2), 92–100.

Rahmad, J. B., Suwandi, S., Soedaryono, C. K. T., Aryanti, L. F. D., & Aprialiasari, D. (2022). Analysis of The Effect of Community's Role in CSR Activities on the Image of the Company of Minarak Brantas Gas, Inc. *ADI Journal On Recent Innovation*, *3*(2), 153–171.

Roh, T., Park, B. Il, & Xiao, S. S. (2023). Adoption of AI-Enabled Robo-Advisors in Fintech: Simultaneous Employment of UTAUT and the Theory of Reasoned Action. *Journal of Electronic Commerce Research*, *24*(1), 29–47.

Rouidi, M., Hamdoune, A., Choujtani, K., & Chati, A. (2022). TAM-UTAUT ond The Acceptance of Remote Healthcare Technologies by Healthcare Professionals: A Systematic Review. *Informatics in Medicine Unlocked*, *32*, 101008.

Siala, H., & Wang, Y. (2022). SHIFTing Artificial Intelligence to be Responsible in Healthcare: A Systematic Review. *Social Science & Medicine*, *296*, 114782.

Sun, L., Gupta, R. K., & Sharma, A. (2022). Review and Potential for Artificial Intelligence in Healthcare. *International Journal of System Assurance Engineering and Management*, *13*(Suppl 1), 54–62.

Văduva, L. L., Nedelcu, A.-M., Stancu, D., Bălan, C., Purcărea, I.-M., Gurău, M., & Cristian, D. A. (2023). Digital Technologies for Public Health Services after she COVID-19 Pandemic: A Risk Management Analysis. *Sustainability*, *15*(4), 3146.

Venkatesh, V. (2022a). Adoption and Use of AI Tools: A Research Agenda Grounded in UTAUT. *Annals Of Operations Research*, *308*, 1–12.

Venkatesh, V. (2022b). Adoption and Use of AI Tools: A Research Agenda Grounded in UTAUT. *Annals of Operations Research*, *308,* 1–12.

Watini, S. (2023). Development of Java Hands Startup Business Idea Model by Lean Startup Approach. *Startupreneur Bisnis Digital (SABDA Journal)*, *2*(1), 43–50.

Zulkarnain, W., & Andini, S. (2020). Inkubator Bisnis Modern Berbasis I-Learning untuk Menciptakan Kreativitas Startup di Indonesia. *ADI Pengabdian Kepada Masyarakat*, *1*(1), 77–86.