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Emotion recognition system towards sustainability development

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Abstract

Artificial Intelligence (AI), a transformative innovation in the past two decades, is reshaping industries and societies. Emotion Recognition System (ERS), a subset of AI, enables machines and robots to discern human emotions. As more AI solutions incorporate ERS, it has led to the establishment of Emotion AI as a promising development enhancing human-computer interaction (HCI) which is a key feature of Industrial Revolution 5.0. Many researchers suggested that Emotion AI will lead to many potential innovative solutions that can be applied in various sectors. Through Emotion AI we would gain the ability to have better awareness, empathy and emotional intelligence, leading to better engagement. Thus, sustainability practitioners utilising Emotion AI can affect better engagement for their initiatives and realise the desired impact. Since ERS engineers, practitioners and developers are expanding the used of ERS and emotion AI to be part of every individuals lives, therefore, there is a need to understand the perspective of the potential users in adopting ERS and being ready for ERS. This research provides insights into individuals' readiness to integrate ERS into their lives. Specifically, this study examines Malaysian youths' readiness and adoption of ERS. With a sample of 177 respondents using PLS-SEM, the study identifies Attitude, Subjective Norms, Perceived Behavioral Control, Facilitating Conditions and Awareness as determinants of ERS adoption. Furthermore, Technology Aptitude moderates the relationship between the determinants and ERS adoption intention. The findings can help future researchers develop more accurate and impactful ERS technologies that can affect better achievement of sustainability goals.

Keywords: Artificial intelligence, Emotion recognition system, Human-computer interaction, Sustainability, Technology adoption.

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1. Introduction

Emotional is important to address to enable emotion regulation and enhanced well-being [1]. Emotions play an important role in our daily lives. Emotions are a complex structure in the form of human interpretation and emotions may affect the way we live [2]. In psychology, emotions are a projection of a feeling based on personal experiences and they can be emotional clarity and emotional attention [3]. Emotional clarity is the extent to which people can label and identify their emotions [2]. While for emotional attention is the ability to attend to one's emotions and one's emotional needs [1, 2].

Emotion awareness was highlighted in a previous study to be one of the important to influencing learning processes and learner performance [3]. In many aspects, emotional awareness can be one of the examples to determine an individual behaviour, performance, quality, and integration within societies. Emotions have an impact on societies and individuals, thus, indicating that learning about emotions and understanding emotional responses will improve the relationship between humans. In the recent technological transformation, there is a study related to emotional intelligence, where software, computers, and machines need to possess the ability to recognize and understand human emotions. One of the approaches towards emotional intelligence is through artificial intelligence (AI). AI has transformed from just a theory to tangibility over the last few years, with many recent applications from AI transforming businesses, industries, and societies [4]. Inspired by human intelligence, AI seeks to emulate human capabilities such learning process, reasoning, and decision making [5]. With years of advancing and refining AI, technologies or smart devices nowadays are equipped with AI minimizing the need for human intervention [5].

Human emotion will always play a major role in communication and interpersonal bonding between people [6]. People perceive their emotions based on their physical attributes of facial expression, speech expression and body movement [6, 7]. In addition, with recent technological advancement and changes globally, technologies have grown to be part of the daily lives of people [7]. One of the examples of technological advancement is artificial intelligence (AI). AI is an advancement in computer science that allows a computer or machine to learn, train, perform and complete tasks, make decisions, and replicate humans based on experience [5, 8, 9].

In recent technological advancements, AI enhance trust by focusing on beneficence, non-maleficence, autonomy, justice and explicability [5, 10]. In recent years, researchers and scientists explored the sub-AI applications to enhance AI further. One that has been studied over the recent years is developing AI with the capabilities to understand and recognize human emotions [9]. However, there are six basic emotions identified specifically to ensure the learning behaviour of AI to identify human emotions [11]. The six basic emotions are happy, sad, fear, anger, disgust and surprise [11]. These six basic emotions have become the core for scientists and researchers to develop the modalities to recognize human emotions such as physiological modalities signals from humans, physical modalities from human expression and machine learning software modalities. In the last decade, the trend of AI emotion recognition is increasing as shown in Figure 1. Researchers believe that many potential innovative solutions can be gained from AI emotion features. Moreover, the AI emotion is frequently known as an emotion recognition system (ERS) due to researchers and scientists developing the system to enable AI to recognize human emotions.

Over the last decade, the ERS trend has risen due to the direction of technological advancement and digital innovations approach. For example, the fourth industrial revolution (IR 4.0) has seen many technological advancements and digital innovations such as AI, the Internet of Things (IoT), cloud computing, big data and more, transforming the approach of industries and businesses. Specifically, in Malaysia, IR 4.0 has been adopted in industries and businesses to leverage the AI potential and AI capabilities. The Malaysian government has introduced the IR 4.0 policies and AI-Roadmap plan policies to further encourage Malaysian citizens to be ready for technological advancements. The IR 4.0 policies emphasise the need of Malaysian citizen to be ready for changes in terms of digitalization and interconnected nations between societies and technologies[1]. Supported with AI-Roadmap plan are to bring Malaysian citizens aligned with the digital transformation globally. The IR 4.0 policies thrusts and AI-Roadmap highlight the commitment that the government has shown to fully

[1] https://www.ekonomi.gov.my/sites/default/files/2021-07/National-4IR-Policy.pdf (Accessed on 30th March 2022)

integrate the nation to adopting any technological changes[2]. Hence, the introduction of ERS plays a significant impact for technological changes and there is a need for users to understand and adopt ERS since ERS engineers, practitioners and developers are actively developing ERS to be widely adopted globally.

Furthermore, the direction towards the fifth industrial revolution (IR 5.0), will be one of the future innovations, where researchers and scientists expectation of technology to cooperate with humans and work alongside humans [12, 13]. Therefore, the ERS trend implied that it can be one of the innovative approaches to enable human-computer interaction (HCI) which leads towards the direction of IR 5.0. However, in the Malaysian landscape, the policies from the Malaysian government encourage Malaysian citizens to understand and adopt AI widely and gain opportunities through AI, including the emotions AI which is ERS. This has been the motivator for this study to understand the perspective of ERS implementation towards the users. Additionally, engineers, developers and technology makers have identified potential applications of ERS, however, without a specific focus on the user's perspective, there is a gap between the technology maker and the user.

In this study, ERS was identified to be one of the technologies that can help to achieve sustainability, with the concept of sustainability being towards sustainable social communities, human-centred design and eco-friendly technology. ERS links human-centred design by focusing on human emotions and enhancing current technological advancements. Hence, the objectives and the results of this study based on the results of the factors determining the ERS adoption will help the technology makers and developers to understand that societies specifically Malaysian citizen has a positive attitude towards ERS adoption and led to the growth of sustainability goals.

2. Literature Review

Previous studies specified Emotion AI as ERS and it was originally in the field of Affective Computing [14] where computers and machines interact with humans. In the field of AI, many technologies have achieved the possibility of enabling human-computer interaction (HCI). The HCI led to the findings of the ERS which enhance AI innovations. Since then, ERS has become an important area in the field of HCI, focusing on creating robots and machines capable of interacting and communicating with humans, equipped with functions for both understanding human emotions and translating human emotions. Some applications of ERS have been suggested towards the healthcare industries [15] driving car assistance towards smart car implementation [16] marketing purposes [17] education sector [18] and more.

Stress indicates the level of a person's emotions, hence, monitoring the stress level will improve an individual’s environment which contributes to increasing the stress level. ECG is among the modalities that have been thoroughly tested through enabling ERS. Famously known among healthcare practitioners, ECG now has become one of the important pieces of technology in modern devices [19]. One of the examples is the Apple smartwatch's built-in ECG monitoring blood pressure and heart rate which provides freedom to individuals to understand their well-being as well as emotions. In addition, facial recognition and speech recognition have also become the major modalities to enable the recognition of human emotions. A camera such as a webcam can enable computers and machines to analyze human expressions and translate emotions [18] however, it is difficult to accurately define one’s emotions based on facial expressions. Facial recognition has become one of the popular approaches by many big technology maker industries such as Microsoft, Google, Apple and Amazon, to name a few that practically evaluate customer’s emotions.

Speech recognition is one of the famous approaches to enable ERS. Speech recognition can detect a person's emotions based on the tone and voice [6]. Speech recognition detects the pitch of a person’s voice and indicates whether they are angry, happy, or sad [6]. The vibration of our voice can be passed through machine learning, and it will enable whether a certain decibel shows the person’s feelings and emotions. The first three modalities such as ECG, facial expression and speech recognition are mostly identified in previous studies. Another suggestion for ERS in machine learning processes is data mining through text [17]. Text mining is beneficial for marketing and advertising purposes, as the comments and feedback on social media, blogs and websites can analyze whether one’s feelings are happy, angry or sad on a certain level. For example, the seed of words such as, “Argh!” and “Aww” can determine a feeling of someone [17].

The applications of ERS may provide significant benefits to industries and businesses [20]. The importance of ERS implementation enhances the world of digital innovations. Firstly, it can increase security through facial recognition in public places such as banks and airports by identifying potential threats. Furthermore, ERS can assess personality traits in interviews such as potential candidates by analysing their facial expression and their emotions [21]. It is also can be applied to improve the working environment by measuring the facial expressions of employees if they are happy or unhappy in the workplace. Another benefit of ERS is to gain feedback that helps the product understand the real emotions of the customer. Businesses, industries, and companies can arrange a product training session and record the session to analyse body language and facial expressions [22]. Additionally, it can enhance customer services for emotion detection specifically towards healthcare industries and retailers. Retailers can craft a special offer to their customers. Some campaigns improve customers' feelings and emotions, and they will create a pattern based on emotional intelligence from AI. For healthcare industries, emotion recognition can create better care plans and services for employees based on their facial expressions, speech expressions and even through ECG, hence, healthcare industry employees can improve their service to align with the customers’ expectations [15].

2.1. Sustainability Development

Sustainability has spread throughout many different backgrounds of study, specifically in terms of environmental, social, and economic impact [23]. For the last decades, sustainability has become the major study in academics, syllabuses

[2] https://airmap.my/wp-content/uploads/2022/08/AIR-Map-Playbook-final-s.pdf (Accessed on 15th December 2022)

and governance policies to retain the concept of "improving without compromising" in many different aspects [24]. From a technology perspective, globalization enables changes in technological advancement and policy development to achieve continuous economic and social progress [25].

Previous studies on technology and sustainability reviewed that the standardized form of sustainability has formed green technology development [23]. Green technology development has evolved the technologies to be more conscious about environmental and societal impact [23]. In times of economic decline, businesses and industries that implement eco-friendly practices, fostering the well-being of stakeholders while enhancing shareholder value, have shown significant performance compared to their counterparts [26]. This strategy emphasizes financial benefits including decreased operational costs and increased revenues, especially through green technology and the innovation of environmentally sustainable technologies [26].

Sustainability studies reported that organizations comply with governance policies to prevent the decrease of natural resources and materials Zrnić, et al. [25]. Zrnić, et al. [25] has suggested that the use of green technologies and the intervention of governance policies on the stakeholders in the sustainability programmed facilitates productivity and efficiency within work environments and helps in control to optimize the performance of the technologies in general [25].

As mentioned earlier, industries and businesses from IR 4.0 have embraced technological advancement such as AI with many technologies that can be embedded to enhance productivity as well as the well-being of a human. Therefore, technologies that emphasise emotional awareness can be one of the revolutionized advancements. Recognizing others' emotions is crucial for social integration and well-being [27]. Psychologically, this ability relies on distinguishing between oneself and others to identify one's emotional experiences from those of others. In many aspects, emotions play a role in determining performance and productivity in daily life as well as environmental impact.

From business and industry perspectives, sentiments from emotions influence behaviour in the environment, therefore, research related to emotions follows the concept that the recognizing of other's emotions is important through technology enabler [27, 28]. Hence, it is suggested that ERS or emotion AI is a key technology enabler for such purposes. As the previous section suggested, the various applications and modalities present good opportunities for industries to exploit ERS.

Researchers, engineers and innovators have predicted that technologies can enhance human well-being and that the higher integration of technologies into daily life will change societies as we know it [29]. Therefore, advancements such as ERS specifically are expected to greatly enhance HCI leading to better human-centered design between technology and humans as well as the introduction of ERS, it will affect greater emotional intelligence that can also promote sustainability goals in the long term [27].

It is envisioned ERS, or emotion AI provide us with the ability to be more emotionally aware leading to the ability to take actions or design interventions that promote empathy for causes or goals of interest. Including human emotions towards the initiatives for sustainable development. Thus, practitioners of sustainability development via ERS can turn their agendas from unrelatable ideals to meaningful calls to action. Thus, practitioners would have better abilities to ensure support from the communities. One of those groups often seen as less engaged in matters outside popular culture such as sustainability development agenda are the youths. This motivates the study on technology adoption among the youths to understand their sentiments and behaviour towards ERS.

2.2. Technology Adoption Theories

Prior research has proposed various theories to explain consumers' acceptance of new technologies and their intention to use them. This study specifically identifies the Theory of Planned Behaviour (TPB) by Ajzen [30] which provides insight into attitude, subjective norm and perceived behavioural control. Furthermore, this study adopts facilitating conditions from the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh, et al. [31]. Lastly, Diffusion of Innovation (DOI) technology adopter categories by Rogers [32] will be adopted in this study. The three main underlying theories will form the research framework for this study. These theories provide valuable insights into comprehending individuals' acceptance of technology, their intentions, and their behaviours.

2.3. Theory of Planned Behaviour

The primary objective of this study is to gain insights into the readiness of users to adopt ERS; thus, the theoretical framework adopted in this study incorporates the TPB proposed by Ajzen [30]. By incorporating TPB, the study aims to provide a comprehensive understanding of the factors influencing the acceptance of ERS technology. TPB examines the behavioral intentions of individuals, considering their attitudes, subjective norms, and perceived behavioral control [30]. Initially, the Theory of Reasoned Action (TRA), introduced by Ajzen and Fishbein [33] served as the basis for TPB. TPB extends TRA by incorporating perceived behavioral control as a new determinant. TPB consists of attitude, subjective norm and perceived behavioural control, and has been one of the prominent theories in understanding behavioural intention in the technology adoption field. The Theory of Planned Behavior (TPB), building upon the Theory of Reasoned Action (TRA) introduced by Ajzen and Fishbein [33] incorporates perceived behavioural control as a new determinant. It emphasizes the pivotal role of an individual's attitude toward a behaviour, subjective norms influenced by surrounding individuals, and perceived behavioural control in determining behaviour. Widely utilized in assessing social behaviour and technology adoption, TPB has provided valuable insights into how behaviour and intention impact the adoption of various technologies [34-37]. By integrating TPB, this study aims to comprehensively understand the factors driving the acceptance of ERS technology.

2.4. Facilitating Conditions

In the earlier section, it has been identified that environmental support can be one of the determinants. Infrastructure and policies from the government to encourage can be one of the determinants in encouraging behavioural intention to adopt ERS among Malaysian citizens. Facilitating Conditions, as indicated by UTAUT, emphasize the importance of infrastructure support in fostering readiness for ERS adoption [38-41]. This factor assesses whether the country's structural environment supports ERS adoption and if additional encouragement is necessary. It underscores the significance of Malaysian government policies and programs in advancing technological adoption. Hence, this factor encompasses information on infrastructure, policies, and the structural environment.

2.5. Awareness

Considering ERS is a new technological advancement and it is still not yet widely available for users, individual awareness can be the key to readiness, hence, this study added awareness as one of the key determinants for behavioural intention readiness. A thorough search supported the notion that awareness is a key factor in technology adoption. As suggested, new technologies needed some awareness to increase the outreach to the users, while some other technologies did not require awareness to prepare the user [42, 43].

2.6. Diffusion of Innovation

Given the significance of human-centred design, the DOI technology adopter categories theory elucidates how innovations disseminate and are embraced within a social system [44, 45]. This theory categorizes adopters into Innovators, Early Adopters, Early Majority, Late Majority, and Laggards, shedding light on the characteristics of individuals in Malaysian society. Innovators and Early Adopters, demonstrating a keen interest and understanding of technology, play a leadership role in its introduction [44, 45]. The Early Majority adopts technology after it becomes widely available and validated by Innovators and Early Adopters, while the Late Majority adopts it out of necessity [44, 45]. Laggards are the last to adopt due to minimal impact on their lives [44, 45]. These categories delineate varying levels of interest and understanding in technology.

Moreover, the study delves into individuals' technology aptitude, defining it as their ability to effectively use technology as intended by its creators. The high technology aptitude group comprises Innovators and Early Adopters, proficient in using technology with minimal guidance. Conversely, the low technology aptitude group, consisting of the Early Majority, Late Majority, and Laggards, displays less interest in exploring or understanding new technologies, preferring to refrain from following technological trends.

2.7. Hypothesis Development

This study seeks to develop hypotheses concerning the behavioural intention (BI) of users regarding their readiness to adopt Emotion Recognition Systems (ERS). Grounded in the Theory of Planned Behavior (TPB), the first hypothesis posits that individuals' attitudes (AT) toward ERS will significantly influence their BI for ERS adoption readiness. This hypothesis is supported by previous research indicating that positive attitudes toward technology adoption increase the likelihood of adoption. The second hypothesis focuses on the subjective norm (SN), suggesting that perceived social pressure from significant others will impact individuals' readiness to adopt ERS. Similarly, the third hypothesis considers perceived behavioural control (PBC), proposing that individuals' perceptions of their ability to adopt and use ERS effectively will influence their readiness for adoption. The fourth hypothesis addresses facilitating conditions (FC), suggesting that the presence of supportive infrastructure, policies, and programs will enhance individuals' readiness to adopt ERS.

Additionally, the fifth hypothesis examines the influence of awareness (AW), positing that individuals' awareness of ERS and its potential benefits will influence their readiness for adoption. Finally, the sixth hypothesis explores the moderating effect of technology aptitude (TA), proposing that individuals' proficiency and comfort with technology will moderate the relationships between AT, SN, PBC, FC, AW, and BI for ERS adoption readiness. Specifically, individuals with higher technology aptitude may exhibit stronger relationships between these determinants and BI compared to those with lower technology aptitude. These hypotheses collectively aim to elucidate the factors shaping users' behavioural intentions regarding their readiness to adopt ERS, thereby contributing to a deeper understanding of technology adoption processes.

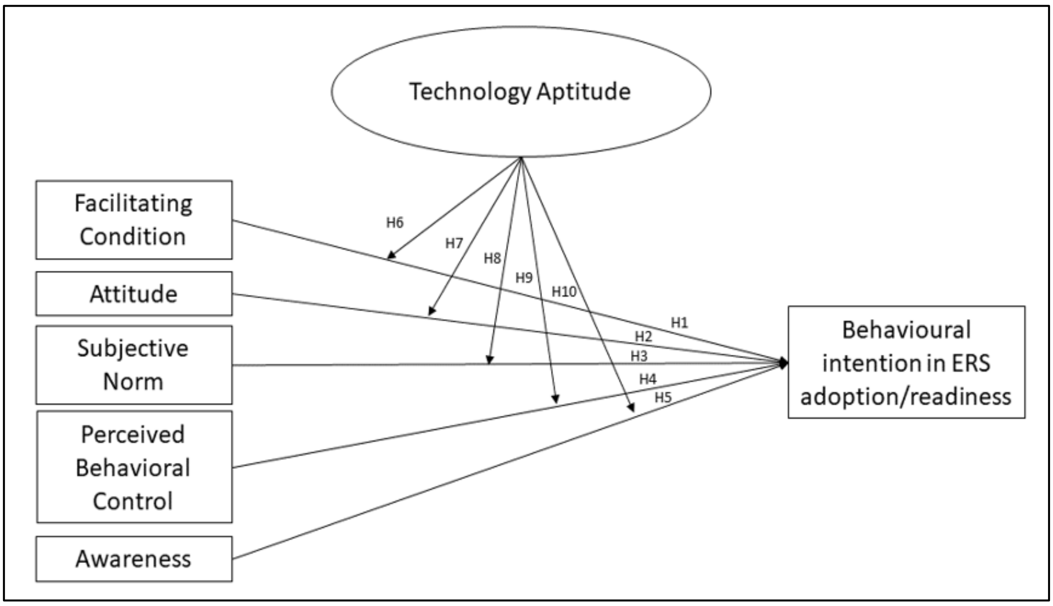

Figure 1.
Research Framework.

Based on the Figure 1, the list of hypothesis from the independent variables involved and moderator variables in this study is listed below:

H_1: Facilitating condition significantly effect behavioural intention in ERS adoption readiness

H_2: Attitude significantly effect behavioural intention in ERS adoption readiness

H_3: Subjective norm significantly effect behavioural intention in ERS adoption readiness

H_4: Perceived behavioural control significantly effect behavioural intention in ERS adoption readiness

H_5: Awareness significantly effect behavioural intention in ERS adoption readiness

H_6: Technology aptitude moderates the effect of facilitating condition towards behavioural intention of ERS adoption readiness

H_7: Technology aptitude moderates the effect of attitude towards behavioural intention of ERS adoption readiness

H_8: Technology aptitude moderates the effect of subjective norm towards behavioural intention of ERS adoption readiness

H_9: Technology aptitude moderates the effect of perceived behavioural control towards behavioural intention of ERS adoption readiness

H_{10}: Technology aptitude moderates the effect of awareness towards behavioural intention of ERS adoption readiness

3. Methodology

A quantitative methodology was used in this study to investigate the phenomenon using the existing theories that construct the theoretical framework [46]. The outcome of the quantitative methodology was based on quantifying problems in a study and understanding their prevalence within a broader scope of the population [46]. The quantitative methodology employs structured data collection methods or surveys that include online surveys, paper surveys, polls, and interviews through in-person or telephone, which are mostly used for quantitative data [46].

The sampling technique involved in this study is purposive sampling or judgemental sampling technique, where the characteristics of purposive sampling are researchers identifying the homogenous characteristics of the target respondent [47, 48]. In this study, the survey will be distributed among the youth, because youths are commonly seen as technology savvy, they are often drivers of technology diffusion and decide the direction of technology advancement based on their usage based on previous studies relating to youth and technology [49, 50]. This can be seen in the terms often used associating youths as the driving forces of technology by Faul, et al. [51] namely, "digital native" and "technology savvy". The identified minimum sample size based on G*Power [52] is 123 respondents.

This study employs self-administered questionnaires on an online survey to collect the data. The online survey was used in this study due to the outreach of online survey to maximize the response within a limited duration when distributing the survey. The demographic profile of this study will have filtered questions, consisting of age (youth) and nationality (Malaysian). Since this study focused on Malaysian youth, these filtered questions will be the first step to filtering out the demographic profile. Specifically, this study employs a 7-Likert scale questionnaire due to the sensitivity and accuracy of the scale ranging from strongly disagree to strongly agree for the respondent to be more precise in their response. A total of 177 completed surveys were gathered.

Furthermore, the data was analyzed through Partial Least Squares-Structural Equation Modelling (PLS-SEM). PLS is a structural equation modelling method based on variance that combines regression analysis and factor analysis to examined the relationship between exogenous and endogenous latent variables [46]. PLS-SEM overcomes the limitations associated with traditional multivariate analysis methods, particularly the stringent assumptions covariance-based SEM (CB-SEM). Moreover, the strictness of sample size and normality are lessened by the PLS-SEM [52, 53]. Hence, PLS-SEM was chosen as the primary analysis approach in this study motivated by the research constructs to test the hypothesis and developing prediction models with small sample size [54].

There are 2 stages involves in PLS-SEM, the first stage is the measurement model, which the outside of the model is assessed and second stage is the structural model, which the inside of the model is assessed [52]. In the measurement model, composite reliability (CR), item loadings, average variance extracted (AVE) are used to measure the convergent validity, and Heterotrait-Monotrait (HTMT) criterion to measure discriminant validity [53, 55, 56]. In the structural model, the variance inflation factor (VIF) measured the collinearity or the common method bias, and the hypothesis testing will be analysed including the coefficient of determination (R^2), effect size (f^2) and predictive relevancy (Q^2).

4. Results and Discussion

Before assessing the structural model, the measurement model is needed to fulfil certain criteria. First is the composite reliability to measures the extent to which the scale provides consistent and stable measurement over time and is free from random error [46]. CR is preferable in the PLS-SEM compared to Cronbach's Alpha [53, 57]. The CR to be reliable must be at least 0.7 [58]. Table 1 shows the results of the reliability CR values. Based on Table 1, the values of CR are greater than the recommended threshold of 0.7, which indicates that the construct consistency in this study has achieved its reliability in the measurement model and indicates the construct involved in this study can be interpreted.

Table 1.
CR Values.

Constructs	CR
AT	0.955
SN	0.938
PBC	0.965
FC	0.935
AWR	0.923
BI	0.945

Next in measurement model is convergent validity, to assess whether multiple indicators of a latent variable converge and measure the same underlying construct [53]. To evaluate the convergent validity is the AVE and the item loadings on the construct [57]. The AVE of the measurement models should be greater than 0.5 [53] and it represents that the observed variables explain at least 50% of the variance in the outer model [52] while the item loadings must load higher than 0.708 [52]. With item loading below the threshold value must be excluded from the construct [52]. Table 2 shows the AVE and item loadings for this study.

Based on the Table 2, it shows that the AVE, which were all above the threshold value of 0.50, moreover, all the item loadings met the threshold value of 0.708 as suggested, as a result, the measurement model has met the convergent validity requirements. Lastly in the measurement model is the discriminant validity which assessed that each construct is different from another construct [52]. Discriminant validity has been assessed through the HTMT criterion [59]. A HTMT ratio of correlations between indicators across constructs measuring different phenomenon (Heterotrait), and the ratio of correlations between indicators across constructs measuring same phenomenon (Monotrait) [46]. If the HTMT ratio of one construct with other construct is less than 0.90, the discriminant validity has been achieved.

Table 3 shows the HTMT ratio of this study. From the Table 3 of HTMT ratio result of this study, all of the construct is less than the threshold value which is 0.90, and indicates that the discriminant validity has been met for this study and every construct does not measuring the same phenomenon. As suggested in using PLS-SEM [52, 56] with all of the measurement models has been met, and all the initial process have been conducted, therefore, it can be further observed on the structural model.

Table 2.
AVE and Item Loadings.

Cons.	AT	SN	PBC	FC	AWR	BI
AVE	0.703	0.655	0.697	0.783	0.666	0.773
AT1	0.767					
AT2	0.797					
AT3	0.848					
AT4	0.839					
AT5	0.847					
AT6	0.851					
AT7	0.861					
AT8	0.855					
AT9	0.875					
SN1		0.79				
SN2		0.828				
SN4		0.799				
SN5		0.821				
SN6		0.83				
SN7		0.819				
SN9		0.795				
SN10		0.792				
PBC1			0.771			
PBC3			0.785			
PBC5			0.841			
PBC6			0.842			
PBC7			0.845			
PBC8			0.868			
PBC9			0.834			
PBC10			0.85			
PBC11			0.837			
PBC12			0.855			
PBC13			0.821			
PBC14			0.864			
FC1				0.875		
FC2				0.91		
FC3				0.896		
FC4				0.857		
AWR1					0.729	
AWR2					0.833	
AWR3					0.87	
AWR4					0.85	
AWR5					0.814	
AWR6					0.793	
BI1						0.85
BI2						0.898
BI3						0.905
BI4						0.862
BI5						0.88

Table 3.
HTMT Ratio.

Constructs	AT	SN	PBC	FC	AWR	BI
AT						
SN	0.839					
PBC	0.796	0.889				
FC	0.637	0.667	0.543			
AWR	0.328	0.508	0.519	0.465		
BI	0.741	0.833	0.887	0.588	0.485	

5. Structural Model

In the structural model, PLS-SEM assess the quality of the inner model which involves the cause-and-effect relationships among the models [46, 52]. Structural model assessment is used to rank models based on how well the predict the endogenous constructs such as the multi-collinearity for each constructs, path coefficients and its significance, the R^2 for endogenous constructs, f^2 for the exogenous constructs, Q^2 for predictive relevance and model fit [55, 60]. To assessed the multicollinearity of the model is analyzing through VIF. The VIF value less than 5 indicate a low correlation of that predictor with other predictors, while a value between 5 to 10 indicates a moderate correlation, while VIF values larger than 10 are a sign for high not tolerable correlation of model predictors [61, 62]. Based on the Table 4, the VIF values for all the constructs including the moderators are within the range of low correlation and moderate correlation. All the values did not obtain the high correlation of model predictors, hence, the exogenous model in this study does not proposed to have any multi-collinearity problems within the construct.

Table 4.
VIF.

Constructs	VIF
AT	6.013
SN	9.023
PBC	7.457
FC	2.703
AWR	2.505
TA x AT	4.462
TA x SN	6.7
TA x PBC	6.197
TA x AWR	2.681
TA x FC	3

The coefficients of the model paths and their significance were obtained from the bootstrapping process in Smart PLS 4 to obtained the results of the t-values and p-values and provide the necessary information for testing the stated research hypothesis. Table 5 shows the full results of the hypothesis tested including the R^2, f^2 and Q^2.

The main focus of the structural model in the PLS-SEM is to test the hypothesis proposed, to examine the relationship between the endogenous and exogenous constructs [45]. The results obtained were based on the t-value and p-value for each relationship calculated. The coefficient is considered significant if the t-value is greater than the critical value, as for this study, a one-tailed test, the t-value is greater than 1.27 at a significance level of 0.10. Hence, both of the values must achieve the same result.

From Table 5 of the hypothesis testing, the results show that 5 hypotheses are supported in this study based on the t and p-values, namely, H1: AT->BI (1.33 & 0.092), H2: SN->BI (1.481 & 0.069), H3: PBC->BI (3.521 & 0.00), H6: TA x AT->BI (1.999 & 0.023) and H8: TA x PBC->BI (1.913 & 0.028). 3 direct hypothesis is supported and 2 moderator hypothesis is supported.

The results indicate a significant causal relationship between the TPB determinants such as attitude, subjective norm and perceived behavioural control on the behavioural intention of ERS adoption readiness. The extended determinants of this study which is facilitating conditions and awareness is not supported in this study. Thus the findings support the hypothesis earlier which is attitude is a significant determinants of ERS adoption, subjective norm is a significant determinants of ERS adoption, perceived behavioural control is a significant determinants of ERS adoption. While 2 moderator that is supported is technology aptitude strengthen the effect of attitude towards behavioural intention and technology aptitude strengthen the effect of perceived behavioural control towards behavioural intention of ERS adoption.

Table 5.
Hypothesis Testing.

Constructs	Hypothesis	T values	P values	f^2	R^2	Q^2	Decision
AT -> BI	H1	1.33	0.092	0.016	0.725	0.5	Supported
SN -> BI	H2	1.481	0.069	0.018			Supported
PBC -> BI	H3	3.521	0	0.114			Supported
FC -> BI	H4	1.217	0.112	0.013			Not Supported
AWR -> BI	H5	0.419	0.338	0.001			Not Supported
TA x AT -> BI	H6	1.999	0.023	0.026			Supported
TA x SN -> BI	H7	1.023	0.153	0.007			Not Supported
TA x PBC -> BI	H8	1.913	0.028	0.031			Supported
TA x FC -> BI	H9	0.503	0.308	0.002			Not Supported
TA x AWR -> BI	H10	0.164	0.435	0			Not Supported

Note: * Two tailed test type and a 0.10 Significance level.

Moreover, results of f^2 from the Table 5, shows that most of the exogenous variable had small effect size to no effect size. Next in the Table 5 is the coefficient of determination, R^2, where the variance in the behavioural intention explained by the exogenous variables. The R^2 value, 0.725, shows that this study has a moderate level where the exogenous variables explained 72.5% of the behavioural intention of ERS adoption readiness. Lastly, in the structural model, is looking into the predictive relevancy, Q^2, to measure the predictive relevance of the endogenous constructs. The threshold value of Q^2 is above 0, where a value that is above 0, shows that the model has a predictive relevance. From the Table 5, the predictive relevance of this study is 0.50 and it is above 0. Hence, the values in this study are well constructed, even though the effect sizes are small or no effect, the model has good explainability and predictive relevance.

6. Model Fit

In PLS-SEM, there is a lacks on accepted method in identifying the model fit of the model [45]. In some previous study, identifying the model fit through the goodness of fit (GoF), as a global criterion of model fit [45].

GoF index is intended to explain the performance of the PLS model at both the measurement and structural levels with a focus on the model's overall prediction performance [55, 56]. Table 6 shows the results of the GoF in PLS-SEM, and the criterion to be measured is the Standardized Root Mean Square (SRMR), of the saturated and estimated model to indicates that the model is good fit for the study including the sample size, indicators and methodology used. Table 6 present the indicator for model fit, the maximum threshold value is 0.08 or 0.10, indicates a good fit for the study in the estimated model [61] which shows that the result of SRMR for the model fit of this study is a good fit (0.055) less than the maximum threshold value recommended in this study.

Table 6.
Model Fit.

GoF	Saturated model	Estimated model
SRMR	0.054	0.055

7. Discussion

This study focused on the adoption level in readiness amongst the Malaysian youth to help the ERS practitioners and developers to develop the technology as impactful to be practical in daily lives. For ERS to be implemented in the daily lives and given the benefit of ERS towards the businesses and industries, it is important for the Malaysian citizen to prepare on the technological advancement such as the advance AI emotions specified further as ERS.

From the five determinants proposed in this study, three of the determinants is supported, and three of the determinants were based on the TPB theories. In line with previous studies [34-36, 62] this study also adopted the TPB theory as the main underlying theory in the theoretical framework. H1 was supported (see Table 5), suggesting that the attitude of Malaysian youth have a significant effect on their behavioural intention for ERS adoption readiness. The finding is consistent with previous studies [34, 35, 62] that suggested attitude can be one of the important keys to accelerate adoption of a specific technology based on compatibility and adaptability in using the technology [34-36]. In other words, with supportive or positive AT, ERS is predicted to have good adoption potential amongst the Malaysian youths. Sustainability development practitioners would be able to use ERS to help them engage the youths better and established generations of more responsible citizens affecting the various sustainability development goals.

Second determinants that was supported is H2, suggesting that subjective norm have a significant influence on behavioural intention of ERS adoption readiness. It is aligned with previous studies [35, 62] where SN was found as an important predictor for technology adoption. The influence of subjective norm (SN) introduces a fresh perspective by considering the impact of individuals' social circles, which encompass family members, peers within organizations or institutions, as well as important individuals and friends who have been exposed to or experienced the technology. SN is utilized in this study to explore whether peer approval, management perception, and social pressure from friends or family members influence adoption readiness for Emotion Recognition Systems (ERS). The study's findings support this hypothesis, underscoring the significance of fostering positive perceptions toward ERS among these groups. This is crucial as it ensures that various influential figures in youths' lives hold favorable attitudes toward ERS, thus positively shaping youths' beliefs about using ERS. Thus, the same is applicable to the sustainability development practitioners. In order for them to ensure good adoption of their ERS, they would need to promote and educate the society on the use as well as benefits of the technology. This would promote endorsement from the social circle of their target users.

Next, the findings of this study support H3, indicating that perceived behavioral control (PBC) is a significant determinant influencing the behavioral intention for Emotion Recognition Systems (ERS) adoption readiness. PBC is defined as individuals' ability to implement adoption independently, encompassing considerations such as technology complexity, financial capacity, and trialability based on users' knowledge [34-36]. Consistent with prior research, which highlights PBC's importance in technology adoption, this study's results reinforce the notion that young individuals who believe they possess the necessary skills and autonomy to decide on ERS adoption are more likely to form the intention to adopt ERS [63]. Despite ERS being a complex technology, individuals are inclined to adopt it if they feel confident and competent enough to master it. Thus, presenting knowledge and information about ERS in an accessible manner can foster positive perceptions about their feasibility, consequently enhancing PBC and intention for adoption. In essence, providing sufficient support, resources, and encouragement can boost users' confidence in their ability to use the technology, thereby accelerating adoption rates. Sustainability development practitioners employing ERS should aim to present the technology in an approachable manner to promote positive PBC among intended users.

Furthermore, the next two hypotheses supported in this study were from the moderation analysis, which saw technology aptitude significantly affecting the relationships between the determinants of ERS adoption readiness. The first supported moderation hypothesis is H6: TA x AT->BI (see Table 5). This indicates that TA significantly influence the relationship between AT and BI. Specifically, high TA reinforces further the determinacy of AT towards BI. Users with high TA and positive attitude would have good propensity to readily adopt ERS. The high TA users were amongst the innovators and early adopters from the DOI categories. Arguably those with high TA most likely would have good technological knowledge and positive attitude technology applications. ERS practitioners when launching any new solutions, in would be best to target the high TA group among Malaysian youths for generating adoption traction that can lead to good market penetration. The high TAs can experience and explore the ERS capabilities and advocate for it towards the rest of the group.

Moreover, the other supported moderation hypothesis is H8: TA x PBC- BI which indicates that TA significantly influences the relationship between PBC and BI. High TA is seen to also affect the determinacy of PBC towards BI. Users with high TA is capable and possess the skills to make decisions to use or adopt ERS and they have the confidence in operating ERS. Hence, the high TA group will be more likely to adopt ERS as these are amongst the innovators and early adopters, they would have the confidence and capabilities needed to use the technology. Therefore, for ERS practitioners, it is important to involve the high TA amongst the Malaysian youths for quick wins when launching a new solution. This would be conducive towards greater adoption rates, since the high TA group can be the demonstrator users that can create confidence in the rest of the target market.

ERS offer multifaceted contributions to advancing sustainability agendas. By leveraging ERS capabilities, organizations and policymakers gain invaluable insights into human emotions, fostering informed and empathetic decision-making aligned with sustainable development goals. The results of the supported hypothesis indicates that a positive AT and PBC shows that the Malaysia youth is ready for ERS adoption. For example, through real-time analysis across diverse contexts like public events or organizational meetings, ERS enhances understanding of stakeholders' emotional landscapes, illuminating their needs, concerns, and motivations surrounding sustainability initiatives. Moreover, ERS nurtures emotional intelligence by heightening awareness of both personal and collective emotions, nurturing empathy, self-awareness, and social consciousness. Armed with this emotional intelligence, decision-makers can craft more strategic and inclusive approaches to sustainability, prioritizing initiatives that not only meet economic objectives but also uphold social and environmental responsibility. ERS also bolsters stakeholder engagement by enabling tailored communication strategies based on emotional responses, fostering increased support and participation in sustainability efforts. Lastly, through emotionally intelligent decision-making, ERS catalyzes innovative solutions to sustainability challenges, encouraging creativity, collaboration, and empathy in addressing complex environmental, social, and economic issues. In sum, integrating ERS into sustainability agendas embodies a holistic and empathetic approach to decision-making, promising more impactful and enduring outcomes for sustainable development.

8. Conclusion

Due to the rising of AI amongst industries, businesses and societies [9]. With the identified determinants and the research framework further support the findings, it shows this study has achieved its objectives which identified the determinants of Malaysian youth behavioural intention of ERS adoption.

ERS can play a crucial role in shaping the sustainability agenda among Malaysian youth by offering unique avenues for engagement and empowerment. Firstly, ERS can be integrated into educational platforms and youth-focused initiatives to gauge the emotional responses of Malaysian youth towards sustainability issues. By analyzing these emotional indicators, policymakers and educators can tailor their outreach efforts to resonate more effectively with the concerns and aspirations of young Malaysians, thereby fostering greater engagement with sustainability initiatives. Moreover, ERS can serve as a tool for enhancing emotional awareness among Malaysian youth, enabling them to develop a deeper understanding of their own emotions and those of their peers in the context of sustainability challenges. Through interactive platforms and applications, Malaysian youth can engage with ERS to explore and reflect on their emotional responses to environmental and social issues, thus cultivating empathy, self-awareness, and social consciousness. By leveraging insights from ERS, policymakers can design targeted interventions and initiatives that appeal to the emotional motivations and values of young Malaysians, thereby fostering a sense of ownership and empowerment in driving sustainable change.

The integration of ERS into sustainability agendas for Malaysian youth holds immense potential for fostering greater awareness, engagement, and empowerment in addressing environmental and social challenges. By harnessing the capabilities of ERS to enhance emotional awareness and intelligence, Malaysian youth can be empowered to become active agents of change in advancing sustainable development in their communities and beyond. However, for ERS practitioners and developers, the results from this study not only beneficial in understanding the user's perspective, the technology will also needed for its sustainability in the long-term development. The trend of green technology has always been the main focus in creating technology to be used that conserve the energy and reduce environmental impact. AI emotions such as ERS deemed to be one of the technology that can reduce the environmental impact due to the cooperation between human and computers with Emotional awareness and emotional regulations play central roles in well-being and psychopathology. This particular study contributes to the understanding of ERS practitioners to understand the importance of ERS sustainability due to emotional awareness deemed to be important not only to human beings but technological advancement.

In ERS, the user will experience the context of conscious awareness and emotional awareness among AI using modalities such as electromyography (EMG), electroencephalography (EEG), Galvanic Skin Response (GSR), motion, body gesture and emotion feedback for the user experience design evaluation. Hence, ERS practitioners and developers aimed to create an environment that focuses on emotional well-being by highlighting the importance of emotional awareness. The results of the study acknowledge other aspects of emotional awareness, such as attention to emotion involving conscious and unconscious investigation of emotions. human-centered design in making technologies integrating with human needs a sustainability development.

Similar to many previous studies, this study also faced several limitations. Firstly, this study is a cross-sectional study which investigates the existence of a particular outcome and the absence of a specific exposure at a given moment in time [64]. Due to budget and time constraint, the limitation observed is that the data collection is collected at a single point in time, which opinion can be changed at a certain time event as suggested by Ferreira, et al. [64]. In cross-sectional study, it is important to address the hypotheses, exploring associations on the variables and assessing the prevalence conditions to meet the primarily objectives of this study. Therefore, it is limited for longitudinal trends which in longitudinal study, a changes over certain period of time will influence in understanding a certain phenomenon.

Secondly, the limitations faced in this study is the scope of study. This study mainly focused on the Malaysian youth as the driving factors of technology adoption specifically ERS, however, considering ERS as an important technology in the future that beneficial for industries, businesses and societies, there is a need to understand for potential users' perception in various age. In addition, with ERS applications identified earlier can be used in various sectors, many potential users from various scope will be interested in exploring ERS, hence, enable ERS practitioners, engineers and scientist to expand the age bracket in terms of the adoption factors. Thus, opinions in the variety of age bracket are also important to enable ERS adoption in larger scale.

Emotions awareness is important for every individual and determines the well-being of a society and community development. In other perspectives, social development relies on the emotion's awareness, for example, a healthy society comes from the mental aspect such as the awareness of one's emotions. Additionally, emotional intelligence promotes technological advancements to enhance society's well-being in social community development [1]. With societies more connected with technologies, and the rise of smart devices that allows individuals to live with AI, enabling AI to interact more with human will only create new opportunities for AI to integrate further with societies.

Future research should explore additional antecedents for ERS adoption readiness, specifically focusing on cultural differences and personal experiences that impact users' willingness to adopt the technology. Investigating negative factors or barriers to ERS adoption could provide deeper insights beneficial to ERS stakeholders. Another important area for future study is the ethical concerns related to ERS, which may vary based on cultural differences and personal experiences, particularly in sensitive areas such as privacy invasion and the potential misuse of emotional data. Additionally, future studies should explore users' perceptions of ERS security measures and their concerns about the storage and handling of emotion-related data, assessing whether strong security and privacy protections enhance adoption. By addressing these areas, future research can offer a more comprehensive understanding of the factors influencing ERS adoption, including its ethical, security, and privacy dimensions. This knowledge will be valuable for researchers and policymakers in shaping the future of ERS technology. In conclusion, this study has achieved its overall objectives on investigating the factors influencing the behavioural intention of youths towards ERS. This is seen as having the potential to contribute towards applications of ERS for sustainability development. ERS provide practitioners ability to gain insights to the sentiments of target groups such as the youths leading to development of initiatives designed to better compel desired supportive behaviours for their agendas. In other words, via ERS we can achieve better emotional awareness which can transform into emotional intelligence enabling strategic decisions that would generate greater sustainable development engagement.

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