A Systematic Literature Review on Emotion Recognition System In Malaysia

Muhammad Nadzree Mohd Yamin
Faculty of Business, Multimedia University, Jalan Ayer Keroh Lama, 75450 Bukit Beruang, Melaka

Kamarulzaman Ab. Aziz
Faculty of Business, Multimedia University, Jalan Ayer Keroh Lama, 75450 Bukit Beruang, Melaka Email: kamarulzaman.aziz@mmu.edu.my

Tan Gek Siang
Faculty of Business, Multimedia University, Jalan Ayer Keroh Lama, 75450 Bukit Beruang, Melaka

Nor Azlina Ab. Aziz
Faculty of Engineering and Technology, Multimedia University, Jalan Ayer Keroh Lama, 75450 Bukit Beruang, Melaka

Abstract

Artificial intelligence (AI) is an important technology that evolved from theories into tangibility with significant impacts and applications across sectors as well as borders. It is also one of the key technologies that gave rise to the fourth industrial revolution (IR 4.0). One key subcategory of AI is the automated emotion recognition system (ERS); the application of AI to recognize human emotional states. ERS is seen as an embedded technology that can be used in our daily lives and environment including the workplace. The importance of ERS will become more significant as we move towards the fifth industrial revolution (IR 5.0), where one of the key aspects identified is the enhancements in human-computer interaction (HCI). ERS has the potential to enable smart HCI, i.e. ERS can be seen as a technology to bridge us from IR 4.0 into IR 5.0. Crucial for this is good adoption or diffusion levels of ERS amongst society. Therefore, there is a need to understand the factors that affect the adoption of ERS. Specifically, this paper seeks to establish and discuss the current ERS research landscape in Malaysia by reporting findings from the systematic literature review covering works over a decade; from the year 2011 to 2022.

Keywords: Emotion recognition system (ERS), Artificial intelligence (AI), Affective computing (AC), The fourth industrial revolutionR1 (IR 4.0), The fifth industrial revolution (IR 5.0), Technology adoption

1. Introduction

Artificial intelligence (AI), is an advancement in computer science that allows a computer or machine to learn and be trained to perform and complete a task or make decisions, replicating how a human being learns from experience [1]. An emotion recognition system (ERS) is an AI that enables a system that accepts various modalities of data, learns and allows the machine to recognize the emotion of the subject. ERS is part of Affective Computing (AC), a field that was brought forward by [2]. According to Rosalind Picard, AC is a computer that relates to, arises from and understands human behaviour. With that being said, AC led to the findings of ERS, and it has been suggested by the previous researcher for ERS as embedded technology the current technology such as AI [1].

In the past decade, ERS has emerged as one of the attractive areas in the field of AC and AI with the vision of what the technology can achieve [3]. To develop a complex system such as robots that can interact and communicate with humans, a previous study has suggested a system with a function for both understanding human emotions and expressing human emotions [4].

Outcomes and expectations from the previous studies show that ERS can be an important technology in the making based on the advantages offered to individuals, society, organizations, businesses and industry via various platforms and applications. For example, ERS in healthcare [5], ERS in driving assistance in the car [6], ERS in the classroom [7] and ERS in smartwatches as the latest addition due to the modalities of smartwatches being the same ERS modalities.

In existing research on ERS, researchers adopted AI algorithms such as convolutional neural network (CNN) and deep neural network (DNN) for emotion recognition based on various data modalities like facial expression, voice intonation, heart signals (electrocardiogram), brain signal (electroencephalogram) and many others. It is important to look into the relationship between ERS and its significance in society and industry specifically in the industrial revolution.

ERS can be seen as embedded technology in various applications that can be used for professional or individual day-to-day use. Based on the modalities for ERS, and the potential applications of ERS to society and the industry, it is important to look into the relationship between ERS and its significance in society and industry specifically in the industrial revolution.

1.1 *Artificial Intelligence (AI)*

AI has transformed from just a theory to tangibility with recent applications from AI to transform businesses, industries and societies [8]. Inspired by human intelligence, AI aims to learn, reason, making decisions like humans [9]. With years of advancing and refining AI, technologies or smart devices nowadays are equipped with AI minimizing the need for human intervention [9].

In recent technological advancements, AI established trustworthiness enabling the AI systems in the aspect of beneficence, non-maleficence, autonomy, justice and explicability [9,10]. The uniqueness of AI is characterized by the integration of AI capabilities with human capabilities [9,11]. AI systems are designed to operate with varying levels as well as defined objectives, predictions and recommendations influenced by real or virtual environments.

AI technologies offer benefits for businesses and industries such as the automation of repetitive and time-consuming tasks that allow humans to focus on higher-value of work [9]. For example, massive restructured data that was once required by human expertise to further analysis, such example, data from written reports, analyzing documents, photos, images and videos can be assisted by AI, with AI considered much faster and more efficient working in completing tasks in a shorter time [9]. Moreover, AI can integrate thousands of computers [9] and other resources to resolve complex problems.

Therefore, AI capabilities are leveraging the need for technological advancement to automate the process further. AI can provide innovative solutions based on the previous example in previous studies towards societies, individuals and industries. With the addition of ERS as an emerging technology, it can enhance technology further by technology to understand human emotions and behavioural responses [9].

1.2 *The Industrial Revolution*

The history of the industrial revolution began in the 18th century with the mechanisation known as the First Industrial Revolution (IR 1.0) which was based on machines powered by water and steam. Today, we are living in the era of the Fourth Industrial Revolution (IR 4.0) where its main characteristics are digitalisation and integration of computers in co-operating with humans. IR 4.0 reshapes individuals' lives and works with digital transformation and emerging technologies that grow the industry further [12].

In IR 4.0, technologies such as artificial intelligence (AI), the internet of things (IoT) and big data services achieve sustainability and productivity [12]. IR 4.0 concept was mainly focused on the manufacturing industry to smart manufacturing but has evolved in the last decade with the involvement of digital transformation. The results create the entire industry, delivery channels become digitization [12,13]. IR 4.0 is a big part of an individual's daily life and industry. However, innovations keep being introduced, soon there will be Fifth Industrial Revolution (IR 5.0) [14].

The main characteristic of I.R 5.0 that differentiate it from I.R 4.0 is specialization where machines and computers are equipped with the ability to understand human and act accordingly [15,16]. As suggested by [16], the industry will enable humans and machines to work together by bringing humans back into the workforce, therefore, IR 5.0 will be seen to unlock the potential of

human-computer interaction (HCI). To signifies human-computer interaction, communication between human-computer need to be enabled. For example in [4,16], the computer system must have the ability to communicate with humans in some form.

Since the used cases of IR 5.0 are still in their formative years, manufacturers must actively organize their way to corporate humans and machines to maximise the opportunity that can be gained in IR 5.0. Technology enablers such as ERS may enhance robots and machines to understand human emotions with the proposition of collaborative robots (Cobots), hence, [4] suggestions in the study can help achieve a better understanding of human-computer interaction.

2. Methodology

This study adopted the systematic literature review (SLR) methodology consistent with prior works [17,18,19,20,21]. This method is ideal when a complete, summary of prevalent knowledge is needed [22]. SLR allows the researchers to identify and synthesise all relevant research in building up to the research gap, that led to the research question and research objectives respectively [21].

In 2009, an international group of systematic reviewers, methodologists and journal editors publish the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and a guideline designed to help authors prepare a complete report for SLR [23]. PRISMA consists of three stages, first one is identification. In this section, keywords or search strings, criteria and database used will be identified. For this study, the search strings were Emotion Recognition System, Youth, Malaysia, Readiness, and Acceptance. The criteria were the OR and AND Boolean operatives [17]. The term Emotion recognition system expanded with synonyms of Emotion Recognition Technology and Emotion Recognition Applications. The search was done using the Lens.org platform. The benefits of using this platform are increasingly recognized by researchers [17,24]. First launched by Cambia in 2000 as Patent Lens, an Australia-based non-profit organization. In 2013 it became The Lens and has since become more than just a patent search platform.

Initially, the search for the Emotion Recognition System, in general, shows a result of 1,050 publications found based on The Lens filter. This study limited the date range from 2011 to 2022 and the document types are journaled articles, conference proceedings articles and dissertations. In the first identification stage, we removed any duplicated publications before moving further into the next stage. Based on the total results, 2 identified publications were removed before the next stage as shown in Fig.1.

The next stage is screening, before narrowing it down to retrieval and eligibility. In this stage, we screened the 1,048 publications by language (selecting papers written in the English language only) and relevance (selecting papers on ERS in Malaysia only). Therefore 2 papers have been excluded because not in the English language. Secondly, since the collection also included technical papers on ERS from the perspective of computer science and informatics, we further filter the papers based on the details of the title and abstract. Those found not focusing on ERS were excluded. Hence, 267 publications were excluded. Thus, the total records that were sought for retrieval such as in Fig.1, were narrowed down to 779.

Then, in the retrieval stage, we need to ensure the records are accessible. A total of 156 papers were identified as not accessible due to subscription restrictions. Due to budget restrictions, it was not possible to purchase subscriptions or individual papers. The remaining records were confirmed to be accessible either under the existing institutional subscriptions or via open access. Ultimately, 623 papers remained for retrieval and were included in the final eligibility screening.

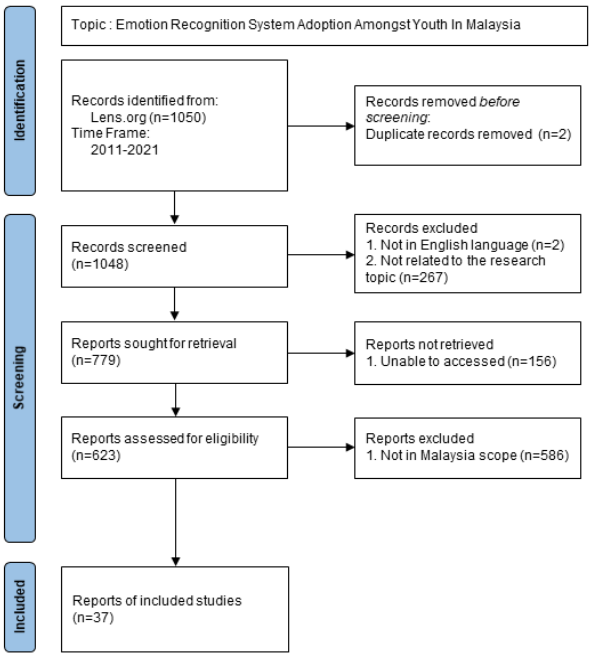

Fig.1.Prisma Flow Diagram

The final screening stage is eligibility according to the scope of the SLR. Here only works reporting from the Malaysian context are the records of interest. A total of 586 records were identified to be out of scope and thus not eligible for inclusion in this study. The final number of records confirmed to be included in this SLR is 37. The following section reports the results and analysis of the final set.

3. Results and Analysis

This section reports the descriptive analysis results of the included 37 records, focusing on the document type, year of publications, subject area, keywords related to the studies and most cited.

3.1 Document Type

The data that has been collected has been classified based on three categories journal article, conference proceedings article and dissertation. These types of research works are selected for the quality control process normally in place before publication. Specifically, the works go through a stringent review process by subject matter experts to verify the quality of the work. Moreover, the journal article and conference proceedings article are chosen due to journal has a better structure while the conference is short and precise that has been used in the conference [25].

Based on Table 1, the majority of the publications are journaled articles; 20 publications or 54.05%, while the rest are conference proceedings articles; 17 publications or 45.95%. The was none for the dissertation category suggesting there is potential for postgraduate research in this area.

Table 1.Document Type

Document Type	Number of publications	% (N=37)
Journal Article	20	54.05%
Conference Proceedings Article	17	45.95%
Dissertation	0	0%
TOTAL	**37**	**100**

3.2 *Year of Publication*

This study review a decade worth of works from the year 2011 to 2022, and the returned publications for each year are different. There is no definitive trend according to the no of publications over the decade (see Fig.2). It can be said that there had been a steady number of conference papers each year, but a relatively increasing trend can be seen for journal articles.

Fig.2. Year of publications

From Fig.2, we see that in the range of 2011 towards 2014 the field of affective computing, artificial intelligence and machine learning is attracting the interest of the researcher to find solutions in creating ERS, however, from 2015 to 2019, the number of publications is not constant, however, 2019 to 2022, the number of publications is increasing again. The upswing in the past 3 years can be due to the technological advancements that enable researchers to test ERS based on the modalities in the real world.

3.3. *Field of Research*

Next, the collected records were analyzed according to their field of research or subject matter (see Table 2). The highest ranking area of study is computer science with a total of 9 articles or 24.32%. Secondly, is engineering with 7 articles or 18.92%.

Table 2. Subject Matter

Field	Frequency	%(n=37)
Computer Science	9	24.32%
Engineering	7	18.92%
Artificial Intelligence	4	10.81%
Information Systems	4	10.81%
Biotechnology	3	8.11%
Computational computers	3	8.11%
Environmental Science	2	5.41%
Social Science	1	2.70%
Human-Computer Interaction	1	2.70%
Material Science	1	2.70%
Software Analytics	1	2.70%
TOTAL	37	100

The majority of the discussions focused on the potential applications, benefits, implementation or deployment, safety, and risk of ERS. However, out of the 37 articles, there is only one research truly within the field of social science; from [26] regarding the awareness and readiness of Malaysian University students for ERS. Arguably, the implications of the study can be extended from the context of Malaysian University students to Malaysian youths in general.

3.4. *Most Cited*

Next, the retrieved records that were included in the studies were analyzed in terms of citation. According to the analytics from Lens.org, the 37 publications collectively garnered 510 scholarly citations. Table 3 shows the top 10 most cited works in the collection. Ranked 1st, the paper by [27] is also one of the earliest publications in the retrieved records, thus it is expected to have a high citation. Furthermore, [27] mostly discussed the modalities that can be used for ERS. Such example, the electrocardiogram (ECG) is one of the modalities for ERS. Since the paper is a review, it provides a useful compilation of related works, and this also contributes towards a higher citation number.

Table 3. Top 10 most cited

Authors	Title	Year	Cites
Jeritta et al.	Physiological signals based human emotion recognition: A Review	2011	223
Murugappan & Murugappan	Human emotion classification using wavelet transform and KNN	2011	52
Seng et al.	A combine rule based and machine learning audio-visual emotion recognition approach	2018	43
Rashid et al.	Human emotion recognition from videos using spatio temporal and audio features	2012	37
Jeritta et al.,	Electrocardiogram based emotion recognition system using empirical mode decomposition and discrete fourier transform	2013	32
Bakhtiyari & Husain	Fuzzy model of dominance emotions in affective computing	2014	22
Wani et al.	A comprehensive review of speech emotion recognition systems	2021	21
Chew et al.	Audio emotion recognition system using parallel classifiers and audio feature analyzer	2011	13
Jeritta et al.	Emotion detection from QRS Complex of ECG signals using hurst exponent from different age groups	2013	10

Hasnul et al.	Electrocardiogram based emotion recognition applications in healthcare : A Review	2021	9

From table 3, it can be observed that the earlier works tend to focus on the technical development of ERS; from developing modalities to establishing the system. More recent works such as [5], classified the applications that can benefit ERS such as the ECG-based ERS for healthcare applications. Meanwhile, [28] reviewed works on speech-based ERS.

4. Discussion

The trend for ERS has been increasing, although there is a gap between time and studies based on Fig.2. However, the momentum of the publications returned has risen from 2019 to 2022. ERS is not seen as a new technology, instead, the previous researcher suggested ERS is seen as an embedded technology through existing devices and technologies [29]. Given the advantages and continued advancement of AI, machine learning as well as deep learning, ERS has the potential to be the enabler of new features in various applications that utilize recognition of human emotions [30].

The following sections discuss the key insights derived from the retrieved 37 publications. Specifically, the discussion focused on modalities, applications of ERS, research gaps identified, limitations, and future directions for research in ERS.

4.1. *Modalities*

ERS can be identified through various input data modalities, such example, physiological modalities, psychological modalities and data mining modalities. These modalities have been majorly developed in the field of computer science, engineering, artificial intelligence, information systems, biotechnology and computational computers.

4.1.1 *Physiological Modalities*

In physiological modalities, it is consisting of electroencephalography (EEG), electrocardiography (ECG) and photoplethysmography (PPG). EEG is frequently used in neuroscience, neural engineering, and biomedical engineering to measure human brain signals through the electromagnetic behaviour of specific components [30,31,32]. EEG is most likely the favourite for obtaining high-accuracy data for automated emotions recognitions because EEG processes use the same concept as AI systems that used convolutional neural networks for machine learning and deep machine learning [33,27]. ECG is commonly used by previous researchers in the field of AC due to its potential adoption using a wearable device. In a previous study by [5], ECG was used to detect stress and the benefit of monitoring a patient's emotional stress condition to ensure that a negative tendency is not triggered. Next for EEG, is photoplethysmography (PPG). PPG has been said to be more practical and suitable in real-life use compared to EEG, in combination with ECG as multimodal, it can be implemented as a "wearable device that can collect signals from a person without compromising comfort and privacy" [35,36]. For instance, current technology devices such as a smartwatch have a built-in ECG to detect stress levels and blood pressure, consequently identifying temporal emotional states.

4.1.2 *Physical Modalities*

For physical modalities, the modalities that have been widely used are facial recognition and speech recognition. Facial recognition has gained popularity amongst ERS practitioners due to diverse applications that can be applied in the real world such as marketing purposes, security supervision, online class and gaming experience [36]. Facial expression can determine the six basic emotions, namely, sad, anger, happiness, fear and surprise. Additionally, facial expressions can be used to detect disgust, normality, and drowsiness [37]. Speech recognition as modalities of ERS is capable of detecting human speech and interpreting conditions and emotions for real-life applications [32,38]. According to [39], speech recognition is defined based on someone's voice, the computer can learn what condition they are in, therefore concluding what is the emotion of that person. In [28], a review of the speech emotion recognition system shows that speech recognition detects and classify emotion recognition system, only the inability to handle the real-time problem and different scenario that affect human emotions as human speech is vary based on culture.

4.1.3 *Data Mining Modalities*

In data mining modalities, one paper from [40], suggested that data mining known as text mining is a learning-based algorithm to describe characteristics of text, such as word expression based on human sentiments and emotions. Such example, from social media data mining, the text "Hurray!", can be detected as part of happy emotions [41], and "Argh!" can be detected as anger and frustration, however, there are certain texts that create multiple emotions overlapping with the intended emotions, such as "Awww", which can indicate pleasant sentiments but sometimes it can indicate a pity sentiment [40].

4.2. *Applications*

Based on the conducted SLR, some papers presented the potential applications that can be achieved through individuals, society and industries. Firstly, the education system can be improved with the adoption of ERS [42]. Emotion has a significant influence on the relationship with a performance from the perspective of a learner and instructor as described by [7], and students with positive emotions led to increasing student interest, and student performance and "have higher chances at success". [7] their study suggested a webcam inside a computer laboratory and using a facial recognition modality to identify students' moods and the results show significant differences in the student's moods.

From an individual perspective, emotions can affect driving [6]. This is due to emotions' relationship with focus. For example, anger can lead to poor focus. A poor focus led to an increasing number of accidents, therefore, it is significant for ERS to be embedded in cars for driving safety [6]. Furthermore, [6] used a driving simulation, where a virtual driving experiment was conducted to test ECG-based ERS in identifying human emotions while driving.

In [5], ERS was implemented using ECG in the healthcare industry to "reduce stress and promote relaxation". The ECG-based ERS helps a person with mental stress to identify negative and positive emotions. Furthermore, ERS can be suggested as a supporting aid for people with certain disorders such as down syndrome, autism, and even elderly people. It will be using facial expressions in real-time video as automated emotion recognition and a computer advisor that advises on how we can react appropriately [43,3].

ERS can be potential in marketing strategy. Such example in brand awareness, product acceptance can be analyzed based on the response of human facial expressions in a live launch or video and images [43]. For example, a small group of people in a room are introduced to a product, and their reactions through facial expressions will be recorded and evaluated by ERS whether they are happy, disgusted, or anxious.

In another aspect, in video games, the developer of games has an objective which is to "fulfil his or her dream" while playing games through immersive gameplay, interesting storyline and intensive graphics [44,45]. Implementation of emotion detection can improve engagement between entertainment agents and end-user by alternatively using multimodalities such as speech recognition and EEG in the controller which can improve understanding of human emotions towards intangibles products such as music or movies [43]. In addition, with virtual reality (VR) technology in recent years, the developer can enhance the game further with real-time ERS usage towards understanding the player.

4.3. *Gaps*

With the valuable insights based on the previous paper, there are several gaps identified that motivate this study. The objective of this study particularly is to gain insights into adopters' perspectives. The results of performing SLR are to understand the recent study on ERS and the existing gap between previous research and studies. From the results of performing the SLR on the specified topic, in Malaysia, there is a smaller number of returned publications with only 37 papers (see figure 1), specifically, studies regarding ERS adoption. Previous research signifies that ERS contributes within the aspect of the engineers and scientists, however, in real-life problems, there will be a different situation that might not apply.

Based on the Lens search, the availability of ERS is limited due to ERS being practically known amongst researchers related to the field of computer science, engineering, artificial intelligence and information systems. And when we narrowed down the scope to Malaysia, the trend of publication is slower during the early year between 2011-2016 due to the technology is

still in a growth state. However, in 2017-2021, the publications are getting momentum again along with the advancement of technology, and emotion recognition has gotten recognizability throughout Malaysia. Next, we dive deep into the adoption towards the Malaysian population. In 2021, there one paper signifies the acceptance of Malaysian university students towards ERS [26]. This paper discusses the perspective of Malaysian university student awareness towards ERS whether they know about ERS and are ready to adopt the technology or they are still unaware of the technology.

In conclusion, there is still a lack of studies related to ERS in Malaysia and ERS adoption and readiness in Malaysia. This study will help to gain better insights on the perspective of ERS adoption and readiness and contribute to the practitioners and policy making by the government to ensure that ERS is more practical to use amongst users and important determinants of user's adoption in ERS.

4.4. *Limitations*

Conducting the SLR studies, and analyzing the previous paper, some limitations have been found and highlighted by the previous researchers. Firstly, the security and privacy from the emotional recognition. As machines evolve for to better over the next few years, there is a part where for humans, exposing privacy is the last part to do. Although in marketing, there is a benefit of ERS to be implemented, however, there is a risk to privacy and security, as capturing facial recognition and analyzing text data mining can feel like invading privacy and security breach without consent.

Secondly, another study [29], suggested that there is uncertainty for ERS as a limitation due to recognizing human emotions can create fear amongst humans. Specifically, in the workplace, emotion will play an important role in determining performance, productivity and efficiency, however, there will be at times when humans do not want to be measured for their emotions and observing their behaviour, therefore, will create unpleasant surroundings.

Next, from the perspective of social science, there is a limited number of papers from SLR conducted that focuses on ERS readiness and adoption. There is a need to understand the perspective of users that will be going to face the technology and the perceived usefulness of the technology matters in predicting accurately the technology will be performing in real-life.

4.5 *Future Directions*

From the paper published in Lens, the future directions for ERS there is a need for more papers for ERS as suggested that ERS applications will benefit individuals and societies in everyday lives. In addition, ERS can play a major role in the industries as suggested by the previous researcher due to the rising of the industrial revolution as seen in IR 4.0 with AI development is significant.

Concurrently, IR 5.0 key takeout focuses on human-computer interaction (HCI), there is a significant relationship between ERS in IR 5.0 with AI can be the decision makers for robots and ERS as a subpart of AI enhancing robots further with enabling the human-computer interaction [46]. As we live in the direction of technological advancement era, understanding recent development in technologies will increase the scope and understanding more about technology and human capabilities and the achievement of human and computer relationships.

5. Conclusion

Acknowledgement

This work was supported by "TMR&D Grant 2021: Emotion Recognition System (ERS) for Smart Homes Malaysia".

References

1. Kodhai, E., Pooveswari, A., Sharmila, P., & Ramiya, N. (2020). Literature Review on Emotion Recognition System. 2020 International Conference on System, Computation, Automation and Networking, ICSCAN 2020, 18–21. https://doi.org/10.1109/ICSCAN49426.2020.9262389
2. Picard, R. W. (1999). Affective Computing for HCI. Proceedings of the 8th HCI International on Human-Computer Interaction: Ergonomics and User Interfaces, 829–833. http://dl.acm.org/citation.cfm?id=647943.742338
3. Haridas, A. V., Marimuthu, R., & Chakraborty, B. (2020). Emotion Recognition System for Specially Needed People with Optimized Deep Learning

Algorithm. In 2020 Fourth International Conference on Inventive Systems and Control (ICISC). IEEE. https://doi.org/10.1109/icisc47916.2020.9171190
4. Yoshitomi, Y. (2021). Human–computer communication using recognition and synthesis of facial expression. Journal of Robotics, Networking and Artificial Life, 8(1), 10–13. https://doi.org/10.2991/jrnal.k.210521.003
5. Hasnul, M. A., Aziz, N. A. A., Alelyani, S., Mohana, M., & Aziz, A. A. (2021). Electrocardiogram-Based Emotion Recognition Systems and Their Applications in Healthcare-A Review. Sensors (Basel, Switzerland), 21(15), 5015. https://doi.org/10.3390/s21155015
6. Wang, X., Guo, Y., Ban, J., Xu, Q., Bai, C., & Liu, S. (2020). Driver emotion recognition of multiple-ECG feature fusion based on BP network and D-S evidence. IET Intelligent Transport Systems, 14(8), 815–824. https://doi.org/10.1049/iet-its.2019.0499
7. Putra, W. B., & Arifin, F. (2019). Real-Time Emotion Recognition System to Monitor Student's Mood in a Classroom. Journal of Physics: Conference Series, 1413(1). https://doi.org/10.1088/1742-6596/1413/1/012021
8. Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management, 53(March), 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104
9. Choung, H., David, P., & Ross, A. (2022). Trust in AI and Its Role in the Acceptance of AI Technologies. International Journal of Human-Computer Interaction, March. https://doi.org/10.1080/10447318.2022.2050543
10. Thiebes, S., Lins, S., & Sunyaev, A. (2021). Trustworthy artificial intelligence. Electronic Markets, 31(2), 447–464. https://doi.org/10.1007/s12525-020-00441-4
11. Krafft, P. M., Young, M., Katell, M., Huang, K., & Bugingo, G. (2020). Defining AI in policy versus practice. AIES 2020 - Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, 72–78. https://doi.org/10.1145/3375627.3375835
12. Ghobakhloo, M. (2020). Industry 4.0, digitization, and opportunities for sustainability. Journal of Cleaner Production, 252, 119869. https://doi.org/10.1016/j.jclepro.2019.119869
13. Mohamed, N., Al-Jaroodi, J., & Lazarova-Molnar, S. (2019). Leveraging the Capabilities of Industry 4.0 for Improving Energy Efficiency in Smart Factories. IEEE Access, 7, 18008–18020. https://doi.org/10.1109/ACCESS.2019.2897045
14. Aslam, F., Aimin, W., Li, M., & Rehman, K. U. (2020). Innovation in the era of IoT and industry 5.0: Absolute innovation management (AIM) framework. Information (Switzerland), 11(2). https://doi.org/10.3390/info11020124
15. Sumi, K. (2016). Affective Human Computer Interaction. Proceedings of International Conference on Artificial Life and Robotics, 21(2), 244–248. https://doi.org/10.5954/icarob.2016.is2
16. George, A. S., & George, A. S. H. (2020). Industrial Revolution 5.0: the Transformation of the Modern Manufacturing Process To Enable Man and Machine To Work Hand in Hand. Journal of Seybold Report, 15(9), 214–234. https://doi.org/10.5281/zenodo.6548092
17. K.G, P., De Alwis, C., & I., W. (2022). The Facets of Gender Stereotypes Change: A Systematic Literature Review. SSRN Electronic Journal, June 2022. https://doi.org/10.2139/ssrn.4117570
18. Kumar, S., Kar, A. K., & Ilavarasan, P. V. (2021). Applications of text mining in services management: A systematic literature review. International Journal of Information Management Data Insights, 1(1), 100008. https://doi.org/10.1016/j.jjimei.2021.100008
19. Kuss, D. J., Kristensen, A. M., & Lopez-Fernandez, O. (2021). Internet addictions outside of Europe: A systematic literature review. Computers in Human Behavior, 115, 106621. https://doi.org/10.1016/j.chb.2020.106621
20. Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. Journal of Business Research, 122(September 2020), 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009
21. Van Dinter, R., Tekinerdogan, B., & Catal, C. (2021). Automation of systematic literature reviews: A systematic literature review. Information and Software Technology, 136(March), 106589. https://doi.org/10.1016/j.infsof.2021.106589
22. Schmeisser, B. (2013). A systematic review of literature on offshoring of value chain activities. Journal of International Management, 19(4), 390–406. https://doi.org/10.1016/j.intman.2013.03.011
23. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., & Moher, D. (2021). Updating guidance for reporting systematic reviews:

development of the PRISMA 2020 statement. Journal of Clinical Epidemiology, 134, 103–112. https://doi.org/10.1016/j.jclinepi.2021.02.003

24. Mart ń-Mart ń, A., Thelwall, M., Orduna-Malea, E., & Delgado L ópez-C ózar, E. (2021). Google Scholar, Microsoft Academic, Scopus, Dimensions, Web of Science, and OpenCitations' COCI: a multidisciplinary comparison of coverage via citations. In Scientometrics (Vol. 126, Issue 1). Springer International Publishing. https://doi.org/10.1007/s11192-020-03690-4
25. Eckel, E. J. (2009). The Emerging engineering scholar: A citation analysis of theses and dissertations at western michigan university. Issues in Science and Technology Librarianship, 56. https://doi.org/10.29173/istl2470
26. Aziz, N. A. A., Aziz, N. H. A., Ismail, S. N. M. S., Khan, C. M. T., Hasnul, M. A., Rahman, A., Rahman, T. A., & Aziz, K. A. (2021). Awareness and Readiness of Malaysian University Students for Emotion Recognition System. The International Journal of Integrated Engineering, 13(6), 299–309. https://doi.org/10.30880/ijie.2021.13.06.026
27. Jerritta, S., Murugappan, M., Nagarajan, R., & Wan, K. (2011). Physiological signals based human emotion recognition: A review. Proceedings - 2011 IEEE 7th International Colloquium on Signal Processing and Its Applications, CSPA 2011, 410–415. https://doi.org/10.1109/CSPA.2011.5759912
28. Wani, T. M., Gunawan, T. S., Qadri, S. A. A., Kartiwi, M., & Ambikairajah, E. (2021). A Comprehensive Review of Speech Emotion Recognition Systems. IEEE Access, 9, 47795–47814. https://doi.org/10.1109/ACCESS.2021.3068045
29. Landowska, A. (2019). Uncertainty in emotion recognition. Journal of Information, Communication and Ethics in Society, 17(3), 273–291. https://doi.org/10.1108/JICES-03-2019-0034
30. Alhalaseh, R., & Alasasfeh, S. (2020). Machine-learning based emotion recognition system using EEG signals. Computers, 9(4), 1–15. https://doi.org/10.3390/computers9040095
31. Craik, A., He, Y., & Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: A review. Journal of Neural Engineering, 16(3). https://doi.org/10.1088/1741-2552/ab0ab5
32. Jerritta, S., Murugappan, M., Wan, K., & Yaacob, S. (2014). Electrocardiogram-based emotion recognition system using empirical mode decomposition and discrete Fourier transform. Expert Systems, 31(2), 110–120. https://doi.org/10.1111/exsy.12014
33. Fang, W. C., Wang, K. Y., Fahier, N., Ho, Y. L., & Huang, Y. De. (2019). Development and Validation of an EEG-Based Real-Time Emotion Recognition System Using Edge AI Computing Platform With Convolutional Neural Network System-on-Chip Design. IEEE Journal on Emerging and Selected Topics in Circuits and Systems, 9(4), 645–657. https://doi.org/10.1109/JETCAS.2019.2951232
34. Suhaimi, N. S., Mountstephens, J., & Teo, J. (2020). EEG-Based Emotion Recognition: A State-of-the-Art Review of Current Trends and Opportunities. Computational Intelligence and Neuroscience, 2020. https://doi.org/10.1155/2020/8875426
35. Tong, Z., Chen, X., He, Z., Tong, K., Fang, Z., & Wang, X. (2018). Emotion Recognition Based on Photoplethysmogram and Electroencephalogram. Proceedings - International Computer Software and Applications Conference, 2, 402–407. https://doi.org/10.1109/COMPSAC.2018.10266
36. Rathour, N., Khanam, Z., Gehlot, A., Singh, R., Rashid, M., Alghamdi, A. S., & Alshamrani, S. S. (2021). Real-time facial emotion recognition framework for employees of organizations using raspberry-pi. Applied Sciences (Switzerland), 11(22). https://doi.org/10.3390/app112210540
37. Kundu, T., & Saravanan, C. (2018). Advancements and recent trends in emotion recognition using facial image analysis and machine learning models. International Conference on Electrical, Electronics, Communication Computer Technologies and Optimization Techniques, ICEECCOT 2017, 2018-Janua, 1–6. https://doi.org/10.1109/ICEECCOT.2017.8284512
38. Shinde, A. S., & Patil, V. V. (2021). Speech Emotion Recognition System: A Review. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3869462
39. El Ayadi, M., Kamel, M. S., & Karray, F. (2011). Survey on speech emotion recognition: Features, classification schemes, and databases. Pattern Recognition, 44(3), 572–587. https://doi.org/10.1016/j.patcog.2010.09.020
40. Zucco, C., Calabrese, B., Agapito, G., Guzzi, P. H., & Cannataro, M. (2020). Sentiment analysis for mining texts and social networks data: Methods and tools. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(1), 1–32. https://doi.org/10.1002/widm.1333
41. Murthy, A. R., & Anil Kumar, K. M. (2021). A Review of Different Approaches for Detecting

Emotion from Text. IOP Conference Series: Materials Science and Engineering, 1110(1), 012009. https://doi.org/10.1088/1757-899x/1110/1/012009

42. Bouhlal, M., Aarika, K., AitAbdelouahid, R., Elfilali, S., & Benlahmar, E. (2020). Emotions recognition as an innovative tool for improving students' performance and learning approaches. Procedia Computer Science, 175, 597–602. https://doi.org/10.1016/j.procs.2020.07.086
43. Arrais, J. P., Laranjeira, A., Oliveira, G., & Ribeiro, B. (2017). Deep learning in digital marketing: brand detection and emotion recognition. International Journal of Machine Intelligence and Sensory Signal Processing, 2(1), 32. https://doi.org/10.1504/ijmissp.2017.10009120
44. Hippe, Z. S., Kulikowski, J. L., Mroczek, T., & Wtorek, J. (2014). Human-Computer Systems Interaction: Backgrounds and Applications 3. Advances in Intelligent Systems and Computing, 300, 51–62. https://doi.org/10.1007/978-3-319-08491-6
45. Vinola, C., & Vimaladevi, K. (2015). A survey on human emotion recognition approaches, databases and applications. Electronic Letters on Computer Vision and Image Analysis, 14(2), 24–44. https://doi.org/10.5565/rev/elcvia.795
46. Watada, S., Obayashi, M., Kuremoto, T., & Mabu, S. (2014). A Decision Making System of Robots Introducing a Re-construction of Emotions Based on Their Own Experiences. Journal of Robotics, Networking and Artificial Life, 1(1), 27. https://doi.org/10.2991/jrnal.2014.1.1.6
47. Kawada, K., & Tamai, T. (2018). Development of Teaching Support Material for Nurturing Cooperation through Play. Journal of Robotics, Networking and Artificial Life, 5(3), 169. https://doi.org/10.2991/jrnal.2018.5.3.6

Authors Introduction

Mr. Muhammad Nadzree Mohd Yamin

Muhammad Nadzree Mohd Yamin is a Master of Philosophy (Management) student from Multimedia University. He obtained his Bachelor of Business Management (Hons) in Management (First Class) from Multimedia University in 2021.

Assoc. Prof. Dr. Kamarulzaman Ab. Aziz

Kamarulzaman Ab. Aziz is currently an associate professor at the Faculty of Business, Multimedia University. His research interest includes Cluster Development, Technology and Innovation Management, Entrepreneurship and Commercialization.

Mr. Terence Tan Gek Siang

Tan Gek Siang is a lecturer in the Marketing Management Department, Faculty of Business, Multimedia University. He teaches business and management subjects at both undergraduate and postgraduate level. He is currently the Deputy Head of International Relations in the Faculty of Business. His research interests are in tourism marketing, user acceptance of information technology, virtual reality, augmented reality, and business management.

Assoc. Prof. Dr. Nor Azlina Ab. Aziz

Nor Azlina Ab Aziz is an associate professor in the Faculty of Engineering and Technology at Multimedia University, Melaka. She is interested in the field of soft computing and its application in engineering problems. More specifically, her focus is in the area of swarm intelligence and nature inspired optimization algorithm.