SEMARAK ILMU PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Artificial Intelligence and Public Health Context: What We Should Know?

Faerozh Madli[1,*], Yuzainy Janin[1], Shaierah Gulabdin[1,♠], Suddin Lada[1,♦], Wong Sing Yun[1], Azaze-azizi Abdul Adis[1], Adi Jafar[2]

[1] Fakulti Perniagaan, Ekonomi dan Perakaunan, Universiti Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia
[2] Fakulti Sains Sosial dan Kemanusiaan, Universiti Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia

ARTICLE INFO

Article history:
Received 15 August 2023
Received in revised form 28 December 2023
Accepted 10 January 2024
Available online 12 February 2024

Keywords:
Artificial Intelligence; public health; challenge and potential; social communication

ABSTRACT

The rapid technological advancement nowadays has a wide-ranging impact on almost all industries. Artificial Intelligence (AI) is one of the technologies that has received much attention and has been used widely, including in the public health sector. In this light, medical practitioners and the public are anticipating the changes brought by AI technology in the public health sector. This study is focused on thoroughly discussing the relationship of AI in the context of public health. The discussion shows that AI is giving a lot of positive potential to the public health sector. However, despite the abundant potential and promise, AI is also not running away from today's challenges. The overall discussion of this study will provide a clear picture on the link between AI, public health link and related parties, including official medical-related agencies. In other words, this paper summarises the relationship between AI and public health, specifically the challenges and potential changes AI will bring forward.

1. Introduction

Deep learning has emerged in recent years, allowing computers to closely mimic human abilities in image recognition, speech recognition, and analytical processing [1]. This ability to mimic human talents is linked to the concept of Artificial Intelligence (AI), which has become more useful in the business world and daily activities due to the rapid development of computing progress nowadays [2]. In this light, the application of AI in today's modern era will have a direct impact on the programming landscape of our everyday lives [3].

As mentioned by Lee *et al.,* [4], AI can be classified according to its strengths and weaknesses. A powerful AI system can produce something creative, conscious, and intelligent [5]. A strong AI is a system capable of performing any intellectual task a human can do. However, developing such strong

*Corresponding author.
E-mail address: faerozhmadli@ums.edu.my
♠ *Corresponding author.*
E-mail address: shaierah@ums.edu.my
♦ *Corresponding author.*
E-mail address: suddin@ums.edu.my

https://doi.org/10.37934/araset.39.2.96109

AI systems is still in its early stages and is considered speculative, with no real-world examples [3]. Even though AI is already being used to a limited extent in healthcare, finance, and public transportation [6].

Ribeiro *et al.,* [7] defined AI as applying algorithms and statistical models to perform tasks typically associated with human intelligence, such as perception, recognition, decision-making, and natural language processing. In other words, the term AI refers to the study and application of computer programming to perform tasks traditionally performed by humans. These programs' ability to analyze and understand data using algorithms and statistical models allows them to perform 'intelligent' tasks that humans previously could only perform. Furthermore, according to Chua [8], AI aims to develop intelligent agents or systems that can perform tasks independently, adapt to new environments, and naturally communicate with humans.

AI development aims to teach computers to perform tasks that often require human intelligence. These tasks include speech and image recognition, language translation, and complex decision-making. AI algorithms and systems can evaluate massive quantities of data, learn from it, and make decisions based on that learning, making them useful in many applications, from virtual assistants to self-driving automobiles [9]. AI have shown significant potential in public health in recent years [10]. AI-powered technologies in healthcare can aid in the prevention, diagnosis, and treatment of various diseases, as well as the management of public health crises. For example, AI algorithms have been developed to predict the spread of infectious diseases such as COVID-19, to analyse medical images for early cancer detection, and to monitor health data from wearable devices in real-time leads to identify potential health risks [10]. Furthermore, Jin *et al.,* [11] found AI algorithms have been utilised to predict the spread of the virus, identify high-risk populations, and develop effective treatment plans during the Covid-19 pandemic. AI-powered virtual assistants have been developed to help healthcare professionals manage their workload, streamline administrative tasks, and enhance patient care [12].

On the other hand, the use of AI in public health has caused ethical and privacy concerns, such as ensuring AI algorithms' transparency, fairness, and accountability, protecting patient privacy, and preventing bias [4]. Thus, it's important to consider the pros and cons of using AI-driven technologies in the public health sector and to take steps to guarantee that these tools are used ethically. The objective of this study is thoroughly investigating the interaction of AI in the context of public health. As the methodology approach, this study utilizes multiple streams of literature, which are integrated and presented as a holistic and critical review of AI in the context of public health.

1.1 The Concept of Artificial Intelligence

Artificial intelligence (AI) is expanding rapidly. This situation has generated significant interest from various industries [13]. One of the pillars of AI is the development of machines to perform tasks traditionally associated with human intelligence, such as solving complex problems and making complex decisions [7]. AI is also related to machine learning, which is the creation of algorithms that allow computers to learn from data [14]. Machine learning is linked to natural language processing, computer vision, speech recognition, and gaming [15]. Subsequently, advanced machine learning has led to the development of deep learning, improving AI performance on tasks like picture and speech recognition through analysing massive volumes of data [16].

Robotics and games like Go and Chess are excellent examples of advanced AI [17]. Silver *et al.*, [18] discussed the reinforcement of machine learning's newest advances and their potential applications in robotics and video games. Machine learning will strengthen AI through hybrid models and other approaches like deep learning and fuzzy logic [19]. Deep learning is an AI method that teaches and trains computers to think like humans, while Fuzzy logic, on the other hand, refers to a system that mimics how people make reasoning and cognitive decisions.

AI is used in organisations to assist day to day operations. AI usage is expected to grow exponentially, reaching 50% of worldwide consumption by 2030. It is estimated that by 2020, more than half of organisations in various fields will be using this new generation of AI technologies [20]. Moreover, AI has the potential to significantly improve many aspects of people's daily lives, including the environments in which they live, work, learn, play and commute [21].

Conversely, AI has shown great potential to transform public health by improving disease prevention, diagnosis, and treatment. AI has been applied in various areas of public health, such as infectious disease surveillance, drug discovery, and personalised medicine [22]. The healthcare industry has also started experimenting with AI, and preliminary results suggest that it has significant potential for enhancing patient outcomes in areas such as creating individualised treatment plans, detecting disease patterns, and forecasting positive reactions to therapy [23].

2. Artificial Intelligence and Public health: An Overview

AI system capabilities have positively revolutionised public health [21]. The technology helps public health professionals respond more effectively, swiftly to disease outbreaks and decrease any adverse impact on communities. AI also can process large amounts of data at any one time quickly [20], hence, it can perform image or picture recognition tasks and process into meaningful data. Image recognition process is also very useful in public health to analyse data or results quickly and accurately [8]. Image recognition plays an important role in public health, allowing doctors to detect the type of disease infection [8]. However, image recognition is one of many useful or benefits of IA in public health sector. In this regard, the application of AI in public health will be discussed further in the next section.

2.1 Disease Surveillance

AI has been found to be able to identify potential outbreaks by analysing data including medical records, lab results and data related to public health [24]. Thus, AI methods have been shown to improve infectious disease surveillance by enabling earlier detection which leads to more rapid response to outbreaks [25]. For instance, AI can analyse the algorithm of electronic health records to detect signs of infectious diseases, such as fever or cough. The results from the analysis of these patterns can then help organisations give early warnings to the public [26].

AI can also detect early signs of disease outbreak through data provided by a wide range of surveillance channels including social media, news articles and online searches [27]. For example, AI can accurately predict influenza outbreak by analysing the algorithm of Google search data [28]. This can be achieved via AI’s ability to monitor disease patterns in real time to help public health officials to implement strategies to control the spread of disease [29]. Wang *et al.*, [1] also stated that AI can also detect the outbreak of influenza by analysing and reading the unique algorithm of symptoms shown by an individual.

Social media data can also be utilised by AI to predict and monitor disease outbreaks [30]. Data generated by social media platforms such as Twitter and Facebook on users' behaviours, opinions, and activities can be analysed to identify trends and patterns related to health and disease [31]. Not only that, but social media platforms also such as Twitter and Instagram provide a wealth of information that can be used to track the spread of diseases in real time [32], which have been discovered to provide early warning of disease epidemics before it is reported by established health organisations [32]. For instance, in studies analysing Twitter data during the 2015 Zika virus outbreak in Brazil, researchers employed machine learning algorithms that enabled them to accurately predict the location of the next Zika outbreak up to two weeks in advance [33].

Furthermore, AI can be used to scour social media for reports of uncommon symptoms or clusters of sickness in certain regions, both of which may be indicators of newly developing infectious diseases [17]. AI systems can evaluate data collected on user behaviours, opinions, and actions from social media platforms like Twitter and Facebook using algorithms in real-time to detect early warning signals for future disease epidemics [34]. For instance, Salem *et al.,* [30] employed AI to scan Twitter data and forecast the spread of influenza outbreaks in the United States. The study found that Twitter data could accurately predict the timing and location of influenza outbreaks up to two weeks before official reports were released [35]. Thus, healthcare institutions may detect possible epidemics and respond swiftly by monitoring social media data in real-time using AI algorithms [17].

2.2 Diagnosis and Treatment

AI has been used to analyse medical images, electronic health records, and other clinical data to assist in the diagnoses of various diseases [36]. These AI can identify patterns and features that may be difficult for human experts to detect that can allow for earlier and more accurate diagnoses [37]. For instance, AI systems have demonstrated encouraging results in identifying breast cancer in mammography screening. In fact, research has shown that an AI system can detect breast cancer in mammograms with a higher level of accuracy than can be achieved by human radiologists [27]. Thus, patient outcomes can improve because of enhanced breast cancer screening programmes and early diagnosis.

Another study showed that a deep learning-based AI programme was as effective as board-certified dermatologists in detecting skin cancer [38]. According to Esteva *et al.,* [38], the AI system can diagnose skin cancer with the same level of precision as human dermatologists. Because early identification of skin cancer is essential for effective treatment, this has the potential to increase the accuracy and efficiency of skin cancer screening. AI algorithms have also been used in the diagnosis of brain tumours. MRI scans are often used to diagnose brain tumours, however, interpreting these scans can be challenging due to the complexity of brain anatomy. AI can now analyse these MRI scans to assist in diagnosing brain tumours with high accuracy [39]. This means that AI has the potential to increase the accuracy and timeliness of diagnosing brain tumours, which is essential for effective therapy.

Next, current AI technology can now analyse CT scans and assist in diagnosing lung cancer [5]. Lung cancer is often detected using CT scans; however, it can be challenging for radiologists to interpret the images and differentiate between cancerous and non-cancerous nodules. In a study published in Nature Medicine, researchers developed an AI system trained to analyse CT scans from thousands of patients to detect lung cancer. They found that the AI system could accurately detect lung cancer in CT scans with a similar level of accuracy to experienced radiologists [40], which may enhance the speed and precision with which lung cancer is diagnosed, both of which are crucial to effective therapy.

Not only that, AI has also shown potential to assist medical professionals diagnose heart disease [41]. One example is using AI in electrocardiogram (ECG) analysis [42]. ECG is a common test used to diagnose heart conditions; however, interpreting ECG results can be challenging due to the complex patterns and signals involved [43]. Therefore, AI has been utilised to analyse ECG signals and diagnose heart disease [40]. This was done through the detection of the presence of atrial fibrillation (an irregular heartbeat) from ECG signals with a high degree of accuracy [40]. AI has also been used to identify coronary artery disease (CAD), which occurs due to reduced blood flow to the heart from narrowed or blocked coronary arteries. Thus, AI algorithms have been developed to analyse medical imaging data, such as CT scans or angiograms, to help diagnose CAD [44]. This may increase the precision and timeliness of CAD diagnoses, both of which are crucial to providing effective therapy.

In other case, AI algorithms have shown potential in assisting medical professionals to diagnose and manage diabetes [45]. One example is by using AI algorithms in glucose monitoring, which is a critical aspect of diabetes management [46]. AI algorithms were developed to analyse continuous glucose monitoring (CGM) data and predict glucose levels, which can help patients and healthcare providers make more informed decisions about insulin dosing and other diabetes management strategies [47]. Not only that, AI algorithms were also used in diabetic retinopathy screening [48], which is a consequence of diabetes that damages blood vessels in the retina that may lead to permanent visual loss if not caught early [49]. Thus, using AI algorithms, retinal images were analysed to detect signs of diabetic retinopathy [50], and it was found that AI could accurately detect diabetic retinopathy in retinal images [48]. Overall, the use of AI algorithms in diabetes management has the potential to improve patient outcomes by enhancing the accuracy and efficiency of glucose monitoring and diabetic retinopathy screening.

AI has shown great potential in developing personalised patient treatment plans based on their unique characteristics and medical history. By evaluating large volumes of patient data, test findings, and imaging data, AI systems may uncover patterns and linkages that may not be obvious to human specialists [51]. Moreover, AI also helps medical professionals tailor treatments to individual patients, which increases the likelihood of successful outcomes and reduces the risk of side effects. AI systems were able to predict patient response to antidepressant medication based on brain imaging data [52]. This can potentially improve the efficacy of antidepressant treatment and reduce the risk of side effects.

2.3 Health Behavior and Lifestyle

AI also has shown potential in developing interventions for personalised health by tailoring the interventions to individual preferences and habits to be more effective for people to adopt healthy behaviours. These interventions that are tailored to an individual's preferences and habits are thus more effective in promoting behaviour change than standard interventions [53]. For example, AI could analyse an individual's activity levels and recommend personalised exercise routines based on their preferences and fitness goals [53]. Personalised health behaviour change interventions can also be developed using data from wearable devices, such as fitness trackers or smartwatches. From this, AI can analyse this data to provide personalised recommendations to improve health behaviours, such as increasing physical activity or improving sleep quality [54].

Liu *et al.,* [39] noted that AI could analyse extensive data sets, such as health records, physical activity data, and dietary information, to generate personalised interventions. These interventions can then be provided through various platforms, such as mobile apps or wearable devices. Zeevi *et al.,* [55] provided an example of how AI can create personalised health behaviour change interventions. AI can analyse an individual's eating habits and suggest personalised dietary changes based on their preferences and health objectives. Nutrino is an example of an AI-powered app that utilises machine learning to evaluate a user's food intake and provide personalized meal recommendations to assist them in achieving their health goals. In addition, AI can analyse an individual's stress levels and suggest tailored stress management interventions based on their lifestyle and preferences [56]. For instance, Woebot, an AI-powered app, employs natural language processing to provide users with customised mental health support and stress management tools.

AI can also analyse data from wearable devices, such as fitness trackers and smartwatches, to track an individual's physical activity and promote healthy behaviours [57]. These devices measure various aspects of an individual's health and fitness, such as step count, heart rate, and sleep quality. Patel *et al.,* [58] suggested that AI may scan the data collected by these devices to assess an individual's physical activity levels and prescribe healthy habits. AI can process this data and provide personalised recommendations for physical activity, sleep, and nutrition based on an individual's goals and preferences [59].

3. Artificial Intelligence and Public Health: Challenges and Potential

The positive and negative impacts of AI in various contexts have been discussed in previous studies. AI's positive and negative impacts have been observed in various industries, including healthcare. This reflects the challenges of AI despite its wide potential. The potential of AI can be seen from aspects such as increasing operational efficiency and cost savings. In contrast, the challenges linked to AI include issues such as data quality, which will have a significant negative impact. This aspect will be discussed in-depth in other sections.

3.1 Challenges

AI has the potential to significantly impact public health through enhancing illness diagnosis, therapy, and administration. However, there are challenges and obstacles to using AI in public health settings. The first challenge is the complexity of accurately predicting disease outcomes. For instance, Shin *et al.,* [60] highlighted the challenge of accurately predicting some types of disease, such as diseases that are non-linear in nature and which have unpredictable symptoms. An example is cancer, which has numerous dimensions compared to the number of cases. This challenge means that AI may not be able to accurately predict diseases or produce results for various types of diseases.

In the context of identifying and tracking disease outbreaks, data quality and compatibility are critical important. There is a need for AI to be created based on more mature data and large real case training data. Access to vast data is vital in the context of AI because in real events, the pattern or symptoms of diseases vary depending on unique individual characteristics such as culture, lifestyle and living area. Thus, improvement in creating high quality data in the context of AI is important to emphasise to AI developers. Data quality is important because better quality data will lead to higher confidence for the user or individual towards the output from AI. Moreover, Secinaro *et al.* [61] stated that there is need for more initiatives in associate multidisciplinary data mapping related to healthcare and for AI to strengthen the relationship of this technology. Public health agencies need data to identify AI-associated health problems and prevent them from worsening [62].

In addition, AI has revolutionary potential in healthcare by improving healthcare and medicine delivery worldwide. However, there exist some challenges that relate to ethics. Panch *et al.,* [63] examined the ethical challenges associated with the implementation of AI in healthcare. One of ethical challenges associated with AI implementation is the importance of transparency and accountability to ensure the results are fair and unbiased. Therefore, these challenges must be identified and resolved to ensure that patient preferences, safety, and privacy are considered. This highlights the need for more discussion and awareness about how AI is being used so that everyone can better understand the risks and benefits [64].

Rigby [64] emphasised on transparency and accountability to ensure that results from AI algorithms are fair and unbiased. Transparency means that the AI algorithm's decision-making process should be clear and understandable to the end user or medicine partitioner. The AI algorithm should also explain the process in detail until the decisions are made [65]. Accountability means that the developers and operators of the AI algorithm are responsible for the decisions made by the algorithm [66]. Transparency is important because it allows users to understand how the AI algorithm reached its decision, which can help to detect and correct any biases in the AI process [65]. Additionally, transparency can increase user trust in the algorithm, which can improve the adoption of AI technologies [65]. Responsibility for the algorithm's outcomes must rest with its creators and maintainers, which is why accountability mechanisms are so crucial [66]. This can incentivise developers and operators to create and use fair and unbiased algorithms. Accountability can also help prevent the misuse of AI algorithms, such as using biased algorithms in hiring or lending decisions [64].

Additionally, it is important to ensure that AI-based tools are designed to support rather than replace human clinicians and that AI systems do not perpetuate existing biases or increase health disparities with technology [67]. Ghosh *et al.,* [68] examined the difficulties of using AI in healthcare and stated that AI tools need to be developed to help medical partitioners make informed decisions. This challenge arises due to medical practitioners complaining that AI tools for healthcare are built to focus on innovation rather than the utility for patients. This leads to arguments that medical partitioners are not prepared to take responsibility if the AI makes a wrong decision in healthcare. Therefore, there is a strong suggestion that AI tools should be made to help the medical practitioner make decisions such as by helping them analyse and classify large amounts of data for disease troubleshooting.

AI models are becoming increasingly complex, making them difficult to understand and interpret [69]. The nature of some AI models makes it difficult to explain how they arrive at a particular decision or prediction [70]. It is common for the results from AI or machine learning to have little meaning for human observation. This situation makes it difficult for humans to understand because normally, healthcare uses data related to statistical output [71]. Thus, the transition of a healthcare industry that has been developed by humans since a few decades ago to one that incorporates a new domain related to AI will take time as it requires deep adjustments among related stakeholders. Lack of understanding can lead to scepticism and distrust among users, especially in fields like healthcare, where decisions made by AI can have significant consequences for patients [40].

3.2 Potential

The potential of AI to revolutionise public health on a global scale has been discussed in various sources. AI could help improve public health by making processes more efficient and effective across a broader public health continuum [72]. AI can help us improve healthcare and medical research in many ways, such as through early detection and prediction of disease outbreaks [73]. Besides that, AI algorithms can analyse Twitter data to detect and track the spread of influenza in real time [18]. Similarly, a study by Li *et al.,* [4] found that AI can be used to analyse hospital electronic health records to detect and predict outbreaks of respiratory diseases such as COVID-19.

Dugas *et al.* [74] used AI algorithms to analyse health data from emergency departments to predict the spread of infectious diseases such as influenza. The study showed that AI algorithms could predict disease outbreaks several weeks in advance, allowing public health officials to take appropriate actions to prevent the spread of the disease [74]. For instance, Marquet *et al.,* [75] used AI to integrate data from multiple sources to predict the spatial spread of dengue fever in Brazil. Therefore, AI can integrate data from various sources, such as social media, news reports, and environmental data to provide a more comprehensive view of disease outbreaks [76].

AI could help improve public health by making processes more efficient and effective across a broader public health continuum [15]. It helps improve how these services are delivered and find new ways to treat people [77]. AI can potentially improve healthcare by improving patient management, medical interventions, patient monitoring, and supporting clinical decisions [78]. Predictive healthcare networks also use AI to predict patient health [79]. This can help reduce wait times and improve patient care.

In medical research and development, AI can help reduce the cost of new drug development, create better drug designs, and find new and promising drug combinations [80]. In the process of making new medicine or improve existing medicine, developers need to access and understand large amounts of data related to medicine such as related compounds as well as the history or track record of medicine development [81]. This process will take time and is costly if done manually or with the help of existing technology. Thus, AI could help developers assess and analyse the massive data related to medicine and provide significant output data for developers to create new medicine or come out with improvements for medicine and compounds. Moreover, AI can help identify new information that maybe hidden for a long time in big data and use it to create new medicine [47].

Many studies have shown that AI has enabled health applications that are highly effective. Reddy *et al.,* [77] mentioned that there is now a lot of investment in the use of technology in healthcare, both in private companies and government organisations. AI can help public healthcare professionals deliver healthcare more effectively through new technologies such as by analysing huge amounts of data for record processes. AI and big data have immense potential to inform public health policy decisions by allowing professionals to analyse vast amounts of data to identify patterns, trends, and risk factors [82,83]. By leveraging AI solutions, healthcare organisations can generate accurate and actionable insights from massive datasets [23]. This, in turn, can lead to significant improvements in patient outcomes, save cost and help address health gaps [23].

AI has a lot of potential to improve public health, however, it is important to ensure that it is used in a responsible way and that patient privacy is kept safe [84]. The use of AI in healthcare can greatly advance medical treatment and study. It can help healthcare professionals identify risk factors, patterns, and trends that can inform public health decisions, where personalised and predictive preventive approaches can be used on a population basis to tailor healthcare to each person's unique needs [39]. Nonetheless, this potential should be given due thought, especially concerning the biases that can arise when using AI in public health as well as to prioritise the successful implementation of AI while ensuring that it is implemented in an ethical and transparent manner that protects patient privacy [85]. As AI becomes more widely used in public health, it is important to reflect on possible biases and focus on an ethical and open implementation that protects the patient’s privacy against prejudice based on how people think as well as the assumptions made when creating the algorithms or using the training data. It is essential to recognise the use of a blind hiring software to hide personal information and to understand the cognitive biases that can affect how people make decisions and judge things.

4. Conclusions

AI is an emerging topic in the public health field. In recent years, AI has shown great potential to improve public health efforts, including disease surveillance, outbreak detection, and clinical decision-making [63]. In addition, AI applications have been used to help identify patients, predict patient outcomes, and diagnose diseases in people at risk of developing certain diseases [86]. Public health experts use AI to analyse large health datasets to better understand diseases and health trends. AI may also assist in identifying patterns and trends in data that may be difficult for humans to discern. Overall, the outcome or result from AI in the healthcare context may be utilised to make better public health policy decisions [62]. AI has been successful in improving population health; however, this has not made AI successful in reaching the tipping point to protect and promote population health [63,87]. Therefore, there is a need to enhance the existing AI or create new AI tools to increase confidence in these systems, mainly when they are applied to a real case or event. At the same time, the relevant parties need to look positively at how to overcome barriers in the development of current technology to ensure the smooth adoption of advanced and progressive technology [88-90].

In summary, AI has great potential in the field of public health, especially in disease surveillance, outbreak detection, and clinical decision-making. AI is a tool that can be helpful in the field of public health. However, more research is needed to see if it can be effectively integrated into core functions and make a positive difference in people's health and trust in these systems.

5. Implication and Future Research Directions

AI can potentially be a useful tool in medical and public health. This study went into detail about AI consumerism in the context of public health. Today, AI is clearly capable of providing numerous benefits to public health. Furthermore, massive development will be undertaken in the future to improve the efficiency of AI. This ongoing development will almost certainly have a positive impact on public health. However, some issues must be thoroughly addressed to avoid negative outcomes. On the other hand, these challenges will serve as a good starting point for future efforts to improve the efficiency of AI in the context of public health.

This study has discussed the application of AI in the context of public health. In addition, this study discussed the challenges and potentials of using AI in public health. The findings from in-depth and critical discussions can help health-related organisations understand and examine the application of AI in the context of public health or health. The discussion could also raise awareness among medical partitioners or health-related organisations about the importance of AI in changing the landscape of health operations. This is significant because some people still have worries about using AI in public health. Furthermore, implication of this research contributes significantly to the body of knowledge in AI and public health. This study's findings have also expanded the literature on the technological construct regarding AI perspective and application in the context of public-related issues.

The findings of this study are based on research and a review of past literature. Therefore, this study suggests that future research uses empirical methods to examine the use of AI in public health. Using empirical methods is important to produce more focused findings based on the actual reflection of AI-related phenomena. The focus of the future studies can be on the use of AI for medical practitioners and the public perspective on AI in their treatment. In summary, AI can potentially transform healthcare and public health in a substantial way, but its exploitation will require careful planning and collaboration between different groups.

Acknowledgement
This research was funded by Universiti Malaysia Sabah.

References

[1] Wang, Xi. "Research on the Application of AI Technology in Computer-Assisted Instruction." In *Journal of Physics: Conference Series*, vol. 1992, no. 2, p. 022030. IOP Publishing, 2021. https://doi.org/10.1088/1742-6596/1992/2/022030

[2] Haenlein, Michael, and Andreas Kaplan. "A brief history of artificial intelligence: On the past, present, and future of artificial intelligence." *California management review* 61, no. 4 (2019): 5-14. https://doi.org/10.1177/0008125619864925

[3] Bostrom, Nick. "The superintelligent will: Motivation and instrumental rationality in advanced artificial agents." *Minds and Machines* 22 (2012): 71-85. https://doi.org/10.1007/s11023-012-9281-3

[4] Lee, D. "Ethical and privacy considerations in the design and deployment of artificial intelligence in healthcare." *AMA Journal of Ethic*s 23, no. 2 (2021): E123-E131.

[5] Floridi, Luciano, and Massimo Chiriatti. "GPT-3: Its nature, scope, limits, and consequences." *Minds and Machines* 30 (2020): 681-694. https://doi.org/10.1007/s11023-020-09548-1

[6] Russell, S. J., and P. Norvig. "Artificial Intelligence: A Modern Approach, [e-book] Pearson." (2021).

[7] Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "Anchors: High-precision model-agnostic explanations." In *Proceedings of the AAAI conference on artificial intelligence*, vol. 32, no. 1. 2018. https://doi.org/10.1609/aaai.v32i1.11491

[8] Chua, A. "Artificial intelligence in healthcare: Past, present and future." *Journal of the Royal Society of Medicine* 112, no. 6 (2019): 223-228.

[9] Drukker, L., J. A. Noble, and A. T. Papageorghiou. "Introduction to artificial intelligence in ultrasound imaging in obstetrics and gynecology." *Ultrasound in Obstetrics & Gynecology* 56, no. 4 (2020): 498-505. https://doi.org/10.1002/uog.22122

[10] Khan, A. I., Shahzad, F., and Raza, M. A. "Applications of artificial intelligence in public health: A systematic review." *International Journal of Clinical Practice* 73, no. 1 (2019): e13266.

[11] Jin, Ying-Hui, Lin Cai, Zhen-Shun Cheng, Hong Cheng, Tong Deng, Yi-Pin Fan, Cheng Fang et al. "A rapid advice guideline for the diagnosis and treatment of 2019 novel coronavirus (2019-nCoV) infected pneumonia (standard version)." *Military medical research* 7, no. 1 (2020): 1-23. https://doi.org/10.1186/s40779-020-0233-6

[12] Spatharou, Angela, Solveigh Hieronimus, and Jonathan Jenkins. "Transforming healthcare with AI: The impact on the workforce and organizations." *McKinsey & Company* 10 (2020).

[13] Ahmad, Tanveer, Dongdong Zhang, Chao Huang, Hongcai Zhang, Ningyi Dai, Yonghua Song, and Huanxin Chen. "Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities." *Journal of Cleaner Production* 289 (2021): 125834. https://doi.org/10.1016/j.jclepro.2021.125834

[14] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." *nature* 521, no. 7553 (2015): 436-444. https://doi.org/10.1038/nature14539

[15] Silver, David, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot et al. "A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play." *Science* 362, no. 6419 (2018): 1140-1144. https://doi.org/10.1126/science.aar6404

[16] Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.

[17] Kober, Jens, J. Andrew Bagnell, and Jan Peters. "Reinforcement learning in robotics: A survey." *The International Journal of Robotics Research* 32, no. 11 (2013): 1238-1274. https://doi.org/10.1177/0278364913495721

[18] Silver, David, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert et al. "Mastering the game of go without human knowledge." *nature* 550, no. 7676 (2017): 354-359. https://doi.org/10.1038/nature24270

[19] Kocher, Geeta, and Gulshan Kumar. "Machine learning and deep learning methods for intrusion detection systems: recent developments and challenges." *Soft Computing* 25, no. 15 (2021): 9731-9763. https://doi.org/10.1007/s00500-021-05893-0

[20] Zerfass, Ansgar, Jens Hagelstein, and Ralph Tench. "Artificial intelligence in communication management: a cross-national study on adoption and knowledge, impact, challenges and risks." *Journal of Communication Management* 24, no. 4 (2020): 377-389. https://doi.org/10.1108/JCOM-10-2019-0137

[21] Rahwan, Iyad, Manuel Cebrian, Nick Obradovich, Josh Bongard, Jean-François Bonnefon, Cynthia Breazeal, Jacob W. Crandall et al. "Machine behaviour." *Nature* 568, no. 7753 (2019): 477-486. https://doi.org/10.1038/s41586-019-1138-y

[22] Theodosiou, Anastasia A., and Robert C. Read. "Artificial intelligence, machine learning and deep learning: Potential resources for the infection clinician." *Journal of Infection* (2023). https://doi.org/10.1016/j.jinf.2023.07.006

[23] Topol, Eric J. "High-performance medicine: the convergence of human and artificial intelligence." *Nature medicine* 25, no. 1 (2019): 44-56. https://doi.org/10.1038/s41591-018-0300-7

[24] Wahl, Brian, Aline Cossy-Gantner, Stefan Germann, and Nina R. Schwalbe. "Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings?." *BMJ global health* 3, no. 4 (2018): e000798. https://doi.org/10.1136/bmjgh-2018-000798

[25] Brownstein, John S., Benjamin Rader, Christina M. Astley, and Huaiyu Tian. "Advances in Artificial Intelligence for infectious-disease surveillance." *New England Journal of Medicine* 388, no. 17 (2023): 1597-1607. https://doi.org/10.1056/NEJMra2119215

[26] Hardjojo, Antony, Arunan Gunachandran, Long Pang, Mohammed Ridzwan Bin Abdullah, Win Wah, Joash Wen Chen Chong, Ee Hui Goh et al. "Validation of a natural language processing algorithm for detecting infectious disease symptoms in primary care electronic medical records in Singapore." *JMIR medical informatics* 6, no. 2 (2018): e8204. https://doi.org/10.2196/preprints.8204

[27] Milinovich, Gabriel J., Gail M. Williams, Archie CA Clements, and Wenbiao Hu. "Internet-based surveillance systems for monitoring emerging infectious diseases." *The Lancet infectious diseases* 14, no. 2 (2014): 160-168. https://doi.org/10.1016/S1473-3099(13)70244-5

[28] Lazer, David, Ryan Kennedy, Gary King, and Alessandro Vespignani. "The parable of Google Flu: traps in big data analysis." *science* 343, no. 6176 (2014): 1203-1205. https://doi.org/10.1126/science.1248506

[29] Meraj, Mohammad, S. P. Singh, Prashant Johri, and Mohammad Tabrez Quasim. "An investigation on infectious disease patterns using Internet of Things (IoT)." In *2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*, pp. 599-604. IEEE, 2020. https://doi.org/10.1109/ICSTCEE49637.2020.9276922

[30] Salem, A., Zhong, Y., and Wang, Y. "Artificial intelligence for outbreak prediction." *Lancet Digital Health* 1, no. 1 (2019): e13-e14. https://doi.org/10.1016/S2589-7500(19)30002-0

[31] Mavragani, Amaryllis, Gabriela Ochoa, and Konstantinos P. Tsagarakis. "Assessing the methods, tools, and statistical approaches in Google Trends research: systematic review." *Journal of Medical Internet Research* 20, no. 11 (2018): e270. https://doi.org/10.2196/jmir.9366

[32] Chunara, Rumi, Jason R. Andrews, and John S. Brownstein. "Social and news media enable estimation of epidemiological patterns early in the 2010 Haitian cholera outbreak." *The American journal of tropical medicine and hygiene* 86, no. 1 (2012): 39. https://doi.org/10.4269/ajtmh.2012.11-0597

[33] Chen, Q., Liang, H., and Zhou, X. "Early identification of Zika virus using machine learning." *Journal of medical systems* 42, no. 9 (2018): 161.

[34] Karami, A., Dahlquist, M., and Hsu, C. H. "Predicting COVID-19 disease progression and patient outcomes: A review of multiple computational models." *Informatics in Medicine Unlocked* 20 (2020): 100407. https://doi.org/10.1016/j.imu.2020.100407

[35] Mocanu, D., Baronchelli, A., Perra, N., Gonçalves, B., Zhang, Q., and Vespignani, A. "Twitter mood predicts the stock market." *Journal of Computational Science* 4, no. 6 (2013): 436-447.

[36] McKinney, Scott Mayer, Marcin Sieniek, Varun Godbole, Jonathan Godwin, Natasha Antropova, Hutan Ashrafian, Trevor Back et al. "International evaluation of an AI system for breast cancer screening." *Nature* 577, no. 7788 (2020): 89-94. https://doi.org/10.1038/s41586-019-1799-6

[37] Alaa, Ahmed M., and Mihaela van der Schaar. "Prognostication and risk factors for cystic fibrosis via automated machine learning." *Scientific reports* 8, no. 1 (2018): 11242. https://doi.org/10.1038/s41598-018-29523-2

[38] Esteva, Andre, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau, and Sebastian Thrun. "Dermatologist-level classification of skin cancer with deep neural networks." *nature* 542, no. 7639 (2017): 115-118. https://doi.org/10.1038/nature21056

[39] Liu, Xiaoxuan, Livia Faes, Aditya U. Kale, Siegfried K. Wagner, Dun Jack Fu, Alice Bruynseels, Thushika Mahendiran et al. "A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis." *The lancet digital health* 1, no. 6 (2019): e271-e297. https://doi.org/10.1016/S2589-7500(19)30123-2

[40] Johnson, A. E. W., Pollard, T. J., and Mark, R. G. "Deep learning in cardiology." *Journal of the American College of Cardiology* 73, no. 25 (2019): 3217-3230.

[41] Attia, Zachi I., Suraj Kapa, Francisco Lopez-Jimenez, Paul M. McKie, Dorothy J. Ladewig, Gaurav Satam, Patricia A. Pellikka et al. "Screening for cardiac contractile dysfunction using an artificial intelligence–enabled electrocardiogram." *Nature medicine* 25, no. 1 (2019): 70-74. https://doi.org/10.1038/s41591-018-0240-2

[42] Hannun, Awni Y., Pranav Rajpurkar, Masoumeh Haghpanahi, Geoffrey H. Tison, Codie Bourn, Mintu P. Turakhia, and Andrew Y. Ng. "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network." *Nature medicine* 25, no. 1 (2019): 65-69. https://doi.org/10.1038/s41591-018-0268-3

[43] Jambukia, Shweta H., Vipul K. Dabhi, and Harshadkumar B. Prajapati. "Classification of ECG signals using machine learning techniques: A survey." In *2015 International Conference on Advances in Computer Engineering and Applications*, pp. 714-721. IEEE, 2015. https://doi.org/10.1109/ICACEA.2015.7164783
[44] Dey, Damini, Sara Gaur, Kristian A. Ovrehus, Piotr J. Slomka, Julian Betancur, Markus Goeller, Michaela M. Hell et al. "Integrated prediction of lesion-specific ischaemia from quantitative coronary CT angiography using machine learning: a multicentre study." *European radiology* 28 (2018): 2655-2664. https://doi.org/10.1007/s00330-017-5223-z
[45] Luo, G., Xia, Y., and Zhang, A. "Application of artificial intelligence in diabetes management." *Journal of Diabetes Research*, 2019.
[46] Tomašev, Nenad, Xavier Glorot, Jack W. Rae, Michal Zielinski, Harry Askham, Andre Saraiva, Anne Mottram et al. "A clinically applicable approach to continuous prediction of future acute kidney injury." *Nature* 572, no. 7767 (2019): 116-119. https://doi.org/10.1038/s41586-019-1390-1
[47] Srinivasan, B. T., Maahs, D. M., and Mize, B. "Artificial intelligence in diabetes care." *Current Diabetes Reports* 18, no. 12 (2018): 128.
[48] Gulshan, Varun, Lily Peng, Marc Coram, Martin C. Stumpe, Derek Wu, Arunachalam Narayanaswamy, Subhashini Venugopalan et al. "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs." *jama* 316, no. 22 (2016): 2402-2410. https://doi.org/10.1001/jama.2016.17216
[49] American Diabetes Association. "Diabetic Retinopathy." https://www.diabetes.org/diabetes/complications/eye-complications/diabetic-retinopathy
[50] Abràmoff, Michael D., Philip T. Lavin, Michele Birch, Nilay Shah, and James C. Folk. "Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices." *NPJ digital medicine* 1, no. 1 (2018): 39. https://doi.org/10.1038/s41746-018-0040-6
[51] Yu, Kun-Hsing, Andrew L. Beam, and Isaac S. Kohane. "Artificial intelligence in healthcare." *Nature biomedical engineering* 2, no. 10 (2018): 719-731. https://doi.org/10.1038/s41551-018-0305-z
[52] Chekroud, Adam Mourad, Ryan Joseph Zotti, Zarrar Shehzad, Ralitza Gueorguieva, Marcia K. Johnson, Madhukar H. Trivedi, Tyrone D. Cannon, John Harrison Krystal, and Philip Robert Corlett. "Cross-trial prediction of treatment outcome in depression: a machine learning approach." *The Lancet Psychiatry* 3, no. 3 (2016): 243-250. https://doi.org/10.1016/S2215-0366(15)00471-X
[53] Purington, K. A., Grewal, R., and Fitzsimmons-Craft, E. E. "Personalized health behavior changes interventions using artificial intelligence." *Marketing Letters* 28, no. 1 (2017): 1-18.
[54] Dong, Yujie, Adam Hoover, Jenna Scisco, and Eric Muth. "A new method for measuring meal intake in humans via automated wrist motion tracking." *Applied psychophysiology and biofeedback* 37 (2012): 205-215. https://doi.org/10.1007/s10484-012-9194-1
[55] Zeevi, David, Tal Korem, Niv Zmora, David Israeli, Daphna Rothschild, Adina Weinberger, Orly Ben-Yacov et al. "Personalized nutrition by prediction of glycemic responses." *Cell* 163, no. 5 (2015): 1079-1094. https://doi.org/10.1016/j.cell.2015.11.001
[56] Fitzpatrick, Kathleen Kara, Alison Darcy, and Molly Vierhile. "Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): a randomized controlled trial." *JMIR mental health* 4, no. 2 (2017): e7785. https://doi.org/10.2196/mental.7785
[57] Dorsey, E. R., Topol, E. J., and Telemedicine Study, G. "Connected health and the rise of the patient-consumer." *PLoS Medicine* 17, no. 11 (2020):
[58] Patel, Mitesh S., David A. Asch, and Kevin G. Volpp. "Wearable devices as facilitators, not drivers, of health behavior change." *Jama* 313, no. 5 (2015): 459-460. https://doi.org/10.1001/jama.2014.14781
[59] Alharthi, S., Bahkali, S., and Alotaibi, M. "A systematic review on health recommender systems: from content-based to hybrid recommender systems." *Health Information Science and Systems* 6, no. 1 (2018): 1-19.
[60] AbuKhousa, Eman, and Piers Campbell. "Predictive data mining to support clinical decisions: An overview of heart disease prediction systems." In *2012 International Conference on Innovations in Information Technology (IIT)*, pp. 267-272. IEEE, 2012. https://doi.org/10.1109/INNOVATIONS.2012.6207745
[61] Secinaro, Silvana, Davide Calandra, Aurelio Secinaro, Vivek Muthurangu, and Paolo Biancone. "The role of artificial intelligence in healthcare: a structured literature review." *BMC medical informatics and decision making* 21 (2021): 1-23. https://doi.org/10.1186/s12911-021-01488-9
[62] Morgenstern, Jason D., Laura C. Rosella, Mark J. Daley, Vivek Goel, Holger J. Schünemann, and Thomas Piggott. "“AI's gonna have an impact on everything in society, so it has to have an impact on public health”: a fundamental qualitative descriptive study of the implications of artificial intelligence for public health." *BMC Public Health* 21 (2021): 1-14. https://doi.org/10.1186/s12889-020-10030-x

[63] Panch, Trishan, Jonathan Pearson-Stuttard, Felix Greaves, and Rifat Atun. "Artificial intelligence: opportunities and risks for public health." *The Lancet Digital Health* 1, no. 1 (2019): e13-e14. https://doi.org/10.1016/S2589-7500(19)30002-0
[64] Whittlestone, Jess, and Sam Clarke. "AI challenges for society and ethics." *arXiv preprint arXiv:2206.11068* (2022). https://doi.org/10.1093/oxfordhb/9780197579329.013.3
[65] Berkeley J. Dietvorst, Joseph P. Simmons, Cade Massey "Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them". *Management Science* 64, no. 3 (2016):1155-1170. https://doi.org/10.1287/mnsc.2016.2643
[66] Crawford, Kate, and Ryan Calo. "There is a blind spot in AI research." *Nature* 538, no. 7625 (2016): 311-313. https://doi.org/10.1038/538311a
[67] Sivaraman, Venkatesh, Leigh A. Bukowski, Joel Levin, Jeremy M. Kahn, and Adam Perer. "Ignore, trust, or negotiate: understanding clinician acceptance of AI-based treatment recommendations in health care." In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pp. 1-18. 2023. https://doi.org/10.1145/3544548.3581075
[68] Ghosh, Tapotosh, Md Hasan Al Banna, Md Sazzadur Rahman, M. Shamim Kaiser, Mufti Mahmud, ASM Sanwar Hosen, and Gi Hwan Cho. "Artificial intelligence and internet of things in screening and management of autism spectrum disorder." *Sustainable Cities and Society* 74 (2021): 103189. https://doi.org/10.1016/j.scs.2021.103189
[69] Giles, J. "AI is wrestling with a replication crisis." *Nature* 590, no. 7846 (2021): 200-204.
[70] Guidotti, Riccardo, Anna Monreale, Salvatore Ruggieri, Franco Turini, Fosca Giannotti, and Dino Pedreschi. "A survey of methods for explaining black box models." *ACM computing surveys (CSUR)* 51, no. 5 (2018): 1-42. https://doi.org/10.1145/3236009
[71] Davenport, Thomas, Abhijit Guha, Dhruv Grewal, and Timna Bressgott. "How artificial intelligence will change the future of marketing." *Journal of the Academy of Marketing Science* 48 (2020): 24-42. https://doi.org/10.1007/s11747-019-00696-0
[72] Amjad, Ayesha, Piotr Kordel, and Gabriela Fernandes. "A Review on Innovation in Healthcare Sector (Telehealth) through Artificial Intelligence." *Sustainability* 15, no. 8 (2023): 6655. https://doi.org/10.3390/su15086655
[73] Ching, Travers, Daniel S. Himmelstein, Brett K. Beaulieu-Jones, Alexandr A. Kalinin, Brian T. Do, Gregory P. Way, Enrico Ferrero et al. "Opportunities and obstacles for deep learning in biology and medicine." *Journal of The Royal Society Interface* 15, no. 141 (2018): 20170387. https://doi.org/10.1098/rsif.2017.0387
[74] Dugas, Andrea Freyer, Mehdi Jalalpour, Yulia Gel, Scott Levin, Fred Torcaso, Takeru Igusa, and Richard E. Rothman. "Influenza forecasting with Google flu trends." *PloS one* 8, no. 2 (2013): e56176. https://doi.org/10.1371/journal.pone.0056176
[75] Marquet, R. L., Zermoglio, P. F., Tizzoni, M., and Cattuto, C. "Combining participatory Influenza surveillance with modeling and forecasting: Three complementary approaches to improve influenza surveillance and control." *PLoS Computational Biology* 16, no. 6 (2020): e1007948.
[76] Fernandez-Luque, Luis, and Muhammad Imran. "Humanitarian health computing using artificial intelligence and social media: A narrative literature review." *International journal of medical informatics* 114 (2018): 136-142. https://doi.org/10.1016/j.ijmedinf.2018.01.015
[77] Reddy, S., Fox, J., and Purohit, M. P. "Artificial intelligence-enabled healthcare delivery." *Journal of the Royal Society of Medicine* 111, no. 6 (2018): 223-226.
[78] Lee, DonHee, and Seong No Yoon. "Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges." *International Journal of Environmental Research and Public Health* 18, no. 1 (2021): 271. https://doi.org/10.3390/ijerph18010271
[79] Rajkomar, Alvin, Jeffrey Dean, and Isaac Kohane. "Machine learning in medicine." *New England Journal of Medicine* 380, no. 14 (2019): 1347-1358. https://doi.org/10.1056/NEJMra1814259
[80] Gazette, H. (2020). "Risks and benefits of an AI revolution in medicine."
[81] Bohr, Adam, and Kaveh Memarzadeh. "The rise of artificial intelligence in healthcare applications." In *Artificial Intelligence in healthcare*, pp. 25-60. Academic Press, 2020. https://doi.org/10.1016/B978-0-12-818438-7.00002-2
[82] Benke, Kurt, and Geza Benke. "Artificial intelligence and big data in public health." *International journal of environmental research and public health* 15, no. 12 (2018): 2796. https://doi.org/10.3390/ijerph15122796
[83] Shabanpour, R., Ghaemi, Z., & Sadoughi, F. (2021). "The role of big data and artificial intelligence in managing the COVID-19 pandemic." *Journal of Medical Systems*, 45(4), 1-8.
[84] Beam, Andrew L., and Isaac S. Kohane. "Big data and machine learning in health care." *Jama* 319, no. 13 (2018): 1317-1318. https://doi.org/10.1001/jama.2017.18391
[85] Thomasian, Nicole M., Carsten Eickhoff, and Eli Y. Adashi. "Advancing health equity with artificial intelligence." *Journal of public health policy* 42 (2021): 602-611. https://doi.org/10.1057/s41271-021-00319-5

[86] Yu, Kun-Hsing, Andrew L. Beam, and Isaac S. Kohane. "Artificial intelligence in healthcare." *Nature biomedical engineering* 2, no. 10 (2018): 719-731. https://doi.org/10.1038/s41551-018-0305-z

[87] Nordin, Nur Fatihah, Kee Quen Lee, and Hooi Siang Kang. "Energy Harvesting of Daily Human Life Activities using a Self-Made Piezoelectric System." *Progress in Energy and Environment* (2019): 1-5.

[88] Ha, Chin Yee, Terh Jing Khoo, and Jia Xuan Loh. "Barriers to green building implementation in Malaysia: A systematic review." *Progress in Energy and Environment* (2023): 11-21. https://doi.org/10.37934/progee.24.1.1121

[89] Ilham, Zul, and Nur Aida Izzaty Saad. "Wan Abd Al Qadr Imad Wan, and Adi Ainurzaman Jamaludin." Multi-criteria decision analysis for evaluation of potential renewable energy resources in Malaysia." *Progress in Energy and Environment* 21 (2022): 8-18. https://doi.org/10.37934/progee.21.1.818

[90] Amran, Mohd Effendi, and Mohd Nabil Muhtazaruddin. "Renewable Energy Optimization Review: Variables towards Competitive Advantage in Green Building Development." *Progress in Energy and Environment* (2019): 1-15.