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Exploring Acceptance of Artificial Intelligence amongst Healthcare Personnel: A Case in a Private Medical Centre

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ABSTRACT: With the rapid proliferation of data in healthcare, it has provided an opportune platform the creation of Artificial Intelligence (AI). AI has brought a paradigm shift for healthcare professionals, promising improvements in quality-of-service delivery. This study aimed to examine the perceived ease of use, perceived usefulness, and subjective norm of healthcare professionals towards artificial intelligence acceptance. A cross-sectional single institutional study of personnels' perception in accepting AI in a hospital was conducted using questionnaire adapted from Technology Acceptance Model. There were 96 (75.6%) of the total population responded. This study has shown significant relationship and the importance between perceived usefulness, and subjective norm to accepting AI. The study results also concluded that the determining factor towards strong acceptance of AI in their practices was those respondents with the most interactions with the patients in clinical management. In pioneering or strengthening the roll-out of AI healthcare projects, focus can be given to these areas for maximal acceptance to improve usage and service outcomes.

KEYWORDS: Artificial Intelligence, Acceptance, Healthcare, Healthcare Professionals

I. INTRODUCTION

The transfer of data from patients to clinicians and the exchange between care providers on decisions, orders, and information, drives the care process within and through organisations. Healthcare data is largely unstructured, including static data from medical charts, diagnostic photographs, surveys, and interactive data from bedside monitors or remote patient tracking. It goes beyond conventional analytical tools' abilities to manage complicated and complex results [1]. However, this knowledge can be scrutinised in depth using big data analytics and artificial intelligence to gain valuable insights that will play a critical role in saving patients' lives. By studying disease trends and monitoring disease outbreaks, AI presents tremendous opportunities in enhancing population health and disease prediction and management [2].

The usefulness of AI offering greater precision, moving beyond manual and cognitive work, has influence specialisms in the healthcare industry. AI can be interpreted as an accurate and efficient instrument that, with little misinterpretation, can analyse and identify trends in inpatient data at a pace and efficiency inconceivable to humans [3]. However, AI should only assist in augmenting human knowledge and intellect than rather the tool that makes the final decision.

However, despite this huge opportunities,machine learning algorithms are still very complex.Putting human life and health outcomes in front ofthemselves, many clinicians and healthcare personnel find it difficult to explain why the recommended course of treatment can be trusted through Artificial Intelligent Software Solution (AISS). A large number of clinician’s trust in AISS is still low to moderate, influenced by several human factors such as user education, past experiences, user biases, and perception towards automation [4]. A survey by the American Healthcare Information and Management Systems Society in 2017 showed low usage of AI technologies in the hospital where only less than just 4.7 per cent of respondents in the survey were adapting artificial intelligence [5].

While the potential advantages and prospects of using AI technologies in the healthcare sector seems exciting, some drawbacks have contributed to the ease of use, such as legal and regulatory restrictions, the availability of accurate and high-quality data, and adequate risk management. In addition, for the development of self-learning algorithms, access to data and the degree of their standardisation and incorporation into medical

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workflows is crucial as the quality of these data directly influences the capabilities and reliability of patient management [6]. For beneficial results, the system should be friendly and easily used. The lack of investment and availability of appropriate infrastructure, systems, or skilled staff and the high degree of complexity and transparency associated with such systems may have impeded AI deployment.

Hence, for successful implementation, a certain degree of understanding, acceptance and confidence on both sides, doctors, medical staff, and patients in AI are crucial [7]. However, resistance still prevails due to a lack of value comprehension and performance from machine learning. In addition, internal stakeholders' opposition and scepticism may lead to the abandonment of such roll-outs hence making the adaptation of AI in healthcare futile [3, 8].

II. RESEARCH MODEL AND HYPOTHESES

Considering the empirical studies reviewed so far, this paper will examine three constructs that influence artificial intelligence acceptance, namely: perceived ease of use, perceived usefulness, and subjective norm. The Technology Acceptance Model (TAM) was applied for this research intent [9]. The research model and the hypotheses generated for this study are shown in below and in Figure 1.

H1: Ease of use of AI has a significant relationship towards artificial intelligence acceptance.

H2: Perceived usefulness of AI has a significant relationship with artificial intelligence acceptance.

H3: Perception of healthcare personnel on the subjective norm of AI has a significant relationship towards artificial intelligence acceptance.

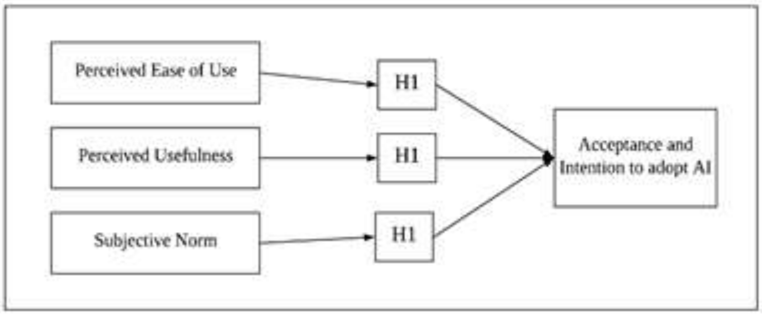

Figure 1 Conceptual Framework

Perceived ease of use is described as the degree to which an individual believes that the use of technology will be effortless [9]. Davis, Bagozzi [10] suggested that perceived ease of use improves perceived utility and increases awareness of technology adoption. Perceived usefulness, is described as the degree to which a person believes that technology will enhance his or her performance [9]. Subjective norms on the other hand, are linked to the level at which an individual would perform due to social pressure in turn will influence AI adoption. TAM is a very reliable model used in various technology adoption [11].

III. METHODOLOGY

This study was designed to use a quantitative approach. The examination of causal relationships across variables was done with Structural Equation Modelling-Partial Least Squares (SEM-PLS). Two kinds of variables were involved, latent (construct) variable, an unobserved variable, and indicator variable, also known as an observed variable of each latent variable. The latent variable is divided into exogenous latent variable and endogenous latent variable. In this study, the exogenous latent variable refers to the ease of use, usefulness, and subjective norm, while the endogenous latent variable is represented by intention to use artificial intelligence. Meanwhile, attitudes on artificial intelligence are the latent mediation variable.

This study was conducted in a Specialised Private Hospital in Klang Valley. Considering the intent of this research to investigate the acceptance by healthcare professionals of AI-based systems, the target group was explicit to include all healthcare and related non-healthcare personnel. Their acceptance is prerequisite for the adoption of the AI systems. Therefore, the samples were targeted universally to all personnel in this hospital.

All 127 healthcare personnel in this study institution were invited to participate in the survey using a self-administered Questionnaire from March to December 2020. These questionnaires were adapted from the definition and constructs of TAM [9, 10, 12]. A small sample of individuals

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representative of the research population involving a group of clinicians from the Malaysian Society of Infusion Nursing that comprised doctors, nurses, pharmacists, and university lecturers were invited to participate in piloting the questionnaire. Out of 45 questionnaires distributed, 35 responded and completed the questionnaires with no further amendments, and the sampling group can answer all the required questions.

The questionnaire comprised of six components formulated to assess each of the theory's major constructs: perceived usefulness, perceived usefulness, subjective norms, and intention to use AI. Four-point Likert scale were employed, with scores of 1 as strongly agree, and 4 strongly disagree. The demographic component was incorporated to examine the profiles of the respondents which include gender, age, professional group, years of experience and question on which field of medicine that they think AI would be most useful.

The six components were as follows:
Section 1 – Demographic Information (5 items)
Section 2- Attitudes on Artificial Intelligence (6 items) Attitude is one of the independent variables in this study and links to positive or negative thinking of performing the behaviour.
Section 3 – Perceived ease of use (6 items). Perceived ease of use is the second independent variable. It links to the degree to which a person believes that using a particular system would be free from effort (10).
Section 4 – Perceived usefulness (4 items) Perceived usefulness is the degree to which a person believes that using a particular system would enhance his or her job performance (TAM).
Section 5 – Subjective Norm (4 items) In this section, the respondents, are the subjective norm, and the questions are testing on their acceptance of AI in their daily practices. This is the fourth independent variable. It is linked to the level at which an individual would perform due to social pressure.
Section 6 – Intention to use Artificial intelligence (3 items) In the final section, the respondents are required to answer the intention to use AI. Intention to use is the dependent variable. It is linked to the level of one's intention to perform a special behaviour and acceptance.
Permission was attained from the management, and respondents provided their consent in completing the study. In addition, the respondents were informed that participation in this study was voluntary and kept anonymous.

IV. RESULTS

A total of 127 questionnaires were distributed via the institution's email, out of which 96 (75.6%) questionnaires were returned and were sufficient for the analysis. In the case of Malaysia, the response rate for a similar survey (using email) is between 10% and 20% [13, 14].

The demographic profile of the respondents is shown in Table 1. Majority of the respondents were female (64.6%). Respondents' age spanned from 26 to 55 years and above. The highest age-group with 34.4% were the 36 - 45 years. Amongst the top professions, 30.2% were clinicians, 24.0% were nurses professionals, 10.4% were pharmacists. The remaining 7.3% were either physiotherapists or medical laboratory technicians, and the least group were radiographers or physiotherapists with 5.2%. Majority of the respondents were with 10 – 20 years' experience (44.8%).

In respond to the question on whether they would use their judgement or would use AI, 88.5% of the respondents would use their judgment as compared to only 11.5% who would use artificial intelligence to assist them in decision-making. The study showed that those with longer working experience tend to use AI more, and the test was significant ($p < 0.05$). Although the other characteristics were not significant, the data show a predominance of using own judgement were amongst females 57.3%, age 46-55 years old 31.3%, and clinicians 28.1%.

TABLE 1 DEMOGRAPHICS AND CHOICE OF USE OF USE

Demographics	Frequency	Percentage (%)	Own Judgement		Artificial Intelligent		P-value
			N= 85	%	N = 11	%	
Gender							
Male	34	35.4	30	31.3	4	4.2	0.944
Female	62	64.6	55	57.3	7	5.2	
Age							
26-35	27	28.1	22	22.9	5	5.2	0.438
36-45	33	34.4	29	30.2	4	2.1	
46-55	32	33.3	30	31.3	2	2.1	
55 And	4	4.2	4	4.2	0	0.0	

Above							
Profession							
Clinician	29	30.2	27	28.1	2	2.1	0.085
Nurse	23	24.0	20	20.8	3	3.0	
Pharmacy	10	10.4	10	10.4	0	0.0	
Radiographer	5	5.2	3	3.1	2	2.1	
Physiotherapist	5	5.2	3	3.1	2	2.1	
Medical Laboratory Tech	7	7.3	7	7.3	0	0.0	
Administrators	7	7.3	7	7.3	0	0.0	
Others	10	10.4	8	8.3	2	2.1	
Experience							
Less Than 10 Years	15	15.6	12	12.5	3	3.1	0.007 *
10 – 20 Years	43	44.8	37	38.5	6	6.3	
More Than 20 Years	38	39.6	36	37.5	2	2.1	

Note: * $p < 0.05$

In the earlier table only 11.5% responded would use AI. However, on the question of whether respondents agree that the diagnostic ability of AI is superior to the clinical experience of human doctors, the response was much higher with 55.3% agreeing to AI has diagnostic ability. Although the analyses in Table 2 shows that this was not significant it did give some element of respondents' preferences and openness towards AI.

TABLE 2 AGREE THAT DIAGNOSTIC ABILITY OF AI IS SUPERIOR TO CLINICAL EXPERIENCE OF HUMAN DOCTORS, BY PROFESSION

Types of Profession	**Strongly agree**	**Agree**	**Disagree**	**Strongly disagree**	**Total (100%)**	**P value**
Clinician	2 (6.9)	7 (24.1)	15 (51.7)	5 (17.2)	29	
Nurse	3 (13.0)	8 (34.8)	9 (39.1)	3 (13.0)	23	
Pharmacy	0 (0)	4 (40.0)	5 (50.0)	1 (10.0)	10	
Radiographer	0 (0)	1 (20.0)	4 (80.0)	0 (0)	5	
Physiotherapist	0 (0)	2 (40.0)	3 (60.0)	0 (0)	5	0.794
Medicallab tech	0 (0)	4 (57.1)	3 (42.9)	0 (0)	7	
Administrators	0 (0)	3 (42.9)	4 (57.1)	0 (0)	7	
Others	0 (0)	3 (30.0)	7 (70.0)	0 (0)	10	
Total	5 (20.0)	32 (33.3)	50 (52.1)	9 (9.4)	96	

Table 3 looked into four areas on the Ease of Use, Perceived usefulness, Subjective norm and Intention to use, to examine the responses at the granular level on their perception related to AI. For Ease of use, each of the responses were statistically significant with the value $p < 0.05$, except to the question "No. 3 Using Artificial Intelligence was clear and understandable". On Perceived usefulness, there was only one question that was significant, that, "Using AI would help me to bettermanage and keep track of my patient progress" with the significant value of $p < 0.001$. There were 4 questions on Subjective norm. None of the responses were significant. However, it can be observed that the results showed a higher preponderance of respondents agreeing and strongly agreeing to each question. Exploring on their Intention to use, all the test results were not statistically significant. The responses showed a small percentage difference of those agreeing and strongly agreeing then otherwise.

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TABLE 3 AGREEMENT ON AI'S EASE OF USE, PERCEIVED USEFULNESS AND SUBJECTIVE NORM

A. Ease of use	**Agree and Strongly Agree**	**Disagree and strongly disagree**	**P-value**
1. Learning to use Artificial Intelligence was easy for me.	76.1%	23.9%	0.031
2. I found it easy to get Artificial Intelligence.	98.9%	1.1%	0.039
3. Using Artificial Intelligence was clear and understandable.	77.1%	22.9%	0.190
4. I found Artificial Intelligence to be flexible to use.	80.2%	19.8%	0.038
5. It was easy for me to become skilful at using Artificial Intelligence.	70.8%	29.1%	0.033
6. I found Artificial Intelligence to be easy to use.	77.1%	22.9%	0.002
B. Perceived usefulness			
1. Using Artificial Intelligence would help me quickly check what medications should patient take.	89.6%	10.4%	0.604
2. Using Artificial Intelligence would help me to better manage and keep track of my patient progress.	93.8%	6.2%	0.001
3. Using Artificial Intelligence would make it easier to manage and keep track of my patient progress.	98.9%	1.1%	0.501
4. I would find Artificial Intelligence to be useful in managing and keeping track of my patient progress.	97.9%	2.1%	0.147
C. Subjective norm			
1. They would expect me to continuously use Artificial Intelligence.	74.0%	36%	0.121
2. None of them would be surprised if I just stopped using Artificial Intelligence.	55.2%	44.8%	0.155
3. They would probably be disappointed in me if I just decided to stop using Artificial Intelligence.	60.4%	39.6%	0.690
4. They would probably make me feel guilty if I quit using Artificial Intelligence.	52.9%	47.1%	0.407
D. Intention to use by the profession			
1. I intend to use Artificial Intelligence in the next months.	59.4%	40.6%	0.311
2. I predict I would use Artificial Intelligence in the next months.	56.2%	43.7%	0.160
3. I plan to use Artificial Intelligence in the next months.	57.3%	42.7%	0.216

Further analysis on the intention to use and likely to use AI in the next month, by profession is shown in Table 4. Although the results were not statistically significant, it was worth analysing the data closely. There were large numbers of healthcare professionals that favoured agreeing with 'intention to use' in the next month, notably amongst clinicians with 62.1%, nurses 78.2% and pharmacist 60%. Although earlier they have scored higher that they will use their own judgement rather than AI, these subsequent responses illustrate a possible self-reflection of developing interest in AI whilst answering the questionnaire. The other healthcare professionals such as the radiographer, physiotherapist, medical lab technician, administrator,

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and all fair below 40% in agreement to use AI in the near future.

TABLE 4 INTENTION TO USE THE ARTIFICIAL INTELLIGENCE IN THE NEXT MONTHS BY PROFESSION

Profession	**Strongly agree N (%)**	**Agree N (%)**	**Disagree N (%)**	**Strongly Disagree N (%)**	**Total N**	**Significant level**
Clinician	0 (0.0)	18 (62.1)	11 (37.9)	0 (0.0)	29	
Nurse	3 (13.0)	15 (65.2)	5 (21.7)	0 (0.0)	23	
Pharmacy	2 (20.0)	4 (40.0)	4 (40.0)	0 (0.0)	10	
Radiographer	0 (0.0)	2 (40.0)	3 (60.0)	0 (0.0)	5	
Physiotherapist	0 (0.0)	2 (40.0)	3 (60.0)	0 (0.0)	5	0.216
Medical lab tech	0 (0.0)	3 (42.9)	4 (57.1)	0 (0.0)	7	
Administrators	0 (0.0)	2 (28.6)	5 (71.4)	0 (0.0)	7	
Others	1 (10.0)	3 (30.0)	5 (50.0)	1 (10.0)	10	
Total	6 (6.3)	49 (51.0)	40 (41.7)	1 (1.0)	96	

A. Goodness-of-fit test for outer model

Before testing the hypotheses, the goodness-of-fit was first assessed by using SmartPLS 3.2.7. on the outer and inner model [15]. The goodness-of-fit test for the outer model involved three measures: convergent validity, discriminant validity, and reliability. The convergent validity of the outer model was tested by examining Factor Loading and AVE (Average Variance Extracted). The result as in Tables 5 shows that the factor loading for all indicators was more than 0.7, and therefore, all the indicators were considered valid in terms of convergent validity. AVE of all latent variables was more than 0.5, which then it can be stated that all latent variables are valid in terms of convergent validity. Thus, the outer model can fulfil convergent validity based on criteria of factor loading and AVE.

B. Discriminant validity

To address discriminant validity, the square root of the AVE was compared against the correlations of the other constructs [16]. As shown in Table 6, the calculated square root of the AVE exceeded the inter-correlations of the construct with the other constructs in the model, which ensured adequate discriminant validity. Thus, in total, the measurement model of the study demonstrated adequate convergent and discriminant validity.

TABLE 5 GOODNESS-OF-FIT TEST

Construct	CR	AVE
Attitudes on artificial intelligence	0.791	0.858
Ease of use	0.789	0.841
Usefulness	0.916	0.864
Subjective norm	0.756	0.834
Intention to use an Artificial Intelligence	0.974	0.848

TABLE 6 DISCRIMINANT VALIDITY

	Attitudes	Ease	Usefulness	Subjective	Intention
Attitudes	**0.781**				
Ease	0.085	**0.861**			
Usefulness	0.414	0.132	**0.812**		
Subjective	0.053	0.301	0.053	**0.934**	
Intention	-0.111	-0.047	-0.086	-0.090	**0.937**

C. Reliability test for outer model

The outer model reliability was tested by examining the composite reliability (CR) of each latent variable. The result of the analysis on outer model reliability was indicated in Table 5. This table demonstrated that the composite reliability rate of all latent variables is higher than 0.7, from which all latent variables were then considered reliable. According to all results of analysis on goodness-of-fit for the outer model in convergent validity, discriminant validity, and reliability thus, an inference can be made that all criteria of validity and reliability have been fulfilled. Thereby, the outer model was perceived as fit.

D. Goodness-of-fit test for inner model

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Goodness-of-fit test for inner model involves an evaluation on R^2 conducted using SmartPLS, and the result is shown in Table 11. The variance R^2 of intention to use artificial intelligence was 0.548, denoting that the three constructs, namely, ease of use, usefulness, and subjective norm, can explain the intention to use artificial intelligence with a variance of 54.8%. In comparison, the remaining 45.2% was explained by other variables beyond the model. The condition for R^2 has been fulfilled, and therefore, the inner model is declared to be fit and can also be used for hypothesis testing.

E. Hypothesis test

The hypotheses were tested by processing values obtained from bootstrapping formulation with SmartPLS 3.2.7. The hypotheses test on direct effect as shown Table 7 indicated that the construct for usefulness and subjective norm were directly and significantly affect attitudes on artificial intelligence acceptance. But on this however was not supported for ease of use, and hence not supported. This hypothesis testing analysis is in line with Baron and Kenny [17], which states that the tests on mediation or moderation effects were possible only if the direct effect was significant. The direct effect in this study was found to be significant. Therefore, the hypothesis test on mediation effect of attitude in ease of use, usefulness, and subjective norm on acceptance of artificial intelligence was conducted. In the indirect effect, the hypotheses were tested similarly, where the values from bootstrapping formulation were processed using SmartPLS 3.2.7. The summary of the hypotheses model is shown in Table 7.

TABLE 7HYPOTHESIS TESTING

Hypotheses	Path	Beta	Standard Error	t value	Decision
Direct Effect Test					
H1	Ease → Attitude	0.1	0.03	3.334	Not Supported
H2	Usefulness → Attitude	0.45	0.041	11.040*	Supported
H3	Norm → Attitude	0.42	0.042	9.965*	Supported
Indirect Effect Test					
H1	Ease → Attitude → Intention	0.06	0.07	1.001	Not Supported
H2	Usefulness → Attitude → Intention	0.33	0.054	5.896*	Supported
H3	Norm → Attitude → Intention	0.34	0.049	7.024*	Supported

Significant at 5% level.

V. DISCUSSIONS

IBM, Watson Health predicted that the widespread proliferation of data over the last few years has driven the creation of numerous artificial intelligence (AI) tools. They are being employed by businesses optimising on data usage, gaining useful insights to help solve challenges and make informed decisions. With the large quantities of medical data and the abundance of information that health institutions gather and retain, healthcare will benefit greatly from AI and machine learning. AI has reached almost all areas of health care and will continue to do so more and the coming years [18, 19]. Hence healthcare providers adopting AI can make informed decisions with a deeper level of understanding or pursue fresh concepts and offer better quality of service delivery.

In this study, eight different types of professions, which make up the healthcare professionals' major components, were surveyed. In their response to whether they agree that AI has useful applications in the medical field, almost 88.6% agree and strongly agree, as described in Table 1. In addition, the study also showed that those with shorter years of experience responded as agreeing that the diagnostic ability of AI is superior to the clinical experience of human doctors. These positive responses are reflective of a responsive workforce which is a good start for the institution to invest in AI. The younger generation would be an asset for continuity and hence for long-term investment. However adequate training and capacity building would be required to improve competence with in-depth knowledge in computer science to provide and strengthen personalised medicine. Some professions may have a quicker update than another which are often dependent on the type of AI tools that is made available in the institution. In addition, further awareness programs can be implemented to adopt AI in decision making by clinicians. With the

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appropriate AI systems, misdiagnosis and delay in treatment can be reduced and prevented.

In this study the radiographers do score low for intention to adopt AI. Naseem, Akhund [20]stated that AI could, in many ways, make medical therapies more successful for a rapidly spreading pandemic like COVID-19. It will help to improve the speed and accuracy of case recognition.For example, in radiology, the average processing time taken by a radiologist for a qualified deep learning algorithm to identify COVID-19 on the CT chest was 4.51 seconds, compared to an average of 10 minutes 9 seconds. Identifying the gaps in this study could help with targeted planning for improvements especially in developing trust and expertise.

This study showed a high percentage of more than 70% overall response that the healthcare professionals agree on the Ease of use of AI (Table 3). These personnel may have either heard or have seen AI at work and how easy it was to use and believed that they can be skilful using it. The hypothesis Perceived Ease of use however was not supported by the model. Respondent may see the bigger picture that in the context of AI to influence the organisation, the technology must exist, operate, and demonstrate potential benefits beyond the ease of use. Floruss and Vahlpahl [6], in their paper, highlighted that users' attitude towards new technology is vital to their acceptance and, ultimately, their progress in making the solution a worthwhile investment. Mahadevaiah, Rv [21], in their study, concluded that instead of pushing a particular software onto the end-users, the software implementation should be formulated as part of a larger, coherent, and department-wide quality improvement plan for it to be successful.

Perceived usefulness is the second independent variable. The findings from this study were significant for a positive relationship between healthcare professionals’ perception of usefulness to use. This study also showed that more than 89% of the respondents recorded perceived usefulness in tracking and follow-up of medications to patients and maintenance and record-keeping of their patients, as shown in Table 3. The respondents agree that AI diagnosis of illness using algorithms for deep learning holds a promising outlook. This will be significant supportive evidence that the project in this hospital adopting AI in the radiology department can head for a good start. Radiology reports for diagnosis and record keeping are very vital for clinicians to build differential diagnoses. In their exploratory meta-analysis, Liu et al. (2019) reviewed that the accuracy of deep learning algorithms is equal to that of health care practitioners, noting that it is important to consider the inclusion of such algorithms in their practices in further studies. Perceived usefulness is then an important variable to ensure the adoption of AI as a part of their clinical decision-making component.

In the present study the subjective norm refers to the respondent's perception of those significant to them such as the heads of department and colleagues. The findings from this study were significant for a positive relationship between the respondent's perception and their intention to use AI. Further analysis of each question on the subjective norm in Table 3 also showed that between 52.9% to 74% of the responses agree and strongly agree to each question. However, each result was not statistically significant, but the analyses gave some indication that the healthcare professionals may be influenced to adopt AI in their clinical management, and this technology has been or will be present in their daily lives.

Amongst the healthcare professionals agreeing with 'intention to use' were popular choice with the clinicians with 62.1%, nurses 78.2% and pharmacists 60%. The analyses also showed that the types of profession that agree and strongly agree that AI has useful application were in the medical field. It was noticeable that the nurses had the lowest percentage of agreeing. This could be due to the lower respondent's sample in the survey amongst nurses or a true reflection of their perceptions. Hence priority could be given by this hospital in creating awareness programs to improve knowledge attitude and acceptance for efficient implementation.

VI. CONCLUSION

This study has shown the significant relationship and the importance of ease of use, perceived usefulness, and subjective norm to accepting AI. This study therefore accepts the Hypothesis H2 and suggested that perceived usefulness in using AI in improving his or her daily activities and for clinical practice. Correspondingly Hypothesis H3 was also accepted, and the study suggested that subjective norm improves if personnel perceive that most of the colleagues around him or her including friends, co-workers, superior officers in the organization accepts AI. Thus, social pressure by the referent group or individuals may influence acceptance and adoption. The study however did not accept Hypothesis H1 which is ease of use.

The result of this study could be used as a good baseline and a good start to invest in AI in the hospital. The findings may be used to be interpreted but with caution by other similar organisations to understand and hence design the appropriate plans for infrastructure and human resource development with appropriate incentives that could better influence adoption of AI.

There are several limitations of this study. Firstly, there was a constraint on the use of electronic media in distributing the online survey questionnaire. As a result, only individuals with internet access and a fair degree of experience with computers or smartphones were eligible to participate. This suggests that without a personal affinity for technology, and not a face-to-face interview may have led to a perceived bias in the responses. In addition, not all staff uses emails frequently, hence not all could not be reached using emails. Secondly on the limitation of the data set with small numbers of each different profession to make conclusive comparison across the profession. A bigger sample size would have given a more varied and deeper analysis and findings. Equally, future studies could include other behavioural factors such as descriptive norm and ease of use to expand the explanatory power of the AI adoption behaviour.

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