Heliyon 10 (2024) e28962

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

ChatGPT-3.5 System Usability Scale early assessment among Healthcare Workers: Horizons of adoption in medical practice

Fadi Aljamaan [a,b], Khalid H. Malki [c], Khalid Alhasan [a,d,e], Amr Jamal [a,f,g], Ibraheem Altamimi [a], Afnan Khayat [h], Ali Alhaboob [a,d], Naif Abdulmajeed [d,i], Fatimah S. Alshahrani [a,j], Khaled Saad [k], Ayman Al-Eyadhy [a,d], Jaffar A. Al-Tawfiq [l,m,n], Mohamad-Hani Temsah [a,d,g,*]

[a] College of Medicine, King Saud University, Riyadh 11362, Saudi Arabia
[b] Critical Care Department, College of Medicine, King Saud University, Riyadh 11362, Saudi Arabia
[c] Research Chair of Voice, Swallowing, and Communication Disorders, Department of Otolaryngology, College of Medicine, King Saud University, Riyadh 11362, Saudi Arabia
[d] Pediatric Department, College of Medicine, King Saud University Medical City, Riyadh 11362, Saudi Arabia
[e] Department of Kidney and Pancreas Transplant, Organ Transplant Center of Excellence, King Faisal Specialist Hospital and Research Center, Riyadh 11211, Saudi Arabia
[f] Department of Family and Community Medicine, King Saud University Medical City, Riyadh 11362, Saudi Arabia
[g] Evidence-Based Health Care & Knowledge Translation Research Chair, Family & Community Medicine Department, College of Medicine, King Saud University, Riyadh 11362, Saudi Arabia
[h] Health Information Management Department, Prince Sultan Military College of Health Sciences, Al Dhahran 34313, Saudi Arabia
[i] Pediatric Nephrology Department, Prince Sultan Military Medical City, Riyadh 11159, Saudi Arabia
[j] Infectious Disease Division, Department of Medicine, King Saud University Medical City, Riyadh 11362, Saudi Arabia
[k] Pediatric Department, Faculty of Medicine, Assiut University, Assiut 71516, Egypt
[l] Specialty Internal Medicine and Quality Department, Johns Hopkins Aramco Healthcare, Dhahran 34465, Saudi Arabia
[m] Infectious Disease Division, Department of Medicine, Indiana University School of Medicine, Indianapolis, IN46202, USA
[n] Infectious Disease Division, Department of Medicine, Johns Hopkins University School of Medicine, Baltimore, MD21218, USA

ARTICLE INFO

Keywords:
Artificial Intelligence
ChatGPT
Healthcare workers usability
System Usability Scale
Saudi Arabia
Digital health
AI in healthcare
Chatbots in medical practice
Healthcare technology

ABSTRACT

Artificial intelligence (AI) chatbots, such as ChatGPT, have widely invaded all domains of human life. They have the potential to transform healthcare future. However, their effective implementation hinges on healthcare workers' (HCWs) adoption and perceptions. This study aimed to evaluate HCWs usability of ChatGPT three months post-launch in Saudi Arabia using the System Usability Scale (SUS).

A total of 194 HCWs participated in the survey. Forty-seven percent were satisfied with their usage, 57 % expressed moderate to high trust in its ability to generate medical decisions. 58 % expected ChatGPT would improve patients' outcomes, even though 84 % were optimistic of its potential to improve the future of healthcare practice. They expressed possible concerns like recommending harmful medical decisions and medicolegal implications.

The overall mean SUS score was 64.52, equivalent to 50 % percentile rank, indicating high marginal acceptability of the system. The strongest positive predictors of high SUS scores were participants' belief in AI chatbot's benefits in medical research, self-rated familiarity with ChatGPT and self-rated computer skills proficiency. Participants' learnability and ease of use

* Corresponding author. College of Medicine, King Saud University, Riyadh, 11362, Saudi Arabia.
E-mail address: mtemsah@ksu.edu.sa (M.-H. Temsah).

https://doi.org/10.1016/j.heliyon.2024.e28962
Received 28 July 2023; Received in revised form 26 February 2024; Accepted 27 March 2024
Available online 7 April 2024

score correlated positively but weakly. On the other hand, medical students and interns had significantly high learnability scores compared to others, while ease of use scores correlated very strongly with participants' perception of positive impact of ChatGPT on the future of healthcare practice.

Our findings highlight the HCWs' perceived marginal acceptance of ChatGPT at the current stage and their optimism of its potential in supporting them in future practice, especially in the research domain, in addition to humble ambition of its potential to improve patients' outcomes particularly in regard of medical decisions. On the other end, it underscores the need for ongoing efforts to build trust and address ethical and legal concerns of AI implications in healthcare. The study contributes to the growing body of literature on AI chatbots in healthcare, especially addressing its future improvement strategies and provides insights for policymakers and healthcare providers about the potential benefits and challenges of implementing them in their practice.

1. Introductions

The COVID-19 pandemic has highlighted the importance of integrating digital technologies in medical practice, including virtual platforms, video-assisted technology, and the integration of Artificial Intelligence (AI), into healthcare systems. The efficient use of these technologies has proven to be crucial in managing healthcare crises from different domains [1]. AI proved to be useful in mitigating the healthcare burden from the early stages of the COVID-19 pandemic to the post-COVID-19 era [2–4]. AI-supported medical systems are showing promising performance, but their practical contribution to the healthcare system needs to be supported by healthcare practitioners' adoption and acceptance of AI technology integration. This includes assessing different available AI driven chatbots system's performance, ensuring having acceptable user perceived usability, safety of their application in medical practice, and to evaluate the technical and human factors affecting their acceptance [5].

Chatbots, as a form of AI, are computer software that interact with human users using natural language. They store information in databases such as Large Language Models (LLM); by identifying keywords from user fed input they can recommend decisions for prompted queries, almost provide answers for any question [6]. AI chatbots, such as ChatGPT, have the potential to revolutionize the way healthcare is delivered [7–9]. AI Chatbots can enhance patient management, reduce healthcare costs, and improve healthcare outcomes [10–12]. In addition, they may support healthcare workers (HCWs) by reducing workload and enabling them to focus on more complex tasks [13]. AI chatbots are new technology being introduced widely in different fields including medical practice, the interactive setting they provide is so fascinating and attractive for usage. However, their implementation in medical practice is not without challenges, of these challenges, ensuring that HCWs adopt them and perceive them friendly for usage, especially with the recent growing literature identifying risks of AI chatbots misinterpreting and even data fabrication or sometimes providing racist or nonsensical answers. Therefore, the failure of HCWs to have positive attitude toward AI chatbot will be a major obstacle for their implementation in healthcare practice. These challenges largely originate from immaturity of these chatbots or failure of them to comprehend and meet the user intentions from one side and users' poor knowledge and training of output data interpretation and the optimal prompt writing technology which is the language used between AI chatbots and users. Therefore, assessing medical personnel perceptions of AI chatbots usability is of utmost importance for their future adoption and guarantee of the best gain from their implementation, paralleling working on improving and tailoring AI chatbots for HCWs needs.

Literature grew rapidly regarding different applications of AI in healthcare practice, addressing different domains like research, medical education, clinical decisions, drug-drug interaction and many others [12,14,15]. Technology adoption and acceptance is governed by multiple factors, including its ease of use, perceived usefulness, presence of facilitating infrastructure and social influence by end users. Literature has shown that incorporating new technology in healthcare practice is majorly facilitated by the above-mentioned factors, to facilitate healthcare workers best achievement, acceptance and adoption of the new platforms [16,17]. Perceived usefulness and ease of use are correlated according to multiple theories addressing technology adoption [18]. System usability (SUS) score has been advocated by its founder Brooke even after decade of its invention to be a valuable tool of assessing modern technology innovations. For proper application and best achievement of AI applications in healthcare practice, users need to be assessed regarding their expectations, acceptance and perceptions in that regard. Few studies assessed AI chatbots usage by HCWs, even the assessment was superficial, subjective and not based on standardized objective scales of assessing users' usability and learnability of these new technologies. For example a German study assessed university physicians perceived requirement and application of AI in medical practice was able to show merely strong association between personal rating of AI in medicine and the self-reported technical affinity level, without more objective assessment [19,20]. A recent study from a Caribbean medical school, assessed faculty usage of ChatGPT for educational and research tasks, came with conclusion of overall positive vision for ChatGPT usage based on Likert scale-built questions, but did not assess its usability based on standard objective criteria [21]. While other studies assessed for example ChatGPT in terms of accuracy and adequacy of its output ignoring the end user feedback about its usability and practicality and perceived usefulness [22].

The System Usability Scale (SUS) is a survey tool designed to assess different innovative technologies or products. It is a widely used tool that assesses the usability of digital systems by measuring the user's satisfaction and the efficiency of the system [23]. Its unique for being simple, quick, flexible for application to different settings and easy to interpret by different stakeholders [24]. It has been widely used in medical practice to assess new services or technologies, implementation of natural language processing technology in

patient-physician interactive applications, and virtual reality integration in medical practice [25–28]. Therefore, we found an urgent necessity to address the applicability and usability of ChatGPT among HCWs in Saudi Arabia three months after its launch. As healthcare is a critical sector that demands high-quality and efficient delivery of services, and Saudi Arabia is ranked among the top three countries in AI technology adaptations [29]. Thus, evaluating the usability of ChatGPT among HCWs can help in the adoption and integration of AI chatbots in healthcare. SUS is a potential tool to assess the usability of ChatGPT among HCWs, addressing its ease of use, learnability, efficiency, and user satisfaction. The findings of this study can contribute to the growing body of literature on AI chatbots in healthcare and inform policymakers and healthcare providers about the potential benefits and challenges of implementing such systems.

2. Methods

This is cross-sectional survey study, utilized the SUS, which is a validated, ten-item scale, that provides a global perspective of technology ease of use and learnability. The SUS tool is universally acceptable tool of assessing digital health applications, for both healthcare providers and end users [30–32]. The survey was conducted over a two-week period (21 Feb – 6 March 2023), and the tool was publicly available for use with the requirement of acknowledging the source of the measure [33]. To ensure a comparable sample size according to previous studies that utilized SUS in medical literature, a minimum sample size of 100 HCWs was targeted [34–36].

The inclusion criteria were HCWs who used ChatGPT for medical purposes and were willing to participate in the survey. The survey tool consisted of two parts (Appendix 1). The first part was constructed by the authors according to experts' opinions addressing participating HCWs usage and familiarity with ChatGPT using a Likert scale, in addition to addressing their sociodemographic characteristics including computer literacy. Second part assessed HCWs who admitted previous usage of ChatGPT for medical purposes regarding satisfaction with ChatGPT and instructed to answer the ten questions that comprise the SUS score. Informed consent was obtained from all participants, and personal identifiers were not collected to ensure confidentiality. The survey was distributed electronically through the SurveyMonkey platform, similar to previous studies that utilized this platform for rapidly deployed electronic surveys among HCWs [37,38]. Convenience sampling was used to reach HCWs through social media groups, such as WhatsApp and Twitter.

The study was approved by the Institutional Review Board (IRB) of the King Saud University (Approval # 23/0155/IRB).

2.1. Statistical analysis

The mean and standard deviation were used to describe continuous variables and the frequency and percentages were used to describe categorically measured variables. The Kolmogrove-Smirnove statistical test of normality and the histogram were used to assess the statistical normality assumption of metric variables. Cronbach's alpha test was used to assess the internal consistency of measured scales. The multiple response dichotomies analysis was applied to describe the questions measured with more than one option. The SUS was calculated as described with the original score and interpreted according to literature [24,39]. The overall score was further dissected into 2 domains ease of use and the system learnability [40]. The SUS score was computed according to its authors' scoring method via rescaling the items into 0–4 points scale then transforming its total score into a 0–100 points scale. The

Table 1
HCWs' sociodemographic and professional characteristics. N = 194.

	Frequency	Percentage
Sex		
Female	56	28.9
Male	138	71.1
Age group		
18–24 years	62	32
25–34 years	62	32
35–44 years	34	17.5
45–54 years	24	12.4
55–64 years	12	6.2
Clinical Role		
Physician	99	51
Medical Interns and students	67	34.5
Nurse	18	9.3
Technicians, therapists, and pharmacists	10	5.2
Healthcare experience		
<5 years	98	50.5
5–10 years	33	17
10–20 years	35	18
>20 years	28	14.4
Participants' perceived computer skill expertise		
Not so familiar	5	2.6
Somewhat familiar	62	32
Very familiar	127	65.5

multivariable linear regression analysis was applied to the HCW's perceptions of ChatGPT (Total SUS score, learnability, and ease of use sub-scores). The associations between predictor variables with their dependent outcome variables in the linear regression analysis were expressed as multivariate adjusted beta coefficients with their associated 95 % confidence intervals. The SPSS IBM statistical computing software version 21 was used for the statistical data analysis and the alpha significance level was considered at 0.050 level.

Cronbach's alpha test of internal consistency showed that the SUS was read and understood by respondents equally reliably with substantial internal consistency, Cronbach's alpha = 0.76.

A SUS score of 68 and above is considered an acceptable score for usability of the evaluated technology, according to healthcare practice evidence of multiple digital healthcare applications and corresponds to SUS literature [30,32].

3. Results

1057 HCWs participated in the survey. 194 HCWs admitted previous utilization of ChatGPT for medical purposes and were included in the study. The majority were males (71.1 %). Almost two thirds were 34 years old or younger. Half were physicians, while 34.5 % were medical students or Interns, the rest were distributed between nurses and other allied healthcare professionals. 50.5 % of the participants had less than 5 years of medical experience, while the rest almost split equally between those who had experience between 5 and 10, 10–20 and more than 20 years. Two-thirds of the surveyed participants expressed high familiarity with computer skills, while the other third was somewhat familiar and only a minority were not familiar at all (Table 1).

Participants were assessed regarding their satisfaction of ChatGPT usage in medical practice, they split almost equally between satisfied and neutral, while a minority (6.7 %) were dissatisfied (Fig. 1). 58 % agreed that ChatGPT would have a positive impact on patients' outcome, 34 % were undetermined and 9 % disagreed (Fig. 2). The majority (84 %) expected it would improve healthcare practice in the future (Fig. 3).

Table 2 presents the participants' SUS score data. The overall mean SUS score was (64.52/100, SD 13.91). That score is interpreted according to Usability.gov website and previous literature as high marginal acceptability of the ChatGPT system (Fig. 2 Appendix) [24,41–43]. The overall score was further dissected into 2 domains, ease of use (Questions 2,4,6,8,10) with mean score 34.1/50, SD 8.77 [44]. Questions 1,3,5,7 and 9 assessed the system learnability with a mean score of 30.43/50, SD 8.83.

Table 4 highlights the participants' characteristics that correlated with the learnability mean score. Familiarity with ChatGPT positively and significantly correlated with participants' learnability score (β coefficient 2.095, $p < 0.001$). Physicians, medical interns, and medical students had significantly higher learnability score (β coefficient 4.052, p.021. 4.144, p.026), respectively. As expected, participants' high ease of use mean score correlated positively and significantly but weakly with their learnability score (β coefficient 0.164, p.021).

Table 5 highlights participants' characteristics correlation with ease-of-use score. The belief that ChatGPT would improve healthcare future was the strongest (β coefficient 4.349, p 010). Self-rated computer skills rated the second (β coefficient 2.859, p.014). Learnability score had a significant positive but weak correlation with their ease-of-use score.

4. Discussion

AI chatbots have recently gained popularity in healthcare practice due to their potential of patient care improvement, enhancement of medical care delivery, and optimization of healthcare systems efficiency. However, AI chatbots potential in medical practice depends on adoption by HCWs, which is governed by their perception of AI chatbots perceived usefulness, ease of use and learnability [28]. Previous studies of HCWs satisfaction with AI chatbots have yielded mixed results [45,46]. In our study, we evaluated HCWs' ChatGPT system usability in Saudi Arabia three months after its launch using the SUS score. Furthermore, we assessed their perception of its adoption in clinical and research settings, that are vital domains of medical practice, and dictate AI chatbots future in healthcare setting [45].

According to our survey, a minority of participants utilized ChatGPT in medical practice 18.3 %. The poll done one month later by

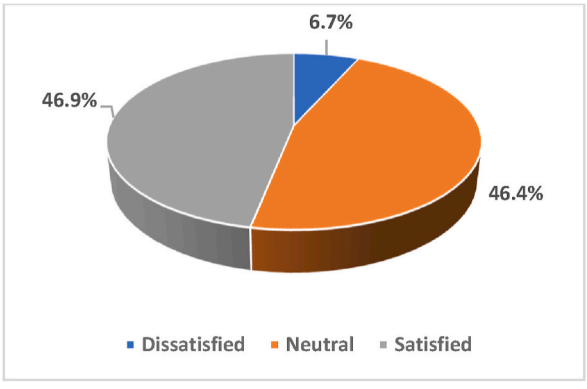

Fig. 1. Participants' satisfaction with ChatGPT's usage in medical practice.

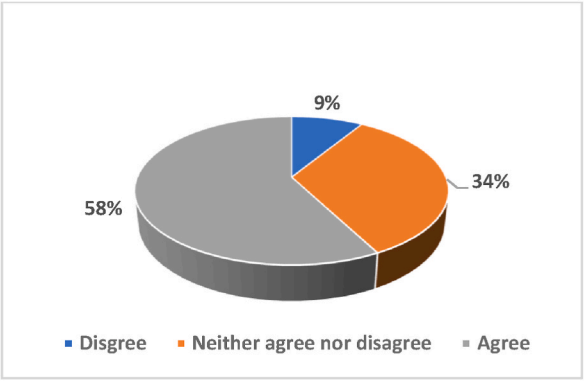

Fig. 2. Participants' perception of ChatGPT impact on patients' outcome improvement.

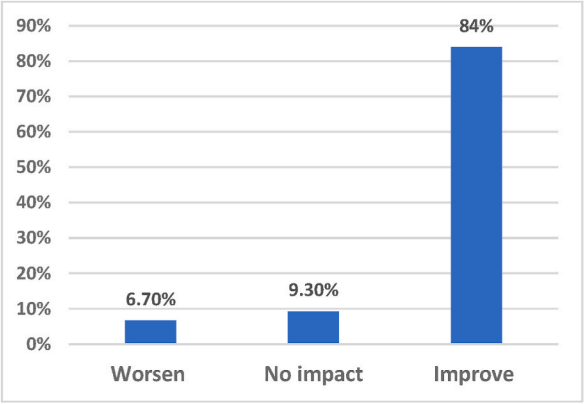

Fig. 3. Participants' expectation of ChatGPT impact on healthcare practice future.

Table 2
Descriptive analysis of the HCW's perceived ChatGPT System Usability Scale and its subscales: learnability and ease of use.

	Mean	SD	Maximum possible score
Overall system usability	64.52	13.91	100 points
Ease of Use	34.1	8.77	50 points
Learnability	30.43	8.83	50 points

HCWs' mean SUS score correlation with their characteristics is shown in Table 3. The strongest positive association was with their belief of AI Chatbots benefit in medical research (beta coefficient = 7.301, p-value = 0.001). Their Self-rated familiarity with ChatGPT scored secondly (beta coefficient = 6.076, p-value<0.001). HCWs' self-rated computer skills proficiency scored third (beta coefficient = 5.441, p-value = 0.002). All the other HCWs' characteristics did not correlate with any significance with the SUS scores.

Table 3
Multivariate Linear Regression Analysis of HCWs ChatGPT SUS score. N = 194.

	Unstandardized Beta Coefficients	Beta coefficient 95.0 % C.I.		p-value
		Lower Bound	Upper Bound	
Sex	0.548	−3.390	4.486	0.784
Age group	−1.043	−2.506	0.420	0.161
Self-rated computer skills	5.441	2.008	8.875	0.002
Familiarity with the ChatGPT	6.076	2.955	9.198	<0.001
ChatGPT utilization in medical research	7.301	2.986	11.617	0.001
(Constant)	43.148	35.039	51.258	<0.001

DV= Health workers SUS* score.
Model R-squared = 0.241, adjusted r-squared = 0.221. Model overall significance = f (5,188) = 11.96, p-value<0.001.
* System usability scale.

Table 4
Multivariate Linear Regression Analysis of HCWs variables associated with learnability sub-score*. N = 194.

	Unstandardized Beta Coefficients	Beta coefficient 95.0 % C.I.		p-value
		Lower Bound	Upper Bound	
(Constant)	15.691	8.600	22.781	<0.001
Sex	−1.141	−3.717	1.435	0.383
Clinical role Physicians	4.052	0.631	7.473	0.021
Clinical role Medical interns and students	4.144	0.505	7.782	0.026
Self-rated computer skills	2.078	−0.165	4.322	0.069
Ease of use score	0.164	0.025	0.302	0.021
Familiarity with ChatGPT	4.105	2.095	6.114	<0.001

DV= Healthcare workers learnability score.
Model R-squared = 0.22, adjusted r-squared = 0.191. Model overall significance = f (7,186) = 7.52, p-value<0.001.
* System usability scale.

Table 5
Multivariate Linear Regression Analysis of HCWs perceived ease of use sub-score*. N = 194.

	Unstandardized Beta Coefficients	Beta coefficient 95.0 % CI		p-value
		Lower Bound	Upper Bound	
(Constant)	19.679	12.183	27.175	<0.001
Sex	1.451	−1.173	4.075	0.277
Years of experience	−0.726	−1.779	0.327	0.175
Self-rated computer skills	2.859	0.596	5.121	0.014
ChatGPT would improve healthcare future	4.349	1.068	7.630	0.010
ChatGPT learnability score	0.186	0.047	0.325	0.009

DV= Health workers' ease of use score.
Model R-squared = 0.145, adjusted r-squared = 0.117. Model overall significance = f (6,187) = 5.30, p-value<0.001.
* System usability scale.

InterMD Company, a knowledge- and information-sharing community platform, showed that 88.5 % of physicians were aware of ChatGPT, but only 38.4 % used it. This highlights growing but reluctant HCWs' adoption of AI chatbots in healthcare practice at the time of our study. Our results correspond to previous work of our Saudi colleagues in a study conducted 2021 where 82 % of HCWs admitted lack of AI use in their medical practice and 71 % expressed lack of formal training for using it [47]. This reluctance or abstinence of HCWs from using AI chatbots in medical practice has been and still an ongoing phenomenon due to multiple barriers, a study that addressed these barriers in 2022 has shown about 92 % of HCWs had low to moderate objective and subjective knowledge of medical AI that was associated with mixed negative attitudes toward medical AI [48]. Even though only 18.3 % of our participants utilized ChatGPT in medical practice according to our study, the vast majority (94 %) admitted being familiar with it, suggesting high level of digital literacy which is a facilitating factor for their future adoption of digital healthcare technologies [49]. These findings align with the growing local and governmental trend of digital technology adoption in the healthcare sector [50].

Interestingly, 58 % of our participants agreed that ChatGPT would have a positive impact on patients' outcomes in the future, while most of them (84 %) expected it would improve healthcare practice in the future. Our findings parallel Wang et al. that expatiated in the HCWs attitudes and knowledge of medical AI, where they found that the majority had moderate knowledge of it, but low negative attitudes and high positive behavioral intentions towards it, while they identified other two profile of users having high or low knowledge base of medical AI and but moderate to high level of negative attitudes towards it. Therefore, we can perceive heterogeneity of HCWs position from medical AI, although there is still some uncertainty about ChatGPT impact on the patients outcomes but still the majority are optimistic of its positive contribution especially those who experienced it and master good knowledge of it [48,51]. AI, including ChatGPT, has the potential to become a valuable tool in healthcare practice, as healthcare providers adapt new technologies into their practice, contributing to patient care, medical research, appraisal of medical literature, and patient-centered AI based healthcare system [49,52].

As we dissected in depth through our participants' perceptions of ChatGPT contribution to medical practice, 57 % expressed high or moderate trust degree of it generating medical decisions, which contrasts findings among Korean physicians, where only 13.5 % perceived low medical evidence and reliability of ChatGPT generating medical answers [50]. This emphasizes the need for further efforts to build trust in AI systems among HCWs. Similarly, this was observed for radiologist and IT specialists who showed high expectations of AI in the future but low confidence, even they had heterogenous attitudes about incorporating AI in medical education, informing patients about AI use in medical practices [53]. Therefore, the future challenge lies in determining the appropriate role of AI in medical practice, perhaps to serve as a supplementary tool, rather than replacing human mind [54–58].

Among our participants perceived obstacles of AI utilization in medical practice, was their concerns of recommending harmful or wrong medical decisions and concerns of medicolegal implications from using it in medical practice, echoing what was reported in

other surveys [50]. This aligns with the broader discussions in the literature about the ethical and legal implications of AI in healthcare [59]. Despite these concerns, half of our participants were satisfied with their experience with ChatGPT in medical practice. This is similar with findings from an earlier study conducted in April 2023, which surveyed 1008 physicians on their experiences with ChatGPT, revealing a 71.8 % satisfaction rate with the chatbot's responses [50]. The favorable feedback highlighted multiple benefits: a reduction in workload through the automation of repetitive tasks such as document completion (28.8 %), a decrease in decision-making time by analyzing a variety of clinical data (22.5 %), and an enhancement in the efficiency of the management process (10.5 %).

According to our study, participating HCWs' overall ChatGPT mean SUS score indicated high marginal acceptability of the new AI system with score of 68, equivalent to 50 % acceptability. That score according to the rich SUS literature data does not reach level of recommending the newly assessed technology (ChatGPT) in our case, but corresponds to neutral perception of the assessed HCWs as per literature [30,42,60–62]. Thus, our results indicate that ChatGPT needs further improvements to boost its usability, acceptability, and perception of usefulness among HCWs, in order to optimize its adoption by HCWs in the future and achieve the best outcomes from its adoption and implementation in healthcare practice. Our surveyed participants' score is comparable to previous AI Chatbot (myHardware)'s SUS score, indicating marginal acceptability and sufficient usability [63]. Digging deep into the participants' perception of ChatGPT technology, showed high individual scores for ChatGPT learnability, which correlated positively with ease-of-use score. That suggest that HCWs who perceived it easy to muse also felt it learnable, which is promising for the future applicability of health practice digitalization and predicts high levels of adoptability of AI technologies like ChatGPT [64,65].

Interestingly, the SUS score did not correlate with participants' age or professional role, pointing to generally decent acceptability from diverse categories of medical personnel including medical students who comprised one third of our sample. Medical students and interns actually had significantly high learnability scores compared to the rest of participants, such finding is expected as this generation is much more familiar and accepting digital intervention than older one and are expected to be the next generation utilizing AI in medical practice very widely. Our findings in that regard are in line with Vlachogianni et al. systematic review that evaluated digital technology application in medical education using SUS scale and concluded SUS scores ranging from 66 to 76 indicating good level of usability [62].

Participants' belief in AI chatbots benefits in medical research strongly correlated with high ChatGPT SUS scores, this suggests that HCWs perception of certain dimensional benefits of AI, specifically in research rather than direct clinical care is a potential area of improving its utilization, this mirrors findings from Ruksakulpiwat et al. systematic review that identified ChatGPT as a potential revolution in medical research in various ways, but were skeptical to ethical and accuracy considerations [66]. As expected, self-rated familiarity with ChatGPT and self-rated computer skills proficiency also correlated with high SUS scores, that echoes the rich literature that stressed the need for incorporating digital and e-health curricula in medical schools, even planning training courses for healthcare professionals implementing AI in their practice.

On the specific dimension of ease of usability, HCWs' expectation of its potential to improve patient outcomes correlated positively and strongly with ease of use score, indicating perception of HCWs that easy to use digital intervention are promising addition to medical system, easy to integrate and practice tool in healthcare practice, being driven by optimism of medical AI potential benefits in supporting healthcare personnel, patients and families, and probably providing medical decisions. In healthcare settings, embracing generative AI and LLMs requires ongoing balance between data-driven insights and human judgment [11]. Clinicians and researchers should seek opportunities for AI to enhance efficiency but also be aware of the challenges involved [67]. Effective adoption of novel technologies depends on collaborative partnerships and communication among stakeholders [68].

From an academic point of view, this research adds a great deal to the body of knowledge regarding HCWs using ChatGPT for medical purposes. It looks at how HCWs view and use ChatGPT in a medical setting, providing insight into the sociodemographic and professional traits of early adopters who have used the technology [52,56]. Valuable information is revealed by the study, such as the fact that younger, male physicians make up most of the users. It also looks at how satisfied HCWs are, what they think ChatGPT will do for patient outcomes, and what the future holds for healthcare practice. In addition, the study uses SUS and its subscales to assess ChatGPT's usability, offering a standard for further investigation and system advancement.

At a practical level, the study's conclusions have applications for ChatGPT training and deployment in healthcare environments, especially as these technologies continue to evolve and will require further adjustments in training and ongoing adaptations with each newer model [69]. Our study finds characteristics that are linked to higher usability scores, including HCWs' self-rated computer skills proficiency, familiarity with ChatGPT, and belief in the advantages of AI chatbots. By using this data, training programs and educational materials designed to meet healthcare workers' needs can be developed, improving their computer proficiency. Additionally, the study shows a positive correlation between learnability scores and ChatGPT familiarity, highlighting the significance of giving HCWs opportunities to become conversant with the system. The study also finds characteristics linked to higher ease of use scores, including self-rated computer skills and the conviction that ChatGPT will advance healthcare in the future. These useful realizations can guide the design decisions made for user interfaces, guaranteeing user-friendly designs that can accommodate users with various levels of computer proficiency. In general, the thorough comprehension of HCWs' perspectives and experiences with ChatGPT provided by the study can help healthcare organizations, legislators, and developers make well-informed decisions regarding the deployment, education, and further development of ChatGPT systems that meet HCWs' requirements and expectations.

This study has several limitations and strengths that should be considered when interpreting the results. Cross-sectional survey design is susceptible to sampling, response, and recall biases. The use of convenience sampling may lead to selection bias, as participants may not be representative of the entire population of HCWs who have used ChatGPT. Additionally, recall bias may influence the results if participants have difficulty remembering their experiences with ChatGPT, however, the launch of ChatGPT only three months ago may minimize recall bias. Being newly launched and introduced to medical practices, ChatGPT users were still limited by

the time of our survey especially from nurses, which limited our sample size, especially the restrictions of service registration in Saudi Arabia by the OpenAI website.

Despite these limitations, this study has several strengths. To our knowledge, this is the first study to evaluate the usability of ChatGPT among HCWs using the System Usability Scale internationally, which is a validated tool that has been widely used in various clinical and medical educational research projects especially digital innovations. Another strength element stems from the diversity of healthcare professional representation, including large medical students' sample, which helps in boosting the results generalizability. The findings of this study can provide valuable insights into the perceptions of HCWs about ChatGPT, its usability, perceived usefulness, learnability, obstacles, and practical implementation. The results can inform the adoption and integration of AI chatbots in healthcare practice, especially with the 2030 Saudi vision healthcare improvement projects [70].

5. Conclusions

In conclusion, the study evaluates the Saudi HCWs ChatGPT usability, one of the widely used AI Chatbots. Also, it underscores the potential and challenges of using ChatGPT among healthcare professionals in Saudi Arabia. The marginal acceptability reflected by SUS scores demonstrates good acceptability level of one of popular AI systems at the time of the study. Potential benefit of ChatGPT in medical research was associated with high expectations of usability. While HCWs expectations of ChatGPT potential to improve patient outcome was associated with its perception being easy to use which reflects their high standards of patient care and efforts to implement any digital intervention raising medical care caliber. Despite concerns regarding erroneous medical advice and legal implications of medical AI, emphasizing the necessity for trust-building measures and ethical concerns' consideration, still, most participants were satisfied and believed in its overall positive impact on patients' outcomes and healthcare practice future. Interest in medical research also correlated with expectations of ChatGPT usability. The study highlights the need for further research to enhance AI chatbots' usability and assess their impact on healthcare outcomes.

Funding

This research received no external funding.

Data availability statement

The deidentified participant data collected for this study will be made available to others upon reasonable request from the corresponding authors, after approval of a proposal, in agreement with the IRB-provided signed data sharing agreement.

CRediT authorship contribution statement

Fadi Aljamaan: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Khalid H. Malki:** Writing – review & editing, Visualization, Resources, Data curation. **Khalid Alhasan:** Writing – review & editing, Validation, Resources. **Amr Jamal:** Writing – review & editing, Validation, Resources, Project administration, Data curation. **Ibraheem Altamimi:** Writing – review & editing, Validation, Data curation. **Afnan Khayat:** Writing – review & editing, Software, Resources. **Ali Alhaboob:** Writing – review & editing, Resources, Funding acquisition, Data curation. **Naif Abdulmajeed:** Writing – review & editing, Resources, Data curation. **Fatimah S. Alshahrani:** Writing – review & editing, Resources, Data curation. **Khaled Saad:** Writing – review & editing, Data curation. **Ayman Al-Eyadhy:** Writing – review & editing, Supervision, Resources, Data curation, Conceptualization. **Jaffar A. Al-Tawfiq:** Writing – review & editing, Writing – original draft, Data curation. **Mohamad-Hani Temsah:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors report no personal or financial conflict of interests to declare.

Acknowledgements

During the preparation of this work the authors occasionally used ChatGPT, an AI chatbot developed by OpenAI, in order to improve some readability and language of this work, without replacing researchers' tasks. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication. We would like to thank hodhodata.com for their statistical analysis and support. The authors are grateful to the Deanship of Scientific Research, King Saud University, for funding through the Vice Deanship of Scientific Research Chairs.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e28962.

Appendix

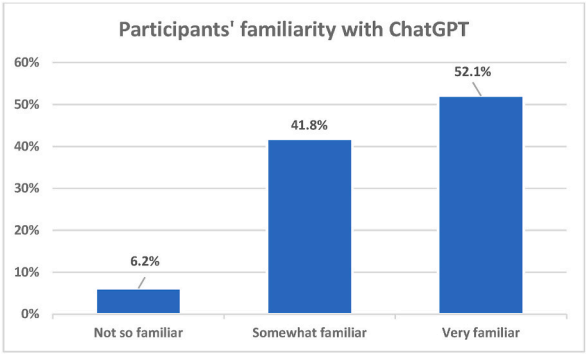

Fig. 1. Appendix

Table 1
Participants' perception of ChatGPT and AI chatbot application in medical practice

	Frequency	Percentage
Participants' trust of ChatGPT generating medical decisions for healthcare providers		
Not at all	15	7.7
A little	68	35.1
Moderate degree	87	44.8
A lot	24	12.4
Participants' perceived utility of ChatGPT in healthcare practice		
Medical decisions	82	42.3
Patients and families' support	101	52.1
Provide appraisal of medical literature	120	61.9
Helping in medical research (e.g., manuscripts drafting)	150	77.3
Participants' perceived obstacles of using AI chatbots including ChatGPT in healthcare practice		
Baffling of AI chatbot platforms suitable in healthcare practice	54	27.8
Patient's confidentiality	54	27.8
AI chatbots might take over human roles	37	19.1
AI chatbots might recommend harmful or wrong medical decisions	94	48.5
Unfamiliarity with using AI Chatbots	30	15.5
Healthcare providers resistance	73	37.6
Medicolegal implications	80	41.2
Others	18	9.3

Table 2
Descriptive analysis of the healthcare workers scoring of SUS questions. N = 194

	Mean (SD)	Mean Rank
I think that I would like to use this system frequently	2.56 (1.07)	7
I found the system unnecessarily complex*	2.67 (0.99)	4
I thought the system was easy to use	2.87 (0.92)	2
I think that I would need the support of a technical person to be able to use this system*	2.67 (1.13)	5
I found the various functions in this system were well integrated	2.60 (0.87)	6
I thought there was too much inconsistency in this system*	2.19 (0.94)	10
I would imagine that most people would learn to use this system very quickly	2.89 (0.93)	1
I found the system very cumbersome to use*	2.29 (0.99)	9
I felt very confident using the system	2.72 (0.89)	3
I needed to learn a lot of things before I could get going with this system*	2.36 (1.17)	8

Mean scores of the 10 SUS questions according to the participants scoring. The highest score was the perception that most people would learn to use this system very quickly followed by the fact that the system was easy to use. While the lowest score was the perception there was too much inconsistency in the system and it is very cumbersome to use.

* Negatively worded items were reverse coded.

Grade Scale	Range	Percentile Range	Adjective Rating	Acceptance Level	Recommendation
A+	84.1–100	96–100	Best imaginable	Acceptable	Recommendable
A	80.8–84.0	90–95	Excellent		
A−	78.9–80.7	85–89			
B+	77.2–78.8	80–84			Neutral
B	74.1–77.1	70–79			
B−	72.6–74.0	65–69			
C+	71.1–72.5	60–64	Good	Nearly acceptable	
C	65.0–71.0	41–59			
C−	62.7–64.9	35–40			
D	51.7–62.6	15–34	Fair		Unrecommendable

Fig. 2. Appendix: SUS score classification

References

[1] S. Sun, Z. Xie, K. Yu, B. Jiang, S. Zheng, X. Pan, COVID-19 and healthcare system in China: challenges and progression for a sustainable future, Global Health 17 (1) (2021) 14.

[2] T.P. Mashamba-Thompson, E.D. Crayton, Blockchain and artificial intelligence technology for novel coronavirus disease-19 self-testing, in: Diagnostics (Basel), vol. 10, 2020. Switzerland.

[3] R. Dabbagh, A. Jamal, J.H. Bhuiyan Masud, M.A. Titi, Y.S. Amer, A. Khayat, T.S. Alhazmi, L. Hneiny, F.A. Baothman, M. Alkubeyyer, et al., Harnessing machine learning in early COVID-19 detection and prognosis: a comprehensive systematic review, Cureus 15 (5) (2023) e38373.

[4] K. Alhasan, J. Al-Tawfiq, F. Aljamaan, A. Jamal, A. Al-Eyadhy, M.H. Temsah, Mitigating the burden of severe pediatric respiratory viruses in the post-COVID-19 era: ChatGPT insights and recommendations, Cureus 15 (3) (2023) e36263.

[5] B. Vasey, M. Nagendran, B. Campbell, D.A. Clifton, G.S. Collins, S. Denaxas, A.K. Denniston, L. Faes, B. Geerts, M. Ibrahim, et al., Reporting guideline for the early stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI, Bmj 377 (2022) e070904.

[6] L. Athota, V.K. Shukla, N. Pandey, A. Rana, Chatbot for healthcare system using artificial intelligence, in: 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 2020, pp. 619–622. *4-5 June 2020 2020*.

[7] A. Rao, M. Pang, J. Kim, M. Kamineni, W. Lie, A.K. Prasad, A. Landman, K.J. Dreyer, M.D. Succi, Assessing the utility of ChatGPT throughout the entire clinical workflow, medRxiv (2023).

[8] Chat generative pre-trained transformer [https://chat.openai.com/chat] Accessed 25 February 2024.

[9] O. Temsah, S.A. Khan, Y. Chaiah, A. Senjab, K. Alhasan, A. Jamal, F. Aljamaan, K.H. Malki, R. Halwani, J.A. Al-Tawfiq, et al., Overview of early ChatGPT's presence in medical literature: insights from a hybrid literature review by ChatGPT and human experts, Cureus 15 (4) (2023) e37281.

[10] A. Haque, M.N.-U.-R. Chowdhury, H. Soliman, Transforming Chronic Disease Management with Chatbots: Key Use Cases for Personalized and Cost-Effective Care, 2023.

[11] M.H. Temsah, A. Jamal, F. Aljamaan, J.A. Al-Tawfiq, A. Al-Eyadhy, ChatGPT-4 and the global burden of disease study: advancing personalized healthcare through artificial intelligence in clinical and translational medicine, Cureus 15 (5) (2023) e39384.

[12] K. Mouloudj, V.L.O. Le, A. Bouarar, A.C. Bouarar, D.M. Asanza, M. Srivastava, Adopting Artificial Intelligence in Healthcare: A Narrative Review. The Use of Artificial Intelligence in Digital Marketing: Competitive Strategies and Tactics, 2024, pp. 1–20.

[13] B. Mesko, The ChatGPT (generative artificial intelligence) revolution has made artificial intelligence approachable for medical professionals, J. Med. Internet Res. 25 (2023) e48392.

[14] M.H. Temsah, F. Aljamaan, K.H. Malki, K. Alhasan, I. Altamimi, R. Aljarbou, F. Bazuhair, A. Alsubaihin, N. Abdulmajeed, F.S. Alshahrani, et al., ChatGPT and the future of digital health: a study on healthcare workers' perceptions and expectations, Healthcare (Basel) 11 (13) (2023).

[15] A. Juhi, N. Pipil, S. Santra, S. Mondal, J.K. Behera, H. Mondal, The capability of ChatGPT in predicting and explaining common drug-drug interactions, Cureus 15 (3) (2023) e36272.

[16] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. 13 (3) (1989) 319–340.

[17] L. Liu, A. Miguel Cruz, Rincon A. Rios, V. Buttar, Q. Ranson, D. Goertzen, What factors determine therapists' acceptance of new technologies for rehabilitation – a study using the Unified Theory of Acceptance and Use of Technology (UTAUT), Disabil. Rehabil. 37 (5) (2015) 447–455.

[18] O.C. Edo, D. Ang, E.-E. Etu, I. Tenebe, S. Edo, O.A. Diekola, Why do healthcare workers adopt digital health technologies - a cross-sectional study integrating the TAM and UTAUT model in a developing economy, International Journal of Information Management Data Insights 3 (2) (2023) 100186.

[19] O. Maassen, S. Fritsch, J. Palm, S. Deffge, J. Kunze, G. Marx, M. Riedel, A. Schuppert, J. Bickenbach, Future medical artificial intelligence application requirements and expectations of physicians in German university hospitals: web-based survey, J. Med. Internet Res. 23 (3) (2021) e26646.

[20] A.S. Poncette, L. Mosch, C. Spies, M. Schmieding, F. Schiefenhövel, H. Krampe, F. Balzer, Improvements in patient monitoring in the intensive care unit: survey study, J. Med. Internet Res. 22 (6) (2020) e19091.

[21] J. Cross, R. Robinson, S. Devaraju, A. Vaughans, R. Hood, T. Kayalackakom, P. Honnavar, S. Naik, R. Sebastian, Transforming medical education: assessing the integration of ChatGPT into faculty workflows at a caribbean medical school, Cureus 15 (7) (2023) e41399.

[22] R. Bommasani, P. Liang, T. Lee, Holistic evaluation of Language Models, Ann. N. Y. Acad. Sci. 1525 (1) (2023) 140–146.

[23] J. Brooke, SUS: a 'quick and dirty' usability scale, in: P.W. Jordan, B. Thomas, I.L. McClelland, B. Weerdmeester (Eds.), Usability Evaluation in Industry, 1986, pp. 189–194.

[24] A. Bangor, P.T. Kortum, J.T. Miller, An empirical evaluation of the system usability scale, Int. J. Hum. Comput. Interact. 24 (6) (2008) 574–594.

[25] C.L. Petersen, R. Halter, D. Kotz, L. Loeb, S. Cook, D. Pidgeon, B.C. Christensen, J.A. Batsis, Using natural language processing and sentiment analysis to augment traditional user-centered design: development and usability study, JMIR Mhealth Uhealth 8 (8) (2020) e16862.

[26] S. Napa, M. Moore, T. Bardyn, Advancing cardiac surgery case planning and case review conferences using virtual reality in medical libraries: evaluation of the usability of two virtual reality apps, JMIR Hum Factors 6 (1) (2019) e12008.

[27] S. Hajesmaeel-Gohari, K. Bahaadinbeigy, The most used questionnaires for evaluating telemedicine services, BMC Med. Inf. Decis. Making 21 (1) (2021) 36.

[28] M. Mol, A. van Schaik, E. Dozeman, J. Ruwaard, C. Vis, D.D. Ebert, A. Etzelmueller, K. Mathiasen, B. Moles, T. Mora, et al., Dimensionality of the system usability scale among professionals using internet-based interventions for depression: a confirmatory factor analysis, BMC Psychiatr. 20 (1) (2020) 218.

[29] Artificial Intelligence Index Report, 2023. https://aiindex.stanford.edu/wp-content/uploads/2023/04/HAI_AI-Index-Report_2023.pdf. (Accessed 25 February 2024).

[30] M. Hyzy, R. Bond, M. Mulvenna, L. Bai, A. Dix, S. Leigh, S. Hunt, System usability scale benchmarking for digital health apps: meta-analysis, JMIR Mhealth Uhealth 10 (8) (2022) e37290.

[31] I. Maramba, A. Chatterjee, C. Newman, Methods of usability testing in the development of eHealth applications: a scoping review, Int. J. Med. Inf. 126 (2019) 95–104.
[32] A. Iftikhar, R.R. Bond, V. McGilligan, S.J. Leslie, K. Rjoob, C. Knoery, C. Quigg, R. Campbell, K. Boyd, A. McShane, et al., Comparing single-page, multipage, and conversational digital forms in health care: usability study, JMIR Hum Factors 8 (2) (2021) e25787.
[33] S.C. Peres, T. Pham, R. Phillips, Validation of the system usability scale (SUS): SUS in the wild, Proc. Hum. Factors Ergon. Soc. Annu. Meet. 57 (1) (2013) 192–196.
[34] L. Spassova, D. Vittore, D.W. Droste, N. Rösch, Randomised controlled trial to evaluate the efficacy and usability of a computerised phone-based lifestyle coaching system for primary and secondary prevention of stroke, BMC Neurol. 16 (2016) 22.
[35] C. Hamilton, M. Lovarini, M. van den Berg, A. McCluskey, L. Hassett, Usability of affordable feedback-based technologies to improve mobility and physical activity in rehabilitation: a mixed methods study, Disabil. Rehabil. 44 (15) (2022) 4029–4038.
[36] I. Drion, L.R. Pameijer, P.R. van Dijk, K.H. Groenier, N. Kleefstra, H.J. Bilo, The effects of a mobile phone application on quality of life in patients with type 1 diabetes mellitus: a randomized controlled trial, J. Diabetes Sci. Technol. 9 (5) (2015) 1086–1091.
[37] F. Papini, S. Mazzilli, D. Paganini, L. Rago, G. Arzilli, A. Pan, A. Goglio, B. Tuvo, G. Privitera, B. Casini, Healthcare workers attitudes, practices and sources of information for COVID-19 vaccination: an Italian national survey, Int. J. Environ. Res. Publ. Health 19 (2) (2022).
[38] M.H. Temsah, S. Alenezi, M. Alarabi, F. Aljamaan, K. Alhasan, R. Assiri, R. Bassrawi, F. Alshahrani, A. Alhaboob, A. Alaraj, et al., Healthcare workers' SARS-CoV-2 omicron variant uncertainty-related stress, resilience, and coping strategies during the first week of the world health organization's alert, Int. J. Environ. Res. Publ. Health 19 (4) (2022).
[39] J. Brooke, SUS: a quick and dirty usability scale, Usability Eval Ind 189 (1995).
[40] Jeff S: Ways to Interpret a Sus Score. In.: MeasuringU. [https://measuringu.com/sus/] Accessed 25 February 2024.
[41] usability.gov [https://www.usability.gov/index.html] Accessed 25 February 2024.
[42] A. Bangor, P.T. Kortum, J.T. Miller, Determining what individual SUS scores mean: adding an adjective rating scale, Journal of Usability Studies archive 4 (2009) 114–123.
[43] J.H. Kim, Y.H. Bae, S.S. Kim, M. Lee, S.H. Ho, Formative usability evaluation of a three-way digital healthcare system for the people with disabilities and their caregivers: a cross-sectional study, Healthcare (Basel) 10 (11) (2022).
[44] J.R. Lewis, J. Sauro, Revisiting the factor structure of the system usability scale, J Usability Studies 12 (4) (2017) 183–192.
[45] M. Milne-Ives, Cock C. de, E. Lim, M.H. Shehadeh, N. de Pennington, G. Mole, E. Normando, E. Meinert, The effectiveness of artificial intelligence conversational agents in health care: systematic review, J. Med. Internet Res. 22 (10) (2020) e20346.
[46] A. Noura, A. Khalid, R. Rupesh, A.M. Khalid, A. Fadi, T. Ibraheem, M. Ruaim, W. Hayfaa, J. Amr, A.A.-T. Jaffar, et al., Exploring perceptions and experiences of ChatGPT in medical education: a qualitative study among medical college faculty and students in Saudi Arabia, medRxiv 2023 (2023), 2007.2013.23292624.
[47] A.A. Qurashi, R.K. Alanazi, Y.M. Alhazmi, A.S. Almohammadi, W.M. Alsharif, K.M. Alshamrani, Saudi radiology personnel's perceptions of artificial intelligence implementation: a cross-sectional study, J. Multidiscip. Healthc. 14 (2021) 3225–3231.
[48] H. Wang, Q. Sun, L. Gu, K. Lai, L. He, Diversity in people's reluctance to use medical artificial intelligence: identifying subgroups through latent profile analysis, Front Artif Intell 5 (2022) 1006173.
[49] M.Y. Jabarulla, H.N. Lee, A blockchain and artificial intelligence-based, patient-centric healthcare system for combating the COVID-19 pandemic: opportunities and applications, Healthcare (Basel) 9 (8) (2021).
[50] Physicians positive on ChatGPT use, but only as diagnostic, prescribing aids [https://www.koreabiomed.com/news/articleView.html?idxno=21059#:~:text=The%20result%20showed%20that%2088.5,they%20earned%20a%20satisfactory%20answer] Accessed 25 February 2024.
[51] The lancet digital H: **ChatGPT: friend or foe?** Lancet Digit Health 5 (3) (2023) e102.
[52] M.H. Temsah, I. Altamimi, A. Jamal, K. Alhasan, A. Al-Eyadhy, ChatGPT surpasses 1000 publications on PubMed: envisioning the road ahead, Cureus 15 (9) (2023) e44769.
[53] F. Jungmann, T. Jorg, F. Hahn, D. Pinto Dos Santos, S.M. Jungmann, C. Düber, P. Mildenberger, R. Kloeckner, Attitudes toward artificial intelligence among radiologists, IT specialists, and industry, Acad. Radiol. 28 (6) (2021) 834–840.
[54] J. Powell, Trust me, I'm a chatbot: how artificial intelligence in health care fails the turing test, J. Med. Internet Res. 21 (10) (2019) e16222.
[55] I. Altamimi, A. Altamimi, A.S. Alhumimidi, A. Altamimi, M.-H. Temsah, Artificial intelligence (AI) chatbots in medicine: a supplement, not a substitute, Cureus 15 (6) (2023).
[56] L. Liu, A. Miguel-Cruz, Technology adoption and diffusion in healthcare at onset of COVID-19 and beyond, Healthc. Manag. Forum 35 (3) (2022) 161–167.
[57] K. Alhasan, R. Raina, A. Jamal, M.H. Temsah, Combining human and AI could predict nephrologies future, but should be handled with care, Acta Paediatr 112 (9) (2023) 1844–1848.
[58] M.H. Temsah, A. Jamal, J.A. Al-Tawfiq, Reflection with ChatGPT about the excess death after the COVID-19 pandemic, New Microbes New Infect 52 (2023) 101103.
[59] C.S. Stafie, I.G. Sufaru, C.M. Ghiciuc, I.I. Stafie, E.C. Sufaru, S.M. Solomon, M. Hancianu, Exploring the intersection of artificial intelligence and clinical healthcare: a multidisciplinary review, Diagnostics 13 (12) (2023).
[60] SUS: a retrospective [http://uxpajournal.org/wp-content/uploads/sites/7/pdf/JUS_Brooke_February_2013.pdf] Accessed 25 February 2024.
[61] J. Sauro, J.R. Lewis, Quantifying the User Experience: Practical Statistics for User Research, Morgan Kaufmann, 2016.
[62] P. Vlachogianni, N. Tselios, Perceived usability evaluation of educational technology using the System Usability Scale (SUS): a systematic review, J. Res. Technol. Educ. 54 (3) (2022) 392–409.
[63] A. Hidayat, A. Nugroho, S. Nurfa'izin, Usability evaluation on educational chatbot using the system usability scale (SUS), 2022 Seventh International Conference on Informatics and Computing (ICIC) 2022 (8-9 Dec. 2022 2022) 1–5.
[64] R. Rudrapati, Using industrial 4.0 technologies to combat the COVID-19 pandemic, Ann Med Surg (Lond) 78 (2022) 103811.
[65] A. Mendoza, L. Stern, J. Carroll, Learnability" as a Positive Influence on Technology Use, 2010, pp. 280–284.
[66] S. Ruksakulpiwat, A. Kumar, A. Ajibade, Using ChatGPT in medical research: current status and future directions, J. Multidiscip. Healthc. 16 (2023) 1513–1520.
[67] O. Melnyk, A. Ismail, N.S. Ghorashi, M. Heekin, R. Javan, Generative artificial intelligence terminology: a primer for clinicians and medical researchers, Cureus 15 (12) (2023).
[68] R. Temsah, I. Altamimi, K. Alhasan, M.H. Temsah, A. Jamal, Healthcare's new horizon with ChatGPT's voice and vision capabilities: a leap beyond text, Cureus 15 (10) (2023) e47469.
[69] M. Cascella, F. Semeraro, J. Montomoli, V. Bellini, O. Piazza, E. Bignami, The breakthrough of Large Language Models release for medical applications: 1-year timeline and perspectives, J. Med. Syst. 48 (1) (2024) 22.
[70] F. Albejaidi, K.S. Nair, Building the health workforce: Saudi Arabia's challenges in achieving Vision 2030, Int. J. Health Plann. Manag. 34 (4) (2019) e1405–e1416.