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Artificial Intelligence in Critical Care Medicine: The Promising Future of Emerging Technologies and Their Impacts on Quality of Medical Services in Emirati Government Hospitals

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Abstract

This study aims to identify the promising applications of AI in critical care medicine. In addition, the study investigated the level of quality of medical services provided in Emirati Governmental Hospitals. Moreover, it aims to determine if there are statistically significant differences in the sample responses regarding the promising applications of AI within critical care medicine based on the study variables. Furthermore, the study assesses the existence of any statistically significant differences in the sample responses. The study adopted a descriptive approach and employed a questionnaire as the primary data collection tool. The research population consisted of administrators, physicians, and nurses working in critical care units in Governmental Hospitals in the United Arab Emirates, while the sample comprised (111) participants. The findings revealed a high understanding of AI applications (mean score of 3.79) and high ratings for medical service quality (mean score of 4.00), with no significant differences based on demographic factors. The study underscores the need for ongoing training in advanced medical technologies to improve service quality.

Keywords

Artificial intelligence, Critical Care, Technologies, quality of medical services, UAE.

Article history

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1. Introduction

Patients with severe illnesses get extensive treatment and surveillance in dedicated hospital units called "critical care units". They are kept under close observation where all of the patient's vital signs are tracked and prompt medical attention is given using modern techniques and advanced technologies (Prasad et al., 2022). Consequently, the majority of these patients rely on life-sustaining equipment (catheters, infusion pumps, mechanical ventilators, and so forth) both pharmacologically and technologically. Worthy to mention is that technology integration into patient care has a long history in critical care. The work of critical care units today differs greatly from that of fifty years ago. Almost all aspects of care require extremely advanced tools (Munro & Hope, 2023). This has paved the way for the introduction of smart critical care units. By enabling real-time monitoring and quick feedback on health data, the smart healthcare model aims to improve the delivery and quality of critical care by enabling timely medical behavior intervention (Dinh et al., 2020).

This smart system uses contemporary science and technology, including big data, robotics, the Internet of Things, communication technologies, and artificial intelligence (AI) (Mao et al., 2023). The study of computer science-based AI aims to develop systems that can carry out the cognitive functions of humans, including learning, pattern recognition, and decision-making (Otero, 2023).The health and well-being of critically ill patients heavily depend on the quality of medical care provided in a critical care unit. While AI is still relatively new in the critical care units, several studies have already outlined how this technology is being used to manage critically ill patients (Gutierrez, 2020; Yoon et al., 2022). Artificial intelligence has the potential to transform critical care medicine through various techniques and applications (Cheng et al., 2023). Critical care is an ideal environment for the use of AI applications such as Big Data Analysis (BDA) and Machine Learning (ML), due to the huge amount of information processed and stored in electronic format concerning such care. These tools can improve clinical research capabilities and clinical decision-making in the future (Reiz et al., 2019).

To make vital decisions, critical care unit physicians frequently need to analyze vast amounts of complex, heterogeneous data. When applied properly, AI can lessen this load by turning data into more useful knowledge. With the help of AI, physicians can better handle very complicated circumstances and forecast negative consequences before they occur (Lovejoy et al., 2019). For patients in need of mechanical breathing, AI may be able to recognize treatable phenotypes, optimize ventilation techniques, and offer therapeutic decision support (Marshall & Komorowski, 2022). AI can significantly change how resources are allocated in critical care units by maximizing the value from big data processing and deriving practical insights that will safeguard and optimize resources (Luo et al., 2022).

Consequently, the current research aims to investigate AI in critical care medicine by showing the promising future of emerging technologies and their potential to enhance the quality of medical services, especially in Emirati Governmental Hospitals.

As a result, the researcher would highlight the main problem of Emirati Governmental Hospitals. Additionally, the researcher would do an extensive literature review that aims to achieve the theoretical aims of the research. Furthermore, methodology, data tools, objectives, questions, and data analysis represent the results, discuss them, and provide a conclusion.

2. Statement of the Problem

Understanding the complexity of acuity, dealing with high individual variation, forecasting worsening, and giving early treatment solutions before complications remain constraints of traditional critical care practice. To provide prompt intervention for critically ill patients, critical care medicine has witnessed the development of improved monitoring systems and different non-invasive and invasive treatment options (Yoon et al., 2022). The Emirati government invests heavily in AI projects to maximize the value of the healthcare sector (Forum, 2023). The UAE has recently concentrated on deploying Artificial Intelligence (AI) projects in the government healthcare sector to aid in the management of chronic diseases and early diagnosis of illness (Alhashmi et al., 2019). The UAE uses AI to develop the quality of medical services being provided by the healthcare sector (Al Badi et al., 2021). Over the last decade, artificial intelligence in critical care has advanced (Cui et al., 2023). Worthy here to mention is that AI is still in its early phases of development; conducting several studies to identify AI-based solutions for critically ill patients within the healthcare system is essential (Juneja et al., 2023). Taking into account that the United Arab Emirates, like many other countries, has recognized the potential of (AI) in improving the quality of medical services being provided by critical care units, the statement of the problem revolves around identifying the promising applications of AI in critical care units in Emirati Governmental Hospitals by shedding the light on its applications in early detection and prediction, clinical decision support, predictive analytics, and patient monitoring and alert systems.

On the other hand, the current study covers a unique research gap in the academic area. Many studies focus on the current study field, but they do not cover the current research objective. For further elaboration, (Almaroooshi, 2022; Abdulla & Al-shami, 2023), did not examine the service quality; they examined the role of applying new technology in the medical services in the UAE. In addition, they highlight the positive effects of technology, especially AI, and its potential for the health sector. Nevertheless, the current study showed a wider knowledge by examining the potential of AI in medical services. Moreover, AI technology has advanced many hospitals in the recent era; it enhances the medical service, which provides a highly competitive medical advantage. Accordingly, Mohamad et al. (2023) investigated artificial intelligence's impact on market positioning and how it affects businesses' ability to compete. In addition, George et al. (2024) highlighted a crucial research gap that includes comparing the several elements that affect customer happiness and service quality by utilizing AI tools. Consequently, the previous review showed that there is a research gap regarding “Artificial Intelligence In Critical Care Medicine: The

Promising Future Of Emerging Technologies And Their Impacts On Quality Of Medical Services In Emirati Governmental Hospitals". In the same vein, the current study highlights the effect of many demographic variables that are important to consider regarding the statistical analysis of the sample responses. This is in harmony with the studies of Brendlin et al. (2022) and Formosa et al. (2022), which indicate that there is a difference in the sample responses regarding the demographic factors, especially the gender variable.

3. Questions of the Study

The questions of the study can be formulated as follows:

1. What are the promising applications of AI within critical care medicine in Emirati Governmental Hospitals?
2. What is the level of quality of medical services within critical care medicine in Emirati Governmental Hospitals?
3. Are there any statistically significant differences in the responses of the study sample regarding the promising applications of AI within critical care medicine attributed to the study variables (gender, age, years of experience, and job position)?
4. Are there any statistically significant differences in the responses of the study sample regarding the quality of medical services within critical care medicine attributed to the study variables (gender, age, years of experience, and job position)?
5. Is there a statistically significant effect of the promising applications of AI on the quality of medical services within critical care units?

4. Objectives of the Study:

The objectives of the study can be reviewed as follows:

1. Determining the promising applications of AI that can be used within critical care medicine in Emirati Governmental Hospitals.
2. Identifying the level of quality of medical services within critical care medicine in Emirati Governmental Hospitals.
3. Verifying the existence of any statistically significant differences in the responses of the study sample regarding the promising applications of AI within critical care medicine, attributed to the study variables (gender, age, years of experience, and job position).
4. Verifying the existence of any statistically significant differences in the responses of the study sample regarding the quality of medical services within critical care medicine attributed to the study variables (gender, age, years of experience, and job position).
5. Shedding light on the statistically significant effect of the promising applications of AI on the quality of medical services within critical care medicine.

5. Significance of the Study

The research has crucial academic and practical implications, contributing to theory, policymaking, and practice. Intensive care is one of the areas where timely, accurate decisions are of paramount importance, and AI solutions, including predictive analytics, machine learning, and diagnostic tools based on data, will add value to the decision-making activity, as well as contribute to greater patient satisfaction and the possibility of minimizing mistakes. A closer look at AI's experience in Emirati Governmental Hospitals is important to determine the possibilities of these sophisticated instruments to support the UAE's healthcare plans. This study provides essential insights into the relationship between AI and the quality of medicine services, which provides an opportunity for practitioners and researchers to investigate it and utilise its results in the future.

In addition to contributing to the theoretical body of knowledge about AI and its applications in the healthcare sector, this research fills significant literature gaps about AI usability in real-life, high-risk environments. Examining how the use of AI can increase medical service quality in the UAE could demonstrate a best practice approach towards the adoption of IT that can serve as an environment for policymakers and healthcare managers if they wish to implement AI responsibly, and in a way that would address the needs of an increasingly resource-constrained environment. Furthermore, it adds to the questions regarding the proper application of AI systems in healthcare, as well as the ethical and operational considerations of such advancements. In addition, it underlines the importance of the cautious utilisation of key approaches in the execution of such innovation to improve the overall medical services for both healthcare staff and patients dealing with the fast-growing field of AI in the context of healthcare.

6. Literature Review

Critical care is a section of a hospital that serves critically ill patients with extremely specialized treatment. As critical care is any setting in which a patient is extremely ill or critically sick, patients can be managed in acute wards, such as emergency rooms, and theatre recovery (Carter & Notter, 2020). In this context, Yoon et al. (2022) indicated that medical research has been stimulated by the rapid development and realization of AI models, which are a result of an unparalleled surge in computing capacity. The idea of artificial intelligence (AI) has been used in several critical care medicine research issues to identify hidden illness patterns within highly noisy and varied clinical datasets. AI models offer practical approaches to disease diagnosis, phenotyping, and prediction that have the potential to change the trajectory of serious illnesses. When there are several treatment alternatives available, they could also result in the best, most customized treatment plans.

In addition, various studies supported the significant role that AI plays in enhancing the quality of medical services. Rahim et al. (2021) concluded that 73.5% of patients were found to be satisfied with the public hospital service, while 26.5% were not. The SERVQUAL dimensions that were found were 64.3% of empathy, 19.5% of assurance, 6.8% of responsiveness, 68.9% of reliability, and 13.2% of reviews of tangible. All SERVQUAL dimensions—except palpable and assurance—were shown to be substantially associated with patient dissatisfaction after adjusting for hospital covariates (reliability, $p < 0.001$; responsiveness, $p = 0.016$; and empathy, $p < 0.001$). Patient dissatisfaction was more likely to occur in rural hospitals ($p < 0.001$). Consequently, POR, with the aid of machine learning technology, offered a practical and workable means of gathering patient opinions regarding the calibre of care and enhancing traditional patient satisfaction surveys. Furthermore, Khan et al. (2021) found that transmission power = average of -10 to -17 dBm, jitter = 34 MS, latency = average of 87 to 95 ms, throughput = 185 bytes, duty cycle = 8%, route of delivery, and answer back variable are used to calculate QoS on the blockchain public network. Therefore, they suggested QoS-ledger, which runs by an AI algorithm, is a viable option for quality-of-service computation that is not restricted to distributed applications in e-healthcare. Based on the aforementioned, various studies highlight the potential of AI tools regarding the quality of medical care services. Moreover, the demographic factors are important while measuring this relation; George et al. (2024) relied on important demographic factors that affect such a relationship. They relied on the age, years of experience, education level, and hospital visits in the last 3 months. Accordingly, the results indicated that there are significant differences in the sample responses. Additionally, Shariff and Chandran's (2024) sample indicated that most of the participants (51.7%) were under 30 years old. Of the participants, 72.8% were men and 27.2% were women. Also, Abu-Salim et al. (2019) showed that, except for the empathy dimension, there were no statistically significant variations between male and female expectations of total service quality as a single construct. Nonetheless, the results verify that there are notable distinctions between male and female patients when assessed in terms of emotion and cognition.

6.1. AI technologies in critical care

Gutierrez defined AI as a system with human-like cognitive abilities, such as the capacity for reasoning, meaning-making, generalization, and experience-based learning (Gutierrez, 2020). Additionally, AI is the process by which a system can mimic human cognitive abilities, such as decision-making, reasoning, generalization, and learning from prior experiences, to accomplish objectives without being specifically programmed for those activities (Saqib et al., 2023). Thus, it can be indicated that AI computer systems are deemed "smart" by humans because they can carry out tasks that typically require human intelligence. AI systems use information to take actions. AI technology has revolutionized the way healthcare workers monitor and treat critically ill patients, leading to substantial breakthroughs in critical care (Gutierrez, 2020). The following are some significant uses of AI in critical care:

- **Disease Identification:** Using the reinforcement learning (RL) approach, a treatment plan for electrolyte replacement in an intensive care unit (ICU) was developed. This system provides care suggestions that can be updated often, based on each patient's unique needs (Saqib et al., 2023). A surplus of alveolar fluid is indicated by pulmonary infiltrates. These could be pleural effusion, cardiac-related pulmonary edema, parapneumonic fluid from disease or inflammation, or, in some cases, blood clots from trauma. With AI's advanced text and picture processing skills, a more precise diagnosis could be obtained in these kinds of scenarios (Yoon et al., 2022).

- **Disease Evolution Prediction:** Continuous pain evaluation by machine learning is crucial for pain management and the administration of painkillers in intensive care units (Saqib et al., 2023). In addition, Nia et al. (2023) indicated that analyzing disease images from high-tech digital devices is the basis for a wide range of medical diagnostics. AI in medical image assessment has resulted in accurate evaluations being carried out automatically, which has decreased physician workload, reduced diagnosis errors and times, and improved performance in disease prediction and detection. Medical image processing-based AI is a vital field of study that employs sophisticated computer algorithms for diagnosis, treatment planning, and prediction, having a significant influence on decision-making processes.
- **Disease Phenotyping:** Because critical illness is complicated, it is uncommon that its signs and symptoms can be boiled down to standard ones. Instead, critical illness has a wide range of manifestations (inherent heterogeneity) and carries a high risk of organ malfunction, which might exacerbate the underlying disease process or the healing process. Our understanding of diagnosing and treating complicated diseases has increased as a result of machine learning phenotyping, which is currently one of the standards for predictive enrichment of upcoming clinical trials. Using time series data, dynamic phenotyping can be carried out to predict clinical deterioration (Yoon et al., 2022).
- **Intelligent Decision Support Systems:** Artificial Intelligence can help physicians with the difficult task of evaluating a patient's risk level for treatment, identifying the patients who are most likely to suddenly deteriorate, and analyzing several tiny outcomes to improve overall patient outcomes (Saqib et al., 2023).

6.2. Effect of AI technologies on the quality of critical care services

Artificial Intelligence has enormous potential to advance patient outcomes and the critical care field. AI has the potential to transform patient care for critically sick patients and increase the effectiveness of health systems by enabling the perception of disease, forecasting changes in pathological processes, and helping in the resolution of clinical decisions (Saqib et al., 2023). Furthermore, Maruthappu et al. (2019) indicated that to make vital choices, clinicians in intensive care units frequently need to analyze vast amounts of complex, heterogeneous data. By converting data into more useful information, AI has the potential to lessen this load. AI has the potential to improve the management of extremely complicated circumstances, forecast unfavorable outcomes before they occur, and free up doctors' time to utilize their human touch and knowledge when providing care.

In this context, Greco et al. (2020) indicated that AI finds a natural home in the widespread use of electronic health records, which gather copious amounts of clinical, laboratory, and monitoring data generated by intensive care units. Reinforcement learning, unsupervised models like neural networks, and supervised learning models like support vector machines and random forests are all included in machine learning. Human judgment-based mapping of labeled data is necessary for supervised models. Reliable predictions are obtained by using unsupervised models. In the critical care unit, machine learning models are used to identify symptoms, including delirium, forecast diseases such as acute renal damage, and suggest treatment measures. As a result, AI is utilized in critical care units because there is a growing amount and quality of data available.

6.3. Challenges of AI technologies in critical care

Nevertheless, there are obstacles in the way of developing and applying AI in critical care. First, without the right foundation, such as de-identification and standardization, data generalization becomes challenging. Second, AI models lack sufficient external validation with visible model architecture, have a high risk of bias, are not reproducible, and comply with reporting requirements sub-optimally. Third, due to their obscurity and probabilistic nature, AI models may present unanticipated moral conundrums. (Yoon et al., 2022). In addition, Kelly et al. mentioned that most AI systems are still far from reaching clinical applicability and much less dependable generalisability, for the majority of medical data types. Blind spots in brittle models might lead to dangerously flawed conclusions. Technical disparities among locations (e.g., differing laboratory equipment and assays, coding definitions, EHR systems, and equipment) as well as local clinical and administrative practices might make generalization challenging (Kelly et al., 2019). Some challenges include the following:

- **Explainability and Interpretability**: Several AI models feature intricate node layers that make it possible for the properties of the incoming data to show more significant hidden patterns. Even if the model could appear to be producing accurate results through that method, the end users are frequently unable to understand the reasoning behind the computation. This can lead to significant opposition in the clinical setting when implementing AI models because medical professionals worry that they could easily break the first rule of patient care by carrying out pointless interventions or altering a treatment plan without sufficient scientific backing. In critical care medicine, this kind of action might be quickly and directly linked to death (Yoon et al., 2022).
- **Lack of Robustness**: Wang et al. (2022) indicated that because laboratory-based AI diagnostic systems are not stable and interpretable, they are not used in clinical settings. Despite several efforts, physicians still find it challenging to use the current machine learning algorithms for analyzing large amounts of lab data. Moreover, Yoon et al. (2022) revealed that due to insufficient clinical trials and research, as well as a dismal rate of reproducibility and prospective assessments, AI is not yet ready for use in real-world clinical settings.

- **Ethical Concerns**: Government healthcare regulation may face challenges if AI becomes widely used. This could lead to the provision of healthcare services by uncontrolled practitioners in unregulated settings. Artificial intelligence technology's decision-making process disregards each patient's unique circumstances by concluding machine learning of the obtained data, which gives rise to ethical, moral, and legal considerations (Ishengoma, 2022). For the majority of researchers and physicians, the use of AI in critical care is still relatively new. It won't be until AI is employed more extensively and becomes evident in the development process and bedside applications that we will truly understand the ethical dilemmas we will face (Yoon et al., 2022).
- **Patient factors**: They involve patients' and families' lack of awareness of newer technologies in healthcare without extensive lay exposure; their unwillingness to utilize noninvasive AI in their care, which is intended to supplement clinical care rather than replace doctors; and their privacy concerns, which include the usage of newer systems. Cloud computing resources comply with HIPAA.
- **Clinician factors**: They include clinicians' lack of awareness due to inadequate instruction in this area during medical school, scepticism of AI techniques, including the inadequacy of more recent deep learning algorithms and their sophistication, worries about the medicolegal implications of using AI, and the absence of conclusive multicenter randomized trials given the dynamic nature of data; the field is fresh and vibrant.
- **Technological factors**: They entail AI systems' less-than-ideal forecasting capabilities and inadequate infrastructure for real-time predictive scoring, given that interoperability and cloud computing technologies are reducing infrastructure hurdles.
- **Systems factors**: These include inadequate methods of implementation, as this has traditionally been disregarded in favour of developing algorithms. Insufficient administrative backing to appropriately integrate AI algorithms into therapeutic applications. Patient care, quality enhancement, and financial incentives are not aligned (Wardi et al., 2023).

6.4. Effect of AI technologies on critical care quality in the UAE

The UAE has recently concentrated on adopting AI projects in the public healthcare sector to aid in the management of chronic illnesses and early identification. Because they positively affect PU and PEU, managerial, organizational, operational, and IT infrastructure aspects ought to be taken into consideration when deciding whether to use AI in the healthcare industry (Alhashmi et al., 2019). In this sense, Khatib & Al-Nakeeb (2021) indicated that the Patient Smart Portal Project (PSP) is one of the most important initiatives that the UAE's Ministry of Health and Prevention (MOHAP) implemented in the HIS. PSP Project is characterized as an efficient patient service that allows customers to browse and schedule appointments online and access their medical records. Data mining can be used to find multivariate correlations in many applications that need to search through enormous data records for hidden connections. This gives managers and decision-makers the information they need to make judgments (Khatib et al., 2021).

7. Methodology

7.1. Study Procedures

The researcher described the field study procedures used to achieve the study's objectives, including the research method, study community, study sample, procedures for confirming its validity and reliability, and the statistical methods used in the analysis of results.

The research relied on the descriptive approach, which Mohamed and Al-Sakanyas (2016) define as an analytical method that depends on sufficient and accurate information about a specific phenomenon or subject over a specified period to obtain practical results that are interpreted objectively and in accordance with the actual data of the phenomenon.

7.2. Study Population and Sample:

The study sample consisted of all administrators, doctors, and nurses working in intensive care units in Governmental Hospitals in the United Arab Emirates, as these individuals represent the study population that was carefully selected for their direct association with providing healthcare and managing critical cases. The sample was determined based on the need to obtain in-depth information from various job categories that directly contribute to critical care, thereby enhancing the quality of data related to the study topic.

The sample included (120) participants from the study community, where (120) questionnaires were distributed to the targeted sample members. The stratified random sampling method was used to ensure that all job categories (administrators, doctors, and nurses) were represented in the sample in a balanced manner, which allows for a clear and comprehensive comparison between the different roles within intensive care units, and ensures that the collected data is comprehensive and provides an integrated perspective on the study topic. Out of the 120 distributed questionnaires, only (111) questionnaires were retrieved for statistical analysis, representing a response rate of (93%) of the total number of distributed questionnaires. This percentage is considered high, indicating the interest and cooperation of the participants in the study. This high response rate contributes to the reliability of the results, as it provides a broad and adequate representation of the various job roles in the sample, enhancing the possibility of generalizing the results to the larger study population.

7.3. Research Sample Characteristics:

The following table shows the distribution of the study sample according to their characteristics

Table 1: Distribution of the study Sample according to their characteristics

Gender	Frequencies	Percentages
Male	45	%40.5
Female	66	%59.5
Total	**111**	**%100**
Age	**Frequencies**	**Percentages**
Less than 30 years	18	%16.2
From 30 to less than 40 years	68	%61.3
From 40 to less than 50 years	11	%9.9
50 years and above	14	%12.6
Total	**111**	**%100**
Years of experience	**Frequencies**	**Percentages**
Less than 5 years	18	%16.2
From 5 to less than 10 years	82	%73.9
10 years and above	11	%9.9
Total	**111**	**%100**
Job position	**Frequencies**	**Percentages**
Administrator	16	%14.4
Physician	21	%18.9
Nurse	74	%66.7
Total	**111**	**%100**

It's clear from the previous table that the highest percentage obtained by the study sample according to gender was (59.5%) for females, followed by the lowest percentage of (40.5%) for males. Regarding age, the highest percentage obtained by the study sample was (61.3%), which falls under the category of "from 30 to less than 40 years," while the lowest percentage of (9.9%) was attributed to "from 40 to less than 50 years." In terms of years of experience, the highest percentage obtained by the study sample was (73.9%), which represents the category "from 5 to less than 10 years," while the lowest percentage of (9.9%) was attributed to "10 years and above". Furthermore, the highest percentage obtained by the sample individuals based on job position was (66.7%) for nurses, while the lowest percentage of (14.4%) for administrators.

The questionnaire description:

This questionnaire includes two main axes; each axis has its dimensions. Accordingly, the researcher reviewed various literature to conclude those dimensions, regarding the first axis “AI Promising Applications in Critical Care”, Ji et al. (2021) highlighted several dimensions such as operation and maintenance, diagnosis efficiency, clinical decisions, and data analytics. In addition, Alanazi (2023) indicates the opportunities of applying AI tools in critical care as follows: decision support systems, predictive analysis, data visualization, NLP, and patient monitoring. Based on the aforementioned, the research relied on four dimensions that include early detection, clinical decision support, predictive analytics, patient monitoring, and alert systems.

Moreover, regarding the second axis “**Quality of Medical Services in Critical Care”,** the researcher reviewed the literature to conclude them; As Jandavath & Byram (2016) and Yusefi et al. (2022) illustrated those dimensions of tangibles, reliability, responsiveness, assurance, and empathy as the main dimensions for this axis.

The following table displays the sections and axes of the questionnaire, the dimensions of the axes, and the number of statements for each of the dimensions:

Table 2: The description of the questionnaire sections, axes, and dimensions

Section I	The demographic data of the study sample		
	Axes	**Dimensions**	**Statements**
Section II	AI Promising Applications in Critical Care	The First Dimension: Early Detection	5
		The Second Dimension: Clinical Decision Support	5
		The Third Dimension: Predictive Analytics	5
		The Fourth Dimension: Patient Monitoring and Alert Systems	5
	Quality of Medical Services in Critical Care	The First Dimension: Tangibles (Physical aspect)	5
		The Second Dimension: Reliability	5
		The Third Dimension: Responsiveness	5
		The Fourth Dimension: Assurance	5
		The Fifth Dimension: Empathy	5

A five-point Likert scale (strongly disagree, disagree, neutral, agree, strongly agree) was used to score the questionnaire statements, with (strongly disagree) given (1), disagree (2), neutral (3), agree (4), and strongly agree (5).

7.4. Study Tool:

The researcher constructed a questionnaire to assess artificial intelligence in critical care medicine: the promising future of emerging technologies and their impacts on the quality of medical services in Emirati Governmental Hospitals.

The questionnaire's validity and reliability were validated through various methods, including arbitrators' validity, which assessed the questionnaire's linguistic formulation, clarity, and relevance of statements. Some statements in the questionnaire were deleted and reformulated upon the agreement of (84%) of the arbitrators. Thus, the final version of the questionnaire consisted of (45) statements distributed across two axes. The internal consistency of the questionnaire was assessed by applying it to a pilot sample of (30) individuals.

7.4.1. The validity of the internal consistency of the questionnaire axes:

- **The first axis: AI Promising Applications in Critical Care:**

The Pearson correlation coefficient between the scores of each statement and the total degree of the dimension to which the statement belongs from the statements on the first axis of the questionnaire was used to calculate the internal consistency validity. The results are shown in the table below:

Table 3: Pearson correlation coefficients between the scores for each statement and the total score for each dimension to which the statement belongs in the first axis: AI Promising Applications in Critical Care

No.	Correlation coefficient	No.	Correlation coefficient
The First Dimension: Early Detection			
1	.965**	4	.807**
2	.972**	5	.870**
3	.879**		
The Second Dimension: Clinical Decision Support			
6	.842**	9	.921**
7	.952**	10	.842**
8	.958**		
The Third Dimension: Predictive Analytics			
11	.928**	14	.965**
12	.966**	15	.910**
13	.914**		
The Fourth Dimension: Patient Monitoring and Alert Systems			
16	.903**	19	. 600**
17	.752**	20	.847**
18	.844**		

** Statistically significant at the significant level of (0.01).

As shown in the previous table, the correlation coefficients of the statements in the first axis, AI Promising Applications in Critical Care, were statistically significant at the level of significance (0.01). All the values of the correlation coefficients were significant, as they ranged in the first dimension between (.807**-.972**), in the second dimension between (.842**-.958**), in the third dimension between (.910**-966**), and in the fourth dimension between (.600**-903**), which indicates the availability of a high degree of internal consistency of the statements of the dimensions of the first axis.

- **The second axis: Quality of Medical Services in Critical Care**

The internal consistency validity was calculated by calculating the Pearson correlation coefficient between the scores of each statement and the total degree of the dimension to which the statement belongs from the statements of the second axis in the questionnaire, and the following table reflects their results:

Table 4: Pearson correlation coefficients between the scores for each statement and the total score for each dimension to which the statement belongs in the second axis: Quality of Medical Services in Critical Care

No.	Correlation coefficient	No.	Correlation coefficient	No.	Correlation coefficient	No.	Correlation coefficient
Tangibles (Physical aspect)				**The Fourth Dimension: Assurance**			
21	.874**	24	.629**	36	.985**	39	.916**
22	.899**	25	.776**	37	.949**	40	.969**
23	.742**			38	.973**		
The Second Dimension: Reliability				**The Fifth Dimension: Empathy**			
26	.799**	29	.930**	41	.875**	44	.861**
27	.734**	30	.926**	42	.854**	45	.911**
28	.872**			43	.893**		
The Third Dimension: Responsiveness							
31	.891**	34	.846**				
32	.797**	35	.891**				
33	.816**						

** Statistically significant at the significant level of (0.01).

As shown in the previous table, the coefficient correlations of the statements in the second axis: quality of medical services in critical care were statistically significant at the level of significance (0.01). All the values of the correlation coefficients were significant, as they ranged in the first dimension between (.629**-.899**), in the second dimension between (.734**-.930**), and in the fourth dimension between (.797**-.891**), in the fifth dimension between (.916**-.985**), and in the third dimension between (.861**-.911**), which indicates the availability of a high degree of internal consistency of the statements of the dimensions of the second axis.

- **Construct Validity** The construct validity of the dimensions of the first axis and the dimensions of the second axis was verified by finding the correlation coefficients between the total score for each dimension and the total mean for each axis, and their results are shown in the following table:

Table 5: Correlation coefficients for the dimensions of questionnaire axes

Axes	Dimensions	Correlation Coefficient
The First Axis: AI Promising Applications in Critical Care	The First Dimension: Early Detection	.963**
	The Second Dimension: Clinical Decision Support	.955**
	The Third Dimension: Predictive Analytics	.956**
	The Fourth Dimension: Patient Monitoring and Alert Systems	.881**
The Second Axis: Quality of Medical Services in Critical Care	The First Dimension: Tangibles (Physical aspect)	.801**
	The Second Dimension: Reliability	.874**
	The Third Dimension: Responsiveness	.954**
	The Fourth Dimension: Assurance	.917**
	The Fifth Dimension: Empathy	.889**

As shown in the previous table, the values of the correlation coefficients for each of the dimensions of the three axes came with high values; as in the first dimension, they ranged between (.881**-.963**), while in the second axis, they ranged between (.801**-.954**), All of them were statistically significant at the level of significance (0.01), which indicates the availability of a high degree of construct validity in the questionnaire axes.

- **The tool reliability :**Cronbach's alpha reliability coefficient was calculated for the dimensions of the three axes and the total reliability coefficient for each axis, and the results are shown in the following table:

Table 6: Cronbach's alpha reliability coefficient for the dimensions of the questionnaire axes

Axes	Dimensions	Cronbach's Alpha Coefficient
The First Axis: AI Promising Applications in Critical Care	The First Dimension: Early Detection	.928
	The Second Dimension: Clinical Decision Support	.932
	The Third Dimension: Predictive Analytics	.932
	The Fourth Dimension: Patient Monitoring and Alert Systems	.970
	Total	.955
The Second Axis: Quality of Medical Services in Critical Care	The First Dimension: Tangibles (Physical aspect)	.933
	The Second Dimension: Reliability	.916
	The Third Dimension: Responsiveness	.893
	The Fourth Dimension: Assurance	.909
	The Fifth Dimension: Empathy	.915
	Total	.930

As seen in the previous table, the values of the reliability coefficients for the dimensions of the first axis: ai promising applications in critical care obtained high values, as the values of the reliability coefficients for the dimensions of the first axis ranged between (.928-.970), and the value of the total reliability coefficient for the dimensions of the first axis: ai promising applications in critical care (.955).and the values of the reliability coefficients for the dimensions of the second axis: quality of medical services in critical care obtained high values, as the values of the reliability coefficients for the dimensions of the second axis ranged between (.893-.933), and the value of the total reliability coefficient for the dimensions of the second axis: quality of medical services in critical care (.930). These values of reliability coefficients highlight the applicability and reliability of the questionnaire.

7.5. Statistical methods:

The researcher used the statistical package for the social sciences (SPSS) program, and the results were extracted according to the following statistical methods:

- **Frequencies and percentages**: to identify the characteristics of the research sample members according to the demographic data of the research sample members.
- **Arithmetic means and standard deviations**: to calculate the averages of the questionnaire statements and the total scores of the questionnaire axes in accordance with the responses of the research sample members.
- **Pearson correlation coefficient**: to calculate the internal consistency.
- **Cronbach's alpha coefficient**: to calculate the reliability of the questionnaire statements.
- **T-test** was calculated to identify the differences between the arithmetic averages of the responses of the research sample individuals according to the study variables at a p-value $<.0.05$.
- **One-way analysis Of Variance (ANOVA)** to investigate the existence of statistically significant differences between the average scores of the study sample due to the study variables.
- **Simple linear regression** is used to study the relationship between two variables: an independent variable (predictor) and a dependent variable (outcome).
- **Range equation:** to determine the arithmetic mean of the responses to each statement, as follows:

The response score was determined, so that the very low degree was represented by (1), low by (2), medium by (3), high by (4), and very high by (5), while the verification degree for each axis was determined as follows:

Category length= $\frac{highest\ limit - lowest\ limit}{level\ No.} = \frac{5-1}{5} = 0.08$

- From 1 to less than 1.80 represents a (very low) response degree.
- From 1.80 to less than 2.60 represents a (low) response degree.
- From 2.60 to less than 3.40 represents a (medium) response degree.
- From 3.40 to less than 4.20 represents a (high) response degree.
- From 4.20 to less than 5 represents a (very high) response degree.

8. Presentation, discussion, and interpretation of research results:-

- **First: Presentation, discussion, and study of the results of the first question: What are the promising applications of AI within critical care medicine in Emirati Governmental Hospitals?**

To answer this question, the mean and standard deviation were calculated for the dimensions of the first axis: AI Promising Applications in Critical Care, and then these dimensions were arranged in descending order according to the mean for each dimension and the following table shows this:

Table No. (7) shows the means and standard deviations of the study sample responses on the dimensions of the first axis: AI promising applications in critical care

No.	Dimensions	Mean	SD	Rank	Response degree
1	The First Dimension: Early Detection	3.93	1.154	1	High
2	The Second Dimension: Clinical Decision Support	3.76	1.196	3	High
3	The Third Dimension: Predictive Analytics	3.63	1.080	4	High
4	The Fourth Dimension: Patient Monitoring and Alert Systems	3.83	1.135	2	High
	Overall Mean	3.79	1.077	--	High

It is clear from the previous table that the overall mean for the first axis: AI promising applications in critical care came with a mean of (3.79), a standard deviation of (1.077), and a (high) response degree. This can be attributed to the importance of applying artificial intelligence in critical care units, as artificial intelligence applications can help in early diagnosis of patients, as they store data faster through artificial intelligence algorithms, which contributes to saving more time and effort for physicians and thus ensuring that patients receive appropriate health care.

These findings were consistent with Lovejoy et al. (2019), who emphasized that clinicians in intensive care units frequently need to analyze vast amounts of complex, heterogeneous data. By converting data into more useful information, AI has the potential to reduce this load, improve the management of extremely complicated circumstances, forecast unfavourable outcomes before they occur, and free up doctors' time to apply their clinical expertise in patient care.

- **Second: Presentation, discussion, and interpretation of the results of the second question, which states: What is the level of quality of medical services within critical care medicine in Emirati Governmental Hospitals?**

To answer this question, the mean and standard deviation of the dimensions of the second axis: quality of medical services in critical care were calculated, and then these dimensions were arranged in descending order according to the mean for each dimension, and the following table shows this:

Table No. (8) shows the means and standard deviations of the sample members' responses on the dimensions of the second axis: quality of medical services in critical care

No.	Dimensions	Mean	SD	Rank	Response degree
1	The First Dimension: Tangibles (Physical aspect)	4.02	1.064	3	High
2	The Second Dimension: Reliability	3.82	1.204	5	High
3	The Third Dimension: Responsiveness	3.93	1.152	4	High
4	The Fourth Dimension: Assurance	4.09	.908	2	High
5	The Fifth Dimension: Empathy	4.14	.789	1	High
	Overall Mean	4.00	.908	--	High

The previous table shows that the overall mean for *the second axis: quality of medical services in critical care* came with a mean of (4.00), a standard deviation of (.908), and a (high) response degree. This was attributed to the high level of medical care in the United Arab Emirates, where critical care units are concerned with the quality of the health services provided, in addition to the availability of qualified and trained medical staff on the use of modern systems, and the existence of effective communication among doctors, which helps them to easily exchange information.

- **Third: Presentation, discussion, and interpretation of the results of the third question :Are there any statistically significant differences in the responses of the study sample regarding the AI promising applications within critical care medicine attributed to the study variables (gender, age, years of experience, and job position)?**

To answer this question, the T-test and One-Way ANOVA were used, as follows:

- **Statistical differences according to the gender variable:**

The T-test was used to identify statistical differences according to the gender variable as follows:

Table No. (9) Means, standard deviations, and t-values, indicating differences between the responses of the study sample regarding the AI promising applications in critical care according to the gender variable

Dimensions	Gender	N	Mean	SD	T	df	Sig. (2-tailed)	Sig
The First Dimension: Early Detection	Male	45	3.79	1.198	1.046	109	.298	Not significant
	Female	66	4.02	1.122				
The Second Dimension: Clinical Decision Support	Male	45	3.60	1.206	1.162	109	.248	Not significant
	Female	66	3.87	1.187				
The Third Dimension: Predictive Analytics	Male	45	3.45	1.055	1.435	109	.154	Not significant
	Female	66	3.75	1.088				
The Fourth Dimension: Patient Monitoring and Alert Systems	Male	45	3.62	1.151	1.581	109	.117	Not significant
	Female	66	3.97	1.111				
Overall Mean	Male	45	3.62	1.083	1.379	109	.120	Not significant
	Female	66	3.90	1.065				

The previous table shows that there were no statistically significant differences at the level of significance of (0.05) between the mean scores of the study sample regarding *the first axis: AI promising applications in critical care* attributed to the variable of gender in *(the first dimension: early detection, second dimension: clinical decision support, third dimension: predictive analytics, fourth dimension: patient monitoring and alert systems*, and the overall mean), this can be attributed to the agreement of the sample's opinions on the importance of artificial intelligence applications in improving and developing the services provided in critical care units, and this is due to the contribution of artificial intelligence applications in increasing the ability to analyze data correctly, in addition to making it easy to monitor the patient.

- **Statistical differences according to the age variable:**

The One-Way ANOVA test was used to identify statistical differences according to the age variable, and its results are shown in the following table:

Table No. (10) Results of the "One-Way ANOVA" indicating the differences between the responses of the study sample members regarding the AI promising applications in critical care according to the variable of age

Dimensions	Source of variance	Sum of Squares	df	Mean Square	F	Sig.
The First Dimension: Early Detection	Between groups	.815	3	.272	.200	.896
	Within groups	145.637	107	1.361		
	Total	146.452	110	--		
The Second Dimension: Clinical Decision Support	Between groups	1.810	3	.603	.415	.743
	Within groups	155.646	107	1.455		
	Total	157.456	110	--		
The Third Dimension: Predictive Analytics	Between groups	2.939	3	.980	.836	.477
	Within groups	125.396	107	1.172		
	Total	128.336	110	--		
The Fourth Dimension: Patient Monitoring and Alert Systems	Between groups	.802	3	.267	.203	.894
	Within groups	140.837	107	1.316		
	Total	141.639	110	--		
Overall mean	Between groups	1.423	3	.474	.402	.752
	Within groups	126.188	107	1.179		
	Total	127.611	110	--		

It can be seen from the previous table that there were no statistically significant differences at the level of significance of (0.05) between the mean scores of the study sample individuals regarding the AI promising applications in critical care according to the variable of age in each of the following dimensions (*the first dimension: early detection, second dimension: clinical decision support, third dimension: predictive analytics, fourth dimension: patient monitoring and alert systems*, and the overall mean). This can be attributed to the fact that the study sample of various ages agreed on the importance of artificial intelligence applications in the field of critical care in hospitals. This consensus contributes to enhancing the quality of services provided and implementing health procedures more effectively.

- **Statistical differences according to the years of experience variable:**

The One-Way ANOVA test was used to identify statistical differences according to the years of experience variable, and its results are shown in the following table:

Table No. (11) Results of the "One-Way ANOVA" indicating the differences between the responses of the study sample members regarding the AI promising applications in critical care according to the variable of years of experience

Dimensions	Source of variance	Sum of Squares	df	Mean Square	F	Sig.
The First Dimension: Early Detection	Between groups	.048	2	.024	.018	.982
	Within groups	146.404	108	1.356		
	Total	146.452	110	--		
The Second Dimension: Clinical Decision Support	Between groups	.102	2	.051	.035	.966
	Within groups	157.354	108	1.457		
	Total	157.456	110	--		
The Third Dimension: Predictive Analytics	Between groups	.540	2	.270	.228	.796
	Within groups	127.796	108	1.183		
	Total	128.336	110	--		
The Fourth Dimension: Patient Monitoring and Alert Systems	Between groups	.552	2	.276	.211	.810
	Within groups	141.087	108	1.306		
	Total	141.639	110	--		
Overall mean	Between groups	.219	2	.110	.093	.911
	Within groups	127.392	108	1.180		
	Total	127.611	110	--		

It is clear from the previous table that there were no statistically significant differences at the level of significance of (0.05) between the mean scores of the study sample members according to the variable of years of experience in the following dimensions: (early detection, clinical decision support, predictive analytics, patient monitoring, and alert systems). This can be attributed to the fact that the study sample members see the importance of applying AI applications in providing health services, by supporting the decision-making process and patient monitoring, which contributes to improving the efficiency of services provided to patients.

- **Statistical differences according to the job position variable:**

The T-test was used to identify statistical differences depending on the job variable as follows:

Table No. (12) Means, standard deviations, and T-values, indicating differences between the responses of study members regarding the AI promising applications in critical care according to the job position variable.

Dimensions	Source of variance	Sum of Squares	df	Mean Square	F	Sig.
The First Dimension: Early Detection	Between groups	.072	2	.036	.027	.974
	Within groups	146.379	108	1.355		
	Total	146.452	110	--		
The Second Dimension: Clinical Decision Support	Between groups	.094	2	.047	.032	.968
	Within groups	157.362	108	1.457		
	Total	157.456	110	--		
The Third Dimension: Predictive Analytics	Between groups	.698	2	.349	.295	.745
	Within groups	127.638	108	1.182		
	Total	128.336	110	--		
The Fourth Dimension: Patient Monitoring and Alert Systems	Between groups	.365	2	.183	.140	.870
	Within groups	141.274	108	1.308		
	Total	141.639	110	--		
Overall mean	Between groups	.238	2	.119	.101	.904
	Within groups	127.373	108	1.179		
	Total	127.611	110	--		

It is clear from the previous table that there were no statistically significant differences at the level of significance of (0.05) between the mean scores of the study sample regarding the AI promising applications in critical care due to the job position variable in each of (*the first dimension: early detection, second dimension: clinical decision support, third dimension: predictive analytics, fourth dimension: patient monitoring and alert systems*, and the overall mean). This can be explained by the fact that the study sample members, with their various job titles, agreed on the importance of applying artificial intelligence in building predictive capacity for artificial intelligence models in allocating resources and planning treatment. In addition to contributing to decision-making processes related to drug doses.

- **Fourth: Presentation, discussion, and interpretation of the results of the fourth question: Are there any statistically significant differences in the responses of the study sample regarding the quality of medical services within critical care medicine attributed to the study variables (gender, age, years of experience, and job position)?**

To answer this question, the T-test and One-Way ANOVA were used, as follows:

- **Statistical differences according to the gender variable:**

The T-test was used to identify statistical differences according to the gender variable as follows:

Table No. (13) Means, standard deviations, and t-values, indicating differences between the responses of the study sample regarding the quality of medical services in critical care attributed to the gender variable.

Dimensions	Gender	N	Mean	SD	t	df	Sig. (2-tailed)	Sig
The First Dimension: Tangibles (Physical aspect)	Male	45	3.92	1.099	.881	109	.380	Not significant
	Female	66	4.10	1.041				
The Second Dimension: Reliability	Male	45	3.68	1.177	1.024	109	.308	Not significant
	Female	66	3.92	1.221				
The Third Dimension: Responsiveness	Male	45	3.78	1.168	1.143	109	.255	Not significant
	Female	66	4.04	1.138				
The Fourth Dimension: Assurance	Male	45	3.95	.960	1.415	109	.160	Not significant
	Female	66	4.19	.864				
The Fifth Dimension: Empathy	Male	45	4.00	.876	1.551	109	.124	Not significant
	Female	66	4.24	.714				
Overall mean	Male	45	3.87	.946	1.321	109	.189	Not significant
	Female	66	4.10	.876				

It can be seen from the previous table that there were no statistically significant differences at the significance level of (0.05) between the mean scores of the study sample regarding the quality of medical services in critical care attributed to the gender variable in all (*the first dimension: tangibles (physical aspect), the second dimension: reliability, the third dimension: responsiveness, the fourth dimension: assurance, the fifth dimension: empathy*, and the overall mean), and this can be attributed to the fact that there is no variance in the opinions of the study sample regarding the importance of providing high-quality health services in critical care units, where health care providers pay attention to deliver clear medical information to patients regarding treatment methods, in addition to ensuring quick response in critical care units.

- **Statistical differences according to the age variable:** The One-Way ANOVA test was used to identify statistical differences according to the age variable, and its results are shown in the following table:

Table No. (14) Results of the "One-Way ANOVA" indicating the differences between the responses of the study sample regarding the quality of medical services in critical care attributed to the variable of age.

Dimensions	Source of variance	Sum of Squares	df	Mean Square	F	Sig.
The First Dimension: Tangibles (Physical aspect)	Between groups	.098	3	.033	.028	.994
	Within groups	124.361	107	1.162		
	Total	124.459	110	--		
The Second Dimension: Reliability	Between groups	.845	3	.282	.190	.903
	Within groups	158.543	107	1.482		
	Total	159.388	110	--		
The Third Dimension: Responsiveness	Between groups	1.767	3	.589	.437	.727
	Within groups	144.100	107	1.347		
	Total	145.867	110	--		
The Fourth Dimension: Assurance	Between groups	.214	3	.071	.084	.969
	Within groups	90.492	107	.846		
	Total	90.706	110	--		
The Fifth Dimension: Empathy	Between groups	.153	3	.051	.080	.971
	Within groups	68.261	107	.638		
	Total	68.414	110	--		
Overall mean	Between groups	.343	3	.114	.135	.939
	Within groups	90.368	107	.845		
	Total	90.711	110	--		

It can be seen from the previous table that there were no statistically significant differences at the significance level of (0.05) between the mean scores of the study sample regarding the quality of medical services in critical care attributed to the variable of age in (*the first dimension: tangibles (physical aspect), the second dimension: reliability, the third dimension: responsiveness, the fourth dimension: assurance, the fifth dimension: empathy*, and the overall mean). This can be explained by the fact that age does not make a significant difference in the sample members' opinions regarding the quality of medical services in critical care, as all ages have equal medical expectations and need for services provided in critical care.

- **Statistical differences according to the years of experience variable:**

The One-Way ANOVA test was used to identify statistical differences according to the years of experience variable, and its results are shown in the following table:

Table No. (15) Results of the "One-Way ANOVA" indicate the differences between the responses of the study sample regarding the quality of medical services in critical care according to the years of experience variable.

Dimensions	Source of variance	Sum of Squares	df	Mean Square	F	Sig.
The First Dimension: Tangibles (Physical aspect)	Between groups	.168	2	.084	.073	.930
	Within groups	124.291	108	1.151		
	Total	124.459	110	--		
The Second Dimension: Reliability	Between groups	.603	2	.302	.205	.815
	Within groups	158.785	108	1.470		
	Total	159.388	110	--		

The Third Dimension: Responsiveness	Between groups	.050	2	.025	.019	.982
	Within groups	145.817	108	1.350		
	Total	145.867	110	--		
The Fourth Dimension: Assurance	Between groups	.271	2	.135	.162	.851
	Within groups	90.435	108	.837		
	Total	90.706	110	--		
The Fifth Dimension: Empathy	Between groups	.328	2	.164	.261	.771
	Within groups	68.085	108	.630		
	Total	68.414	110	--		
Overall mean	Between groups	.244	2	.122	.146	.865
	Within groups	90.467	108	.838		
	Total	90.711	110	--		

It is clear from the previous table that there were no statistically significant differences at the significance level of (0.05) between the mean scores of the study sample regarding the quality of medical services in critical care according to the years of experience variable in (*the first dimension: tangibles (physical aspect), the second dimension: reliability, the third dimension: responsiveness, the fourth dimension: assurance, the fifth dimension: empathy*, and the overall mean). This can be explained by the fact that, regardless of the years of experience of the workers, they are interested in providing high-quality medical services, in addition to their keenness to make patients and their families feel comfortable. In addition, cooperating to exchange information that helps them provide the best health service.

- **Statistical differences according to the job position variable:** The T-test was used to identify statistical differences according to the job variable as follows:

Table No. (16) Means, standard deviations, and t-values, indicating differences between the responses of the study sample members regarding the quality of medical services in critical care according to the job position variable

Dimensions	Source of variance	Sum of Squares	df	Mean Square	F	Sig.
The First Dimension: Tangibles (Physical aspect)	Between groups	.567	2	.284	.247	.781
	Within groups	123.892	108	1.147		
	Total	124.459	110	--		
The Second Dimension: Reliability	Between groups	.112	2	.056	.038	.963
	Within groups	159.276	108	1.475		
	Total	159.388	110	--		
The Third Dimension: Responsiveness	Between groups	.121	2	.061	.045	.956
	Within groups	145.745	108	1.349		
	Total	145.867	110	--		
The Fourth Dimension: Assurance	Between groups	.136	2	.068	.081	.922
	Within groups	90.570	108	.839		
	Total	90.706	110	--		
The Fifth Dimension: Empathy	Between groups	.060	2	.030	.047	.954
	Within groups	68.354	108	.633		
	Total	68.414	110	--		
Overall mean	Between groups	.117	2	.059	.070	.933
	Within groups	90.594	108	.839		
	Total	90.711	110	--		

It is clear from the previous table that there were no statistically significant differences at the significance level of (0.05) between the mean scores of the study sample members regarding the quality of medical services in critical care according to the job variable in (*the first dimension: tangibles (physical aspect), the second dimension: reliability, the third dimension: responsiveness, the fourth dimension:*

assurance, the fifth dimension: empathy, and the overall mean). This can be attributed to the agreement of the study sample on the importance of providing high-quality medical services, as the care unit understands the needs of each patient and the medication needed for them which reduces side effects.

- **Fifth: Presentation, discussion, and interpretation of the results of the sixth question: Is there a statistically significant effect of the AI promising applications on the quality of medical services within critical care units?**

To answer this question, simple linear regression analysis was used, as follows:

Table No. (17) shows the effect of AI-promising applications on the quality of medical services within critical care units

Independent variable	B	Beta	R	R2	T.value	Sig.T
AI Promising Applications in Critical Care	.794	.941	.941a	.886	9.290	.000
Constant	.997					
Adj R2	.885					
F Value	847.153					
Sig F	.000b Significance					

The previous table shows the existence of a statistically significant positive effect of AI's promising applications on the quality of medical services within critical care units. As the value of R (.941a) was found at a significance level of (.000b). AI promising applications also explain (88.6%) of the variance in the quality of medical services within critical care units, according to the value of R2. This can be attributed to the effect of AI applications in improving the quality of critical care in hospitals. This may be due to the ability of AI to analyze a large amount of patient data, which represents their medical history. This helps to improve the diagnostic process, increase the possibility of predicting outcomes, and identify several different treatment options, which helps to improve the quality of healthcare.

9. Discussion:

This section presents the most important findings of the study, organized according to the research questions to provide a comprehensive overview of the role of AI in critical care and the quality of medical services in Governmental Hospitals in the United Arab Emirates. This is aligned with Pavliv & Pasichnyk (2023); they highlighted the essential AI function of the QMS medical cloud platform in resolving significant concerns related to the quality of medical services. A holistic, cloud-based approach can markedly enhance patient care and healthcare results.

The study showed that participants recognize the great potential of AI in enhancing various aspects of critical care. The role of AI in early detection emerged as one of the promising fields, as participants acknowledged its importance in collecting, integrating, and analyzing patient data to assist in early diagnosis and early detection of critical cases, which contributes to improving the response of medical teams. Moreover, this goes in harmony with Ng et al. (2023), who demonstrated that AI, as an alternative reader, can enhance the early identification of breast cancer by applying pertinent predictive characteristics, while minimizing unwanted recalls.

Participants also praised the role of AI in supporting clinical decision-making, as AI enables recommendations based on big data and deep analysis, which enhances the accuracy of decisions and reduces the possibility of errors. This is similar to the findings of Giordano et al. (2021), who suggested that AI may assist in addressing issues associated with various outcome optimization constraints or sequential decision-making processes that hinder personalized patient care.

As for the field of predictive analytics, participants noted that AI can predict the risks of future medical conditions and classify patients according to severity levels, which helps medical teams allocate appropriate resources and attention to each case. This is similar to Ferrara et al. (2024), who showed that AI may be utilized across diverse clinical settings to improve patient safety and aid in error detection.

Moreover, it was noted that AI-powered monitoring and alert systems are essential aspects that can contribute to the continuous monitoring of patients and the detection of changes in their health conditions immediately. This goes in harmony with (Tsvetanov, 2024), who indicated the potential role of AI in enhancing monitoring systems in healthcare services.

In addition to that, the results indicated that participants believe that the quality of medical services provided in critical care units in Governmental Hospitals in the UAE is of a high standard. This shows that there is special attention to physical aspects such as infrastructure, documentation systems, and specialized medical equipment, reflecting the importance that critical care workers give to providing an integrated environment that helps provide distinguished medical services. In the same vein, Neog & Buragohain (2020) highlighted that the quality of medical services provided in critical care units is affected by equipment efficiency.

Participants expressed their appreciation for the extent of commitment to standards such as safety, professionalism, and immediate response, as they consider these standards to reflect the quality of service and ensure patient comfort and safety.

The study also found no statistically significant differences in participants' responses based on demographic variables such as gender, age, years of experience, or occupation. This agreement among participants, regardless of their personal characteristics, seems to indicate a collective awareness of the value of AI in improving diagnostic accuracy and supporting clinical decision-making, and also reflects a broad understanding of the level of quality required in critical care. This consistent approach may contribute to a more inclusive acceptance of the technology among all categories of workers and increase the likelihood of broader adoption of AI applications in the future.

The study also revealed a strong positive relationship between artificial intelligence applications and the quality of medical services, as participants believe that artificial intelligence significantly contributes to improving resource allocation, predicting outcomes, and providing timely medical interventions. It seems that the capabilities of artificial intelligence in diagnosing and monitoring health conditions enhance quality standards in critical care, indicating its great potential to improve service levels and elevate them to higher standards.

In conclusion, the study results demonstrate healthcare workers' appreciation for the promising applications of artificial intelligence in critical care and their recognition of the high level of quality in the medical services provided. The results also confirm the transformative role of artificial intelligence in improving the quality level, highlighting the importance of developing these applications and integrating them into medical practice.

10. Recommendations

Based on the study findings, the following recommendations are proposed:

1. Specialized training programs should be designed on the applications of artificial intelligence in critical care, focusing on how AI-supported systems can be used for early detection and clinical decision-making.
2. Establish a specialized unit responsible for integrating and utilizing artificial intelligence technologies in critical care, including the management of predictive analytics systems and alert systems, to ensure optimal use of advanced technologies in monitoring critical cases and predicting their complications.
3. Establish specific medical work protocols based on AI recommendations and tools to support clinical decision-making. These protocols should include clear procedures for the effective use of alert systems, rapid decision support, and predicting potential risks based on patient data.
4. Encouraging ongoing research on the effectiveness of artificial intelligence applications in improving the quality of medical care in intensive care units, to develop and adapt them to the needs of the healthcare sector in the United Arab Emirates.
5. Enhancing and expanding the use of AI-supported automatic prediction systems to monitor high-risk patients and provide early analyses of the likelihood of health complications.
6. Develop performance standards and specific indicators to evaluate the efficiency of AI-supported systems in critical care units.
7. Improving the integration between electronic medical record systems and artificial intelligence systems to ensure smooth data flow, contributing to comprehensive analysis and accurate prediction of patients' conditions and medical needs.
8. Establishing partnerships between Governmental Hospitals, research centres, and medical universities to develop artificial intelligence technologies and exchange expertise, contributing to the creation of an advanced environment that benefits from the latest innovations in critical care.
9. Supporting and encouraging the development of local artificial intelligence solutions and technologies that meet the needs of critical care units in

Emirat's hospitals, ensuring the fulfillment of specific health requirements and providing specialized care for the local community.

10. Formulating policies and regulations to ensure adherence to the ethics of using artificial intelligence in critical care, in compliance with privacy standards and patient data protection, and to ensure ethical decision-making when using artificial intelligence in diagnosis and treatment.

11. Research proposals: conducting more future research on:

- The impact of AI applications on the quality of medical services provided in the UAE Governmental Hospitals.

References

Abdulla, A. S. M. H., & Al-shami, S. A. (2023). A Study of Technology Innovation Affecting UAE Public Health Care Organisational performance. *Tropical Scientific Journal*, *2*(2), 114–129.

Abu-Salim, T., Mustafa, N., Onyia, O. P., & Watson, A. W. (2019). Gender in service quality expectations in hospitals: The role of cognitive and affective components. *International Journal of Quality and Service Sciences*, *11*(4), 604–619.

Al Badi, F. K., Alhosani, K. A., Jabeen, F., Stachowicz-Stanusch, A., Shehzad, N., & Amann, F. (2021). Challenges of AI Adoption in the UAE Healthcare. *Vision*, 1–15.

Alanazi, A. (2023). Clinicians' views on using artificial intelligence in healthcare: opportunities, challenges, and beyond. *Cureus*, *15*(9), 1–14.

Alhashmi, S. F. S., Salloum, S. A., & Mhamdi, C. (2019). Implementing Artificial Intelligence in the United Arab Emirates Healthcare Sector: An Extended Technology Acceptance Model. *International Journal of Information Technology and Language Studies (IJITLS*, *3*(3), 27–42.

Almatrooshi, H. (2022). *A New Technology-based Tele-Emergency Framework for Emergency Healthcare Provision in the United Arab Emirates* [Ph.D. Thesis, University of Gloucestershire]. England.

Brendlin, A. S., Schmid, U., Plajer, D., Chaika, M., Mader, M., Wrazidlo, R., & Tsiflikas, I. (2022). AI denoising improves image quality and radiological workflows in pediatric ultra-low-dose thorax computed tomography scans. *Tomography*, *8*(4), 1678–1689.

Carter, C., & Notter, J. (2020). COVID-19 disease: a critical care perspective. *Clinics in Integrated Care*, *1*, 1–7.

Cheng, T. Y., Ho, S. Y. C., Chien, T. W., & Chou, W. (2023). Global research trends in artificial intelligence for critical care with a focus on chord network charts Bibliometric analysis. *Systematic Review and Meta-Analysis, Medicine*, 1–13.

Cui, X., Chang, Y., Yang, C., Cong, Z., Wang, B., & Leng, Y. (2023). Development and Trends in Artificial Intelligence in Critical Care Medicine: A Bibliometric Analysis of Related Research over the Period of 2010–2021. *J. Pers. Med*, *13*(2023), 1–10.

Dinh, M. N., Nygate, J., Tu, V. H. M., & Thwaites, C. L. (2020). *& Global Grand Challenges Event Vietnam Group*. Oxford University Clinical Research Unit, Ho Chi Minh City.

Ferrara, M., Bertozzi, G., Fazio, N., Aquila, I., Fazio, A., Maiese, A., & Russa, R. (2024). Risk management and patient safety in the artificial intelligence era: a systematic review. *Healthcare*, *12*(5), 1–15.

Formosa, P., Rogers, W., Griep, Y., Bankins, S., & Richards, D. (2022). Medical AI and human dignity: Contrasting perceptions of human and artificially intelligent (AI) decision making in diagnostic and medical resource allocation contexts. *Computers in Human Behavior*, *133*, 1–13.

Forum, W. E. (2023). *Scaling Smart Solutions with AI in Health: Unlocking Impact on High-Potential Use Cases*. World Economic Forum Publications.

George, T. R., Shewakramani, R., & Nisa, N. (2024). Evaluation of Smart Technologies Applications to Improve Service Quality and Customer Satisfaction: An Investigation of Smart Hospitals in Kerala state, India. *GSAR Journal of Applied Medical Sciences*, *1*(1), 15–22.

Nia, N., Kaplanoglu, E., & Nasab, A. (2023). Evaluation of artificial intelligence techniques in disease diagnosis and prediction. *Discover Artificial Intelligence*, *3*(1), 1–14.

Giordano, C., Brennan, M., Mohamed, B., Rashidi, P., Modave, F., & Tighe, P. (2021). Accessing artificial intelligence for clinical decision-making. *Frontiers in digital health*, *3*, 1–9.

Greco, M., Caruso, P. F., & Cecconi, M. (2020). Artificial intelligence in the intensive care unit. *Seminars in Respiratory and Critical Care Medicine*, *42*(01), 002–009.

Gutierrez, G. (2020). Artificial intelligence in the intensive care unit. *Annual Update in Intensive Care and Emergency Medicine*, 667–681.

Ishengoma, F. R. (2022). Artificial Intelligence in Digital Health: Issues and Dimensions of Ethical Concerns. *Innovación y Software*, *3*(1), 81–108.

Ji, M., Genchev, G. Z., Huang, H., Xu, T., Lu, H., & Yu, G. (2021). Evaluation framework for successful artificial intelligence–enabled clinical decision support systems: mixed methods study. *Journal of medical Internet research*, *23*(6), 1–16.

Juneja, D., Deepak, D., & Nasa, P. (2023). What, why and how to monitor blood glucose in critically ill patients. *World Journal of Diabetes*, *14*(5), 528–538.

Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC medicine*, *17*, 1–9.

Khan, A. A., Shaikh, Z. A., Baitenova, L., Mutaliyeva, L., Moiseev, N., Mikhaylov, A., & Alshazly, H. (2021). QoS-ledger: Smart contracts and metaheuristic for secure quality-of-service and cost-efficient scheduling of medical-data processing. *Electronics*, *10*(24), 1–21.

Khatib, E., Zm, R., & Al-Nakeeb, A. (2021). The effect of AI on project and risk management in healthcare industry projects in the United Arab Emirates (UAE. *Int. J. Appl. Eng. Res*, *6*(1).

Lovejoy, C. A., Buch, V., & Maruthappu, M. (2019). Artificial intelligence in the intensive care unit. *Critical Care*, *23*(1), 1–3.

Luo, M. H., Huang, D. L., Luo, J. C., Su, J., Li, J. K., Tu, G. W., & Luo, Z. (2022). Data science in the intensive care unit. *World J Crit Care Med*, 311–316.

Mao, Z., Liu, C., Li, Q., Cui, Y., & Zhou, F. (2023). Intelligent Intensive Care Unit: Current and Future Trends. *Intensive Care Research*, *3*(2023), 182–188.

Marshall, D. C., & Komorowski, M. (2022). Is artificial intelligence ready to solve mechanical ventilation? Computer says blow. *British Journal of Anaesthesia*, *128*(2), 231–233.

Mohamad, T., Bastone, A., Bernhard, F., & Schiavone, F. (2023). How artificial intelligence impacts the competitive position of healthcare organizations. *Journal of Organizational Change Management*, *36*(8), 49–70.

Mohamed, H. O., & Al-Sakany, S. (2016). *International accounting standards and the global financial crisis*. Academic Book Center.

Munro, C. L., & Hope, A. A. (2023). Artificial Intelligence In Critical Care Practice And Research. *AJCC American Journal of Critical Care*, *32*(5), 321–323.

Jandavath, R. K., & Byram, A. (2016). Healthcare service quality effect on patient satisfaction and behavioural intentions in corporate hospitals in India. *International Journal of Pharmaceutical and Healthcare Marketing*, *10*(1), 48–74.

Neog, N., & Buragohain, P. P. (2020). Household Health Care Expenditure and Utilization of Health Care Services: A Study in Dibrugarh District of Assam. *Indian Journal of Public Health Research & Development*, *11*(6), 752–759.

Ng, A. Y., Oberije, C. J., Ambrózay, É., Szabó, E., Serfőző, O., Karpati, E., & Kecskemethy, P. D. (2023). Prospective implementation of AI-assisted screen reading to improve early detection of breast cancer. *Nature Medicine*, *29*(12), 3044–3049.

Otero, P. (2023). Will artificial intelligence shift the paradigm in pediatrics? *Arch Argent Pediatr*, *121*(6), 1–3.

Pavliv, I., & Pasichnyk, V. (2023, 2023/11/17). *Enhancing the Quality of Medical Services Through the QMS Medical Cloud Platform* 6th International Conference on Informatics & Data-Driven Medicine,

Prasad, N. N., Prasad, M., Ajalkar, D. A., & Prabha, C. (2022). Patient Monitoring System in the context of Artificial Intelligence in ICU. *Bulletin of Environment, Pharmacology and Life Sciences*, *11*(5), 61–67.

Rahim, A. I. A., Ibrahim, M. I., Musa, K. I., Chua, S. L., & Yaacob, N. M. (2021). Patient satisfaction and hospital quality of care evaluation in malaysia using servqual and facebook. *Healthcare*, *9*(10), 1–18.

Reiz, A. N., Hoz, M. A. A. D. L., & García, M. S. (2019). Big Data Analysis and Machine Learning in Intensive Care Units. *Med Intensiva*, *43*(7), 416–426.

Saqib, M., Iftikhar, M., Neha, F., Karishma, F., & Mumtaz, H. (2023). Artificial intelligence in critical illness and its impact on patient care: a comprehensive review. *Frontiers in Medicine*, *10*, 1–8.

Tsvetanov, F. (2024). Integrating AI Technologies into Remote Monitoring Patient Systems. *Engineering Proceedings*, *70*(1), 1–13.

Wang, B., Jing, J., Huang, X., Hua, C., Qin, Q., Jia, Y., & Liu, S. (2022). Establishment of a Knowledge-and-Data-Driven Artificial Intelligence System with Robustness and Interpretability in Laboratory Medicine. *Advanced Intelligent Systems*, *4*(5), 1–17.

Wardi, G., Owens, R., Josef, C., Malhotra, A., Longhurst, C., & Nemati, S. (2023). Bringing the Promise of Artificial Intelligence to Critical Care: What the Experience With Sepsis Analytics Can Teach Us. *Critical Care Medicine*, *51*(8), 985–991.

Yoon, J. H., Pinsky, M. R., & Clermont, G. (2022). Artificial intelligence in critical care medicine. *Annual Update in Intensive Care and Emergency Medicine*, 353–367.

Yusefi, A. R., Davarani, E. R., Daneshi, S., Bastani, M., Mehralian, G., & Bastani, P. (2022). Responsiveness level and its effect on services quality from the viewpoints of the older adults hospitalized during COVID-19 pandemic. *BMC geriatrics*, *22*(1), 1–12.