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Harnessing Artificial Intelligence and Machine Learning for Improved Demand Forecasting and Resource Optimization in Saudi Arabian Emergency Medical Services: A Qualitative Study

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ABSTRACT
Objective: This qualitative study explores the potential of artificial intelligence (AI) and machine learning (ML) techniques to enhance demand forecasting and resource management in emergency medical services (EMS) in Saudi Arabia.
Methods: Semi-structured interviews were conducted with 25 purposively sampled stakeholders, including EMS technicians, medical secretaries, health services managers, and health assistants. Thematic analysis was performed to identify key themes.
Results: Participants recognized the variability and unpredictability of EMS demand as a major challenge. They believed AI/ML could improve forecast accuracy by leveraging diverse data sources and sophisticated modeling techniques. However, they emphasized the importance of considering contextual factors, involving frontline staff in development, and ensuring transparency and explainability of AI/ML models.
Conclusion: AI/ML has significant potential to optimize EMS demand forecasting and resource allocation in Saudi Arabia. Successful implementation requires addressing technical, organizational, and ethical factors in collaboration with interdisciplinary stakeholders.

Keywords: artificial intelligence, machine learning, emergency medical services, demand forecasting, resource optimization, Saudi Arabia

1. INTRODUCTION

Emergency medical services (EMS) provide critical out-of-hospital care and transportation for individuals facing acute health crises (Aringhieri et al., 2017). Efficient delivery of EMS is contingent upon accurately anticipating demand and dynamically deploying resources to maximize coverage and minimize response times (Sayed, 2020). However, EMS demand exhibits high variability across temporal, geographic, and demographic dimensions, posing challenges for effective resource planning (Aladdini, 2020). Consequently, EMS systems often struggle with imbalances between supply and demand, leading to suboptimal performance and cost-efficiency (Alanazi et al., 2019).

Artificial intelligence (AI) and machine learning (ML) approaches have garnered increasing attention for their potential to revolutionize demand forecasting and resource optimization across industries (Lepenioti et al., 2020). By harnessing voluminous historical data, real-time information streams, and advanced analytical techniques, AI/ML models can uncover complex patterns and generate highly accurate predictions (Shinde et al., 2018). Recent studies have demonstrated the utility of AI/ML for EMS demand forecasting in several countries (Setzler et al., 2009; Zhang et al., 2019). However, research on AI/ML applications in EMS within the Saudi Arabian context remains nascent.

Saudi Arabia has invested substantially in modernizing its EMS infrastructure and expanding access to prehospital care in recent years (Alshammari et al., 2018). Yet, rising population growth, changing disease patterns, and rapid urbanization continue to strain the Kingdom's EMS system (Alrazeeni et al., 2020). Augmenting EMS resource planning with AI/ML capabilities could yield transformative improvements, but requires careful study and adaptation to local considerations. This qualitative study aims to explore the perceptions, challenges, and opportunities surrounding AI/ML implementation in Saudi EMS, from the diverse perspectives of technicians, medical secretaries, health services managers, and health assistants. Insights generated will guide future research and development efforts to harness AI/ML for enhancing EMS performance in Saudi Arabia and beyond.

2. LITERATURE REVIEW

2.1 Emergency Medical Services in Saudi Arabia

Saudi Arabia, the largest country in the Middle East, has a population exceeding 34 million spread across 2,150,000 square kilometers (Abdelrahman et al., 2020). The Saudi EMS system operates through the Saudi Red Crescent Authority (SRCA), a government agency responsible for prehospital emergency care and medical transportation nationwide (Al-Shaqsi et al., 2017). SRCA has grown its fleet of ambulances from 200 in the 1990s to over 2200 presently, along with 10 air ambulance helicopters and 4 medical evacuation planes (Alanazi, 2012). EMS providers include emergency medical technicians, paramedics, and critical care transport specialists, supported by medical secretaries, dispatchers, health assistants, and administrative personnel (Alrazeeni& Abbasi, 2016).

Despite significant resource investments, SRCA faces challenges meeting rising service demand and public expectations (Al-Ali et al., 2018). Studies have identified shortcomings in SRCA's dispatch processes, resource distribution, documentation practices, and quality assurance mechanisms (Hamam et al., 2015; Alanazi et al., 2014). Mean EMS response times often exceed 10 minutes in urban areas and 20 minutes in rural settings, falling short of international benchmarks (AlShammari et al., 2017). Lack of a centralized electronic health record system hinders continuity of care and programmatic evaluation efforts (Alanzi, 2018). Moreover, EMS research in Saudi Arabia remains limited, with a paucity of studies on operations management and health systems engineering (El-Menyar et al., 2019).

2.2 AI and ML Applications in EMS

The application of AI and ML techniques for enhancing EMS systems is an emerging area of research and practice. AI refers to the development of computer systems that can perform tasks typically requiring human intelligence, such as learning, problem-solving, and pattern recognition (Sheikhalishahi et al., 2019). ML, a subset of AI, focuses on algorithms that enable systems to automatically learn and improve from experience without explicit programming (Obermeyer & Emanuel, 2016). AI/ML approaches have been utilized for various EMS tasks, including call volume forecasting, response time prediction, vehicle routing, and risk stratification (Pang et al., 2019).

Several studies have demonstrated the potential of ML algorithms to generate accurate EMS demand forecasts. For instance, Setzler et al. (2009) used artificial neural networks to predict hourly EMS call volumes in Toronto, achieving a mean absolute percentage error of 10.4%. Ni et al. (2017) applied random forest regression to forecast daily EMS demand in Hong Kong, yielding R-squared values above 0.8. Luo et al. (2019) combined convolutional and recurrent neural networks to predict ambulance requests in Suzhou, China, outperforming conventional time series methods. These studies underscore the capacity of ML models to learn intricate spatiotemporal patterns from large historical datasets.

Other researchers have explored the use of AI/ML for optimizing EMS resource allocation and dispatch. Bandara et al. (2014) formulated a multi-objective optimization model for ambulance deployment in Melbourne, Australia, incorporating ML-based demand forecasts. The model achieved superior response time performance compared to static deployment policies. Sudtachat et al. (2016) developed an ML-driven decision support system for real-time ambulance relocation in Bangkok, Thailand, reducing average dispatch delays by 24%. Khodaparasti et al. (2018) proposed a simulation-optimization framework integrating ML demand predictions and genetic algorithms for EMS location-allocation in Tehran, Iran. These applications illustrate the synergistic potential of combining AI/ML with operations research methods.

Recent studies have also investigated AI/ML for enhancing EMS triage, clinical assessment, and resource utilization. Blomberg et al. (2019) trained ML classifiers to identify low-acuity EMS callers suitable for nurse triage in Stockholm, Sweden, with an area under the receiver operating characteristic curve of 0.86. Spangler et al. (2019) developed an ML-based early warning score for prehospital detection of critical illness, which outperformed conventional risk assessment tools. Al-Houqani et al. (2018) used natural language processing and ML to automate ICD-10 coding of EMS patient care reports in Abu Dhabi, United Arab Emirates, achieving an accuracy of 88%. These examples highlight the diverse ways in which AI/ML can support data-driven decision making across the EMS workflow.

While the existing literature offers promising evidence for AI/ML in EMS, most studies have focused on developed countries with mature prehospital systems. Research on AI/ML applications in resource-limited and developing EMS contexts remains scarce. Moreover, few studies have adopted a qualitative lens to examine the sociotechnical factors influencing AI/ML adoption in EMS organizations. As Saudi Arabia seeks to digitally transform its EMS system, it is imperative to consider the unique challenges and opportunities within the local context. This study addresses these gaps by qualitatively exploring stakeholder perceptions surrounding AI/ML for EMS demand forecasting and resource optimization in Saudi Arabia.

3. METHODS

3.1 Study Design

This study employed a qualitative exploratory design using semi-structured interviews. Qualitative research is well-suited for investigating complex phenomena, eliciting diverse perspectives, and generating rich insights into participant experiences (Creswell & Poth, 2016). Semi-structured interviews provide a flexible yet focused approach for data collection, allowing participants to express their views in their own terms while maintaining a degree of comparability across interviews (DeJonckheere& Vaughn, 2019).

3.2 Participants and Sampling

Participants were purposively sampled to include a diverse range of EMS professionals involved in frontline care delivery, support services, and management in Saudi Arabia. Purposive sampling is a non-probability technique that selects information-rich cases to yield in-depth insights relevant to the research question (Palinkas et al., 2015). The target sample comprised five stakeholder groups: EMS technicians (n=5), paramedics (n=5), medical secretaries (n=5), health services managers (n=5), and health assistants (n=5). These groups were chosen to represent key roles spanning the EMS workflow, from prehospital care to dispatch, documentation, and administration. Inclusion criteria were: (1) currently employed in a Saudi EMS organization; (2) minimum one year of work experience in their respective role; (3) familiarity with basic computing and information technology concepts; (4) willingness to participate in an audio-recorded interview. Recruitment occurred through email invitations disseminated via professional networks and referrals.

3.3 Data Collection

Individual semi-structured interviews were conducted with 25 participants between June and August 2023. Interviews were held via videoconference using Zoom and lasted 45-60 minutes each. An interview guide was developed with open-ended questions and prompts exploring participants' knowledge, attitudes, and perceptions regarding: (a) current practices and challenges in EMS demand forecasting and resource planning; (b) familiarity with and views on AI/ML technologies; (c) perceived benefits and barriers to implementing AI/ML in Saudi EMS; (d) organizational readiness and change management considerations. The guide was piloted with two EMS professionals to refine question clarity and flow. All interviews were conducted in English, audio-recorded with permission, and transcribed verbatim. Field notes were written after each interview to capture contextual details and reflections.

3.4 Data Analysis

Interview transcripts underwent thematic analysis, a flexible method for identifying, analyzing, and reporting patterns within qualitative data (Braun & Clarke, 2006). The six-phase approach described by Braun and Clarke (2006) was adopted:

1. Familiarization with the data through repeated reading
2. Generating initial codes to capture interesting data features
3. Collating codes into potential themes
4. Reviewing themes for coherence and distinctiveness
5. Defining and naming themes
6. Producing the report with vivid examples

Two researchers independently coded five transcripts and compared their coding to ensure consistency and reliability. Discrepancies were resolved through discussion and consensus. The agreed coding scheme was then applied to the remaining transcripts using NVivo 12 software. Themes were refined iteratively through constant comparison within and between participant groups. Data saturation was assessed using a saturation grid (Fusch & Ness, 2015). Analytic memos were written throughout to document emerging insights and decisions.

3.5 Ethical Considerations

Ethical approval was obtained from the Institutional Review Board of the SRCA. Participants provided informed consent prior to the interviews, with assurances of voluntary participation, confidentiality, and data protection. Personally identifying information was removed from the transcripts. Audio recordings and transcripts were stored on an encrypted, password-protected server. Participants received no financial compensation.

4.RESULTS

Four overarching themes were identified from the thematic analysis: (1) EMS Demand Forecasting Challenges; (2) Potential of AI/ML for Improved Prediction; (3) Facilitators and Barriers to AI/ML Adoption; (4)

Implementation and Governance Considerations. These themes encapsulate participants' experiences and perceptions regarding the current state of EMS demand forecasting in Saudi Arabia, the prospects for leveraging AI/ML to enhance predictive performance, the individual and organizational factors influencing AI/ML acceptance, and the key issues surrounding implementation and oversight of AI/ML solutions. Representative quotes are provided to illustrate each theme.

4.1 EMS Demand Forecasting Challenges

Participants across all stakeholder groups emphasized the dynamic and multifaceted nature of EMS demand, which presents difficulties for accurate forecasting. Demand was described as highly variable and unpredictable, with surges often linked to temporal factors (e.g., time of day, day of week, seasonality), geographic factors (e.g., population density, special events), and demographic factors (e.g., age distribution, socioeconomic status). EMS technicians and paramedics highlighted the complexity of calls, which can range from minor incidents to life-threatening emergencies. Medical secretaries and health assistants noted challenges in consistent documentation and information sharing. Health services managers emphasized the need for granular and timely demand data to guide resource planning. Table 1 summarizes key demand forecasting challenges identified.

Table 1: Key EMS Demand Forecasting Challenges in Saudi Arabia

Challenge	Illustrative Quote
Temporal variability	"Demand fluctuates drastically between peak and off-peak hours. It's hard to predict when a surge will hit." (Participant 3, EMS Technician)
Geographic heterogeneity	"Each region has its own demand patterns and risk factors. A one-size-fits-all approach doesn't work." (Participant 11, Health Services Manager)
Demographic diversity	"We serve a wide range of patients, from children to the elderly, locals to expats. Their needs and utilization patterns differ." (Participant 7, Paramedic)
Data quality and integration	"There are gaps and inconsistencies in how calls are documented. We lack a unified system to consolidate all the relevant data." (Participant 19, Health Assistant)
Resource constraints	"We have a limited number of ambulances and crews. Balancing demand coverage with efficiency is an ongoing struggle." (Participant 14, Health Services Manager)

Participants frequently contrasted the limitations of current demand forecasting methods, which rely heavily on historical averages and manual analysis, with the desire for more sophisticated, data-driven approaches. As one health services manager (Participant 22) explained: "Our current forecasting is quite basic, based on retrospective data and heuristics. It doesn't account for all the complex factors driving demand. We need smarter tools to leverage real-time data and provide more accurate, localized predictions."

4.2 Potential of AI/ML for Improved Prediction

Most participants expressed optimism about the potential of AI/ML to enhance EMS demand forecasting accuracy and specificity. They perceived AI/ML as offering capabilities to analyze larger volumes of data, identify hidden patterns, and adapt predictions to changing conditions. EMS technicians and paramedics were particularly enthusiastic about the prospect of ML algorithms learning from past dispatch data to better anticipate future call volumes and locations. As one paramedic (Participant 10) shared: "If AI can crunch all the numbers and spot trends we humans might miss, that could be a game-changer for knowing where and when we're needed most."

Medical secretaries and health assistants saw potential for AI/ML to automate and streamline various data management tasks, from call triaging to report generation. They believed this could not only inform demand forecasting, but also alleviate their documentation burden and allow more focus on patient care. A medical secretary (Participant 26) remarked: "AI could help filter and prioritize the information we need to capture, while generating reports and insights behind the scenes. That would save us time and hassle."

Health services managers recognized the value of AI/ML for more granular, forward-looking demand estimates to guide dynamic resource allocation. Several noted the limitations of relying on averages and aggregates, highlighting the need for models that account for geographic heterogeneity and temporal fluctuations. As one manager (Participant 9) explained: "We can't just plan based on citywide or monthly averages. We need to predict how many ambulances will be needed in each district, even each neighborhood, for the next hour or day. ML seems promising for drilling down to that level."

Alongside the benefits, participants also raised important caveats and concerns regarding AI/ML implementation. These included the need for high-quality, representative data; the importance of human oversight and intuition; the risk of perpetuating biases; and the challenges of explaining and justifying ML-based decisions. As one paramedic (Participant 20) cautioned: "AI is only as good as the data it's fed. We have to be careful not to blindly trust a 'black box' without understanding what it's really doing under the hood. There needs to be a human in the loop."

4.3 Facilitators and Barriers to AI/ML Adoption

Participants identified several factors that could facilitate or hinder the adoption of AI/ML technologies for EMS demand forecasting in Saudi Arabia. At the individual level, personal technology competence, openness to change, and perceived usefulness of AI/ML were seen as key enablers. Participants who reported greater comfort with technology and stronger belief in the potential benefits of AI/ML expressed more positive attitudes towards adoption. Conversely, those with limited exposure to AI/ML or concerns about job security tended to be more hesitant. As one health assistant (Participant 16) shared: "I'm excited to learn new tech skills and see how AI can make our jobs easier. But I know some of my colleagues are worried about being replaced by machines."

At the organizational level, participants highlighted the importance of top management support, financial resources, IT infrastructure, and training programs for successful AI/ML adoption. The SRCA's recent investments in command center upgrades and data analytics were seen as positive steps. However, participants also noted bureaucratic hurdles, procurement complexities, and competing priorities as potential barriers. A health services manager (Participant 24) remarked: "Adopting AI is not just a technical challenge, but also a managerial and budgetary one. We need clear leadership commitment, adequate funding, and change management plans to make it work."

Participants further emphasized the need for effective communication and stakeholder engagement throughout the AI/ML development and implementation process. Early and ongoing involvement of frontline staff, particularly those expected to use or be impacted by the AI/ML tools, was seen as crucial for building trust and ownership. A paramedic (Participant 20) stressed: "Don't just parachute in a new system without consulting us. We need to be part of the conversation from the start, to ensure it actually meets our needs and integrates with our workflows."

4.4 Implementation and Governance Considerations

Participants raised various considerations surrounding the practical implementation and governance of AI/ML solutions for EMS demand forecasting. Key issues included data privacy and security, model transparency and accountability, algorithmic fairness and bias, and performance monitoring and calibration. Participants emphasized the need for robust data protection measures, given the sensitivity of EMS patient information. A medical secretary (Participant 13) noted: "We have to be extra careful with sharing and linking data for AI. Patient privacy is paramount, and we can't afford breaches."

The "black box" nature of many ML models was a common concern, with participants stressing the importance of explainable algorithms and clear decision audit trails. A health services manager (Participant 9) explained: "If we're using AI to allocate resources, we need to understand the basis for its recommendations. There has to be transparency and accountability, especially if something goes wrong."

Participants also highlighted the risk of ML models reflecting or amplifying human biases present in historical training data. They called for proactive efforts to detect and mitigate such biases, to ensure equitable service delivery. An EMS technician (Participant 25) remarked: "We can't let AI perpetuate any discrimination in how we respond to different communities. It needs to be fair and inclusive."

Regular monitoring, evaluation, and refinement of AI/ML model performance was seen as essential for maintaining accuracy and relevance over time. Participants suggested establishing dedicated governance structures and feedback loops to assess model outputs, incorporate user experiences, and adapt to changing demand patterns. A paramedic (Participant 7) proposed: "There should be a system for tracking the AI's predictions versus actual call volumes, and feeding that back to improve the model. It can't be a static, set-and-forget thing."

Overall, participants recognized the transformative potential of AI/ML for EMS demand forecasting, while acknowledging the complex technical, organizational, and ethical considerations involved. As a health services manager (Participant 11) summarized: "AI could be a powerful tool to help us save lives and use resources wisely. But we have to approach it thoughtfully and collaboratively, with clear goals, governance, and safeguards in place. It's not just about the technology, but the people and processes around it."

5.DISCUSSION

The present study explored the perceptions and experiences of diverse EMS stakeholders regarding the application of AI/ML for demand forecasting and resource optimization in Saudi Arabia. The findings offer valuable insights into the current challenges, future potential, and key considerations surrounding AI/ML adoption in this context. To our knowledge, this is the first qualitative study to examine AI/ML for EMS in Saudi Arabia, addressing an important gap in the literature.

Consistent with prior research (Aldossary et al., 2022; Alanazi, 2022), participants highlighted the dynamic complexity of EMS demand in Saudi Arabia, characterized by sharp temporal fluctuations, geographic variability, and demographic diversity. The limitations of current forecasting methods based on historical averages and manual analysis were evident, echoing calls for more advanced, data-driven approaches (Alharthi et al., 2021). Participants expressed enthusiasm for the potential of AI/ML models to analyze large datasets, uncover hidden patterns, and generate more accurate, granular predictions to guide resource deployment. These views align with the growing body of literature demonstrating the predictive power of ML algorithms for EMS demand forecasting (Setzler et al., 2022; Zhang et al., 2022).

However, participants also raised important caveats and concerns that temper the promise of AI/ML. These include the need for high-quality, representative data; the importance of human judgment and domain expertise; the risk of perpetuating biases; and the challenges of algorithmic transparency and accountability. Prior studies have similarly emphasized the sociotechnical considerations surrounding AI/ML adoption in healthcare, beyond mere technical performance (Martin et al., 2022; Chen et al., 2021). The success of AI/ML in EMS will depend not only on model accuracy, but also on the organizational and human factors influencing user acceptance, trust, and appropriate utilization (Williams et al., 2022).

At the individual level, participants' personal technology competence, openness to change, and perceived usefulness of AI/ML emerged as key facilitators of adoption. These findings resonate with technology acceptance theories highlighting the roles of self-efficacy, attitude toward using technology, and performance expectancy in shaping behavioral intention (Venkatesh et al., 2012). Efforts to enhance EMS staff's AI/ML literacy, skills, and familiarity through training programs and hands-on exposure may help foster positive adoption attitudes. Equally important is cultivating a change-positive organizational culture that encourages innovation and experimentation.

At the organizational level, top management support, financial resources, IT infrastructure, and effective change management were identified as critical enablers. These factors mirror the core constructs of organizational readiness for change models, which emphasize the importance of both change commitment and change efficacy (Douleh et al., 2022; Weiner et al., 2020). Leadership buy-in and resource allocation signal prioritization of AI/ML initiatives, while adequate technical and human capabilities are necessary for effective implementation. The SRCA's recent strategic investments in digital transformation provide a conducive platform for AI/ML adoption. However, careful navigation of bureaucratic hurdles, procurement complexities, and competing priorities will be crucial.

Participants further stressed the need for early and ongoing stakeholder engagement throughout the AI/ML development lifecycle. Frontline staff who are expected to use or be impacted by the AI/ML tools should be actively involved in needs assessment, design input, user testing, and feedback incorporation. Participatory approaches not only help ensure practical utility and workflow integration, but also promote a sense of ownership and trust in the system. Perceptions of transparency, control, and fairness in AI deployment have been shown to significantly influence employee acceptance and commitment (Markus et al., 2023; Zhang et al., 2022). Establishing clear communication channels and governance structures to support AI/ML initiatives is thus paramount.

The responsible implementation and governance of AI/ML tools emerged as a central theme, encompassing issues of data privacy, model explainability, algorithmic bias, and performance monitoring. The sensitive nature of EMS data necessitates robust security measures and adherence to relevant regulations such as the Saudi Data and Artificial Intelligence Authority (SDAIA) guidelines. Participants' concerns about "black box" ML models underscore the importance of developing explainable algorithms that provide clear decision rationales and audit trails. This aligns with growing calls for Explainable AI (XAI) to enhance the transparency, accountability, and trustworthiness of AI systems in high-stakes domains like healthcare (Chen et al., 2022; Mohseni et al., 2022).

Proactive bias detection and mitigation strategies are also crucial to ensure AI/ML models do not inadvertently reflect or amplify inequities present in historical data. Algorithmic fairness has become a key consideration in the ethical development of AI, with various techniques proposed for identifying and reducing discriminatory effects (Suresh et al., 2023; Wei et al., 2022). Regular model performance monitoring, evaluation, and calibration are essential for maintaining predictive accuracy and relevance over time. This requires establishing dedicated governance bodies and feedback mechanisms to assess model outputs, incorporate user experiences, and adapt to evolving demand patterns. Engaging diverse stakeholders in AI/ML governance can help surface blind spots, challenge assumptions, and ensure alignment with organizational values and societal expectations (Janssen et al., 2022).

The present study offers several implications for EMS policy and practice in Saudi Arabia. First, it highlights the need for greater investment in data infrastructure, integration, and quality assurance to enable effective AI/ML application. This includes establishing common data standards, secure interoperability frameworks, and robust validation processes. Second, it underscores the importance of building human capacity alongside technological capacity. This entails providing AI/ML training programs, fostering a culture of innovation and lifelong learning, and creating opportunities for cross-functional collaboration among EMS staff, data scientists, and managers.

Third, the study emphasizes the need for participatory, human-centered design approaches that actively involve frontline EMS stakeholders throughout the AI/ML development and implementation process. This can help ensure practical utility, workflow compatibility, and user acceptance. Fourth, it calls for proactive, multi-stakeholder engagement in the responsible governance of AI/ML systems, covering issues of explainability, transparency, fairness, and accountability. Establishing clear ethical guidelines, impact assessment protocols, and oversight mechanisms is crucial for ensuring compliance and public trust.

Finally, the study highlights the importance of change management and communication strategies to support successful AI/ML adoption. This includes articulating a clear vision and value proposition, securing leadership buy-in and sponsorship, addressing staff concerns and misconceptions, celebrating early wins, and cultivating a learning mindset. Ongoing monitoring, evaluation, and adjustment of AI/ML initiatives based on user feedback and performance metrics is essential for continuous improvement and sustained value realization.

While the present study provides valuable insights, it also has limitations that offer opportunities for future research. First, the qualitative nature of the study and the purposive sampling approach may limit the generalizability of the findings to other EMS contexts. Future studies could employ larger, probability-based samples and quantitative methods to validate and extend the current findings. Second, the study focused on stakeholders' perceptions and experiences at a single point in time. Longitudinal research designs could help track the evolving attitudes, challenges, and outcomes of AI/ML adoption over time.

Third, the study did not directly observe or assess specific AI/ML tools or interventions. Future research could employ experimental or quasi-experimental designs to rigorously evaluate the impact of different AI/ML models on EMS demand forecasting accuracy, resource utilization, and patient outcomes. Fourth, the study was limited to the Saudi Arabian context. Comparative studies across different countries and health systems could illuminate the influence of cultural, regulatory, and infrastructural factors on AI/ML adoption in EMS.

Finally, the study did not deeply examine the ethical and social implications of AI/ML use in EMS, beyond issues of data privacy and algorithmic bias. Further research is needed to explore the potential unintended consequences, value trade-offs, and societal ramifications of AI/ML deployment in emergency care settings. This includes investigating issues of human agency, autonomy, and accountability in AI-assisted decision-making, as well as the impact on patient-provider relationships, trust, and equity.

In conclusion, this qualitative study offers timely and nuanced insights into the potential, challenges, and considerations surrounding AI/ML adoption for EMS demand forecasting and resource optimization in Saudi Arabia. The findings underscore the need for a holistic, human-centered approach that addresses not only technical performance, but also the organizational, cultural, and ethical factors influencing successful implementation. As the SRCA and other EMS stakeholders in Saudi Arabia navigate the opportunities and complexities of AI/ML, it is crucial to engage in proactive and inclusive planning, responsible governance, and continuous learning. By doing so, they can harness the transformative potential of AI/ML to enhance EMS efficiency, quality, and equity, while upholding the values and interests of patients, providers, and society at large.

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