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When One Size Does not Fit All—Artificial Intelligence in Australian Rural Health

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ABSTRACT

Aims: Artificial intelligence (AI) is having an increasing impact on many aspects of our day-to-day lives. This change is also true in healthcare, with various tools being developed to hasten burdensome administrative tasks and increase overall healthcare efficiency, particularly in metropolitan centres.

Context: AI has remained comparatively clear of rural, regional and remote Australian hospitals, where it has the potential to provide significant benefits. Like previous health technology implementations, rural workforce requirements for AI maintenance and support may hinder AI deployment in these areas. While AI has been implemented successfully in metropolitan areas, these models may have limited translatability to rural health settings with significantly different administrative and healthcare systems.

Approach: AI may assist with key issues in rural centres such as resource allocation and timely patient transfer for higher level care. While the potential benefits of AI in rural centres are clear, one must consider key factors in rural centres that may limit the success of AI in these hospitals. Smaller rural populations may limit the ability to train location-specific models, and connectivity issues may impede their effective use.

Conclusion: Specific efforts are required to realise potential benefits of medical AI for rural Australia; addressing connectivity and workforce issues in rural areas is vital to allow for AI and large language models to help benefit rural centres.

1 | Introduction

Artificial intelligence (AI) has significant potential to enhance hospital efficiency and accelerate patient progression through different stages of care. AI-driven solutions, such as the Adelaide Score, a South Australian-developed AI tool for predicting patient discharge, have demonstrated their ability to alleviate metropolitan hospital bottlenecks [1]. However, the applicability of these models in rural and remote centres remains to be investigated. Further investigation is required to ensure AI solutions are tailored to the specific needs of rural centres, improving clinical care while addressing centre-specific needs.

Summary

- What does this paper add?
  - Rural health faces unique challenges that artificial intelligence (AI) may help address.
  - Nuanced aspects of rural health may hinder the implementation of already validated metropolitan AI models.
  - Smaller rural populations may limit the ability of development/training of location-specific AI models.
  - Issues regarding internet connectivity are still prevalent but are slowly alleviated with newer technologies.
- What is already known?
  - AI is already showing substantial benefits within larger Australian metropolitan centres.
  - Constraints that have previously hindered AI development in rural areas, such as connectivity and hardware, are being addressed with newer technologies.
  - Workforce and training constraints in rural areas remain prevalent and will be significant barriers to AI benefit realisation in these centres.

2 | Potential for AI in Rural Health

AI has the potential to improve healthcare delivery in rural settings (see Box 1). However, it is important to consider that any AI tool implemented into clinical practice should function as an adjunct to, rather than a replacement for, standard clinical care [2]. AI-powered tools can accelerate and hasten administrative tasks and enhance clinical staff awareness of patient deterioration risks [3]. AI in rural centres may take many different forms; these may be different from those seen in metropolitan centres. However, their use promotes a similar goal: improving patient care and system efficiency. For example, the different types of application may include tools that estimate the likelihood of patients with subacute presentations requiring transfer to metropolitan centres.

Predictive AI models for hospital transfers could be particularly beneficial in optimising patient preparation and resource allocation for emergency transport service, such as the Royal Flying Doctor Service. These models could function as dynamic dashboards, offering hospitals and transfer services real-time estimates of transfer likelihood based on factors such as clinical deterioration risk and the availability of essential investigations. Additionally, AI tools could assist in identifying patients who require diagnostic tests unavailable at their local hospital, such as magnetic resonance imaging (MRI), enabling better coordination of transport and resource allocation. This would facilitate more efficient planning and scheduling for both the referring rural centres and metropolitan centres.

After developing these tools, generating an evidence base for them through validation and implementation studies may allow the use of AI to enter many areas of routine practice. As with other areas of clinical research, such as drug development, the post-implementation monitoring of adverse effects is vital. There are additional AI-specific considerations that must also be considered, including data and model drift, which can be particularly concerning in closed-source large language models (LLMs). To aid in mitigating these concerns, regular monitoring of these models should occur through governing bodies and regulatory frameworks. Furthermore, there is a risk of bias when developing these models; therefore, monitoring and re-evaluation should include subgroup analyses. The frequency and extent of the re-evaluation of model performance will likely vary depending on its application in the clinical environment. Although it is difficult to provide general timelines, annual checks may provide sufficient monitoring for many of these AI models. If model performance declines, the necessary processes and auditing systems should be in place to enable robust evaluation and provide guidance on when to repeat the derivation of the model, if necessary.

BOX 1 | Selected potential benefits of AI to rural centres.

- Improve clinical resource allocation in rural centres.
- Improve clinician and nursing awareness of the risk of clinical deterioration in hospitals with fewer on-site staff.
- Improve discharge planning for those who live in rural and remote communities.
- Increase tertiary transfer efficiency and planning for services such as the Royal Flying Doctor Service.

The issues with transferability of AI models between diverse healthcare settings are well documented in AI redeployment. A notable example of this is the decline in performance seen with the EPIC sepsis algorithm [4]. Rural centres are particularly vulnerable to this issue, as AI models are typically not trained on rural health data given its limited availability. Ensuring AI models are suitable for rural Australian healthcare systems requires rigorous validation studies using local datasets before implementation. These studies should employ multiple performance metrics and, ideally, include a large sample size. Subsequent implementation in rural centres should acknowledge potential variations in performance when the model is implemented in different patient cohorts. Ultimately, AI implementation should demonstrate tangible improvements in patient- or system-centred outcomes.

3 | The Clinical Uses of AI

LLMs represent an area of promise in AI-driven healthcare. Comparatively old LLM such as ChatGPT 3.5, have demonstrated diagnostic accuracy comparable to physicians when assessed using clinical vignettes [5]. Another study evaluating ChatGPT's triage performance found it matched the proficiency of untrained emergency department doctors [6]. Similarly, Liu et al. found ChatGPT 3.5 generated 'highly understandable and relevant' recommendations based on electronic medical record clinical decision support (CDS) alerts [7]. LLMs as an adjunct triage tools may provide utility in rural centres, particularly those which are staffed by local on-call clinicians who rely on nursing-based triage. LLMs have the potential to reduce overall system and staffing burdens in various administrative duties in rural centres [8]. Along with clinician oversight, LLMs could theoretically reduce administrative burdens and increase the amount of time available to medical and nursing staff in rural centres to provide clinical care.

4 | Constraints in Rural AI Development

Despite AI's potential to enhance healthcare delivery in rural, regional, and remote centres, several geographical and socioeconomic challenges may limit its effectiveness (see Box 2). One of the most pressing concerns is the disparity in digital connectivity between rural and metropolitan areas. Connectivity outages and internet disruptions pose significant risks, not only to the day-to-day functioning of AI models but also to their ongoing development and training [9, 10]. To mitigate these risks, AI developers must incorporate backup measures that ensure continuity of service during connectivity disruptions. Fortunately, advancement in satellite-based broadband technology, such as SpaceX Starlink, offers high-speed internet that rivals metropolitan national broadband network (NBN) services [10]. The integration of reliable satellite internet solutions is crucial for the successful deployment and operation of AI-based systems in rural healthcare settings, ultimately enhancing overall hospital system efficiency.

Improving public attitudes and perceptions toward AI must be recognised by those developing these models. Current reported literature on public perceptions of AI is ever-changing, with shifting attitudes toward wider AI implementation in healthcare, particularly regarding its use in administrative and non-clinical tasks [11]. Perceptions of AI in rural Australia may be shaped by past experiences with technology integrations like telemedicine and electronic medical records, which initially faced challenges related to usability, privacy and digital connectivity. Privacy concerns may be significantly heightened in smaller communities and must be addressed in AI development. Ensuring that datasets are sufficiently large and anonymised to avoid reidentification of data in rural areas is a key aspect of promoting AI acceptability among the public. The integration of rural community members, particularly non-clinical, is vital for successful AI model development and rollout [12] as their involvement can help address concerns, provide local insights, and build trust in the technology. However, just as public engagement in AI has the potential to improve acceptance, involving healthcare staff in its design and deployment can foster greater acceptance of the technology [13].

BOX 2 | Potential drawbacks limiting the use of AI in rural centres.

- Limited representation of populations in training datasets.
- Limited training data size for locally developed models.
- Generalisability of models from metropolitan and other rural centres may vary greatly.
- Connectivity and hardware issues.

Smaller rural healthcare centres, potentially which stand to benefit the most from AI, often face significant challenges in model generalisability due to their unique patient demographics, limited data availability and resource constraints. For AI models to be effective, they must be tailored to the local population and account for various factors influencing patient health [14]. However, regions with small datasets may need to rely on larger datasets sourced from areas with different patient demographics and characteristics. Larger rural centres are typically more resourced, with access to larger datasets, allowing them to develop more specific and precise models for their population. This, however, can inadvertently widen health and resource disparities between rural centres, particularly disadvantaging more remote centres that would otherwise see the most benefit from AI tools. The necessity of tailored AI models further complicates equitable deployment, as their gradual implementation across different local health networks (LHNs) in part on available funding.

Beyond these challenges, AI can impact health equity in other ways. The limited generalisability of AI-driven technologies has been well-documented as a factor contributing to disparities in healthcare access and outcomes [15]. If access to healthcare services in rural communities becomes increasingly reliant on AI, these inequities could worsen. Marginalised groups are also at risk of being under-represented in AI development and training, or represented in a biased manner. To prevent AI from perpetuating or exacerbating existing disparities, diverse stakeholder engagement must be prioritised throughout the development, testing and evaluation process. Subgroup analyses should be conducted at all stages to ensure equitable AI performance across different patient populations and to monitor its impact on health equity.

While developing AI models tailored to individual rural centres would be ideal, financial and workforce constraints present significant barriers. These costs will only increase with the need for tailored software and integration into a wide range of existing hospital systems and clinical or administrative workflows. As with any technology, AI must incorporate fail-safe mechanisms to ensure continuity of care in the event of system disruptions. For example, human oversight and manual intervention should be in place to maintain essential functions if AI tools become unavailable.

5 | Ethics and the Law Surrounding AI

The integration of AI in healthcare raises significant legal and ethical challenges that must be addressed before widespread adoption. Ensuring data safety and confidentiality is crucial when developing AI models, whether it be for use in metropolitan or rural healthcare settings. Additionally, concerns regarding liability, performance, safety and ethical compliance [16] remain key barriers to implementation. Current AI development guidelines, such as those published by the Association for the Advancement of Artificial Intelligence, aim to provide guidance in these areas [16]. Similarly, the Australian Government's ongoing efforts to establish policies for responsible AI use, including input from the Therapeutic Goods Administration, are expected to provide further regulatory clarity [17]. As metropolitan ethics and governance bodies become more responsive to AI, rural-based AI governance frameworks must also evolve to ensure equitable and context-appropriate oversight.

6 | Conclusion

AI holds significant potential to enhance healthcare delivery in rural and remote communities. There are specific use cases unique to these healthcare settings in which AI may assist, such as predicting the need for transfer to a metropolitan centre. However, its development and implementation must address unique rural challenges, including limited data availability, workforce constraints and infrastructure disparities. Developers creating AI models in metropolitan centres should proactively consider their adaptability to rural settings, ensuring that training datasets account for smaller population sizes and diverse healthcare needs. By taking a coordinated and proactive approach to AI development, its full potential in improving healthcare accessibility, efficiency and outcomes for rural and remote healthcare across Australia can be recognised.

Author Contributions

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Conflicts of Interest

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Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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