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Artificial intelligence guided dosing decisions: a qualitative study on health care provider perspectives

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ABSTRACT

Objectives Tailoring medication dosing to an individual's traits is complex, but artificial intelligence (AI) advancements enable greater precision. Our study objectives were to gauge healthcare providers' perspectives on AI-guided precision dosing and to identify barriers and enablers for adopting AI-guided precision dosing into clinical practice.

Methods We conducted a qualitative study using purposive sampling to select a diverse group of healthcare providers, thereby broadening the viewpoints. We explored their receptiveness to AI-enabled dosing and sought to uncover implementation challenges. During the interviews, we introduced CURATE.AI as an example of an AI dosing tool. We analysed the data using deductive methods, coding the data according to the Unified Theory of Acceptance and Use of Technology framework.

Results We interviewed 16 participants (9 doctors, 4 nurses and 3 pharmacists). Interviews revealed diverse perspectives, from hopeful anticipation to recognised challenges. While acknowledging AI's potential to enhance decision-making and patient safety, concerns about AI's suitability for complex cases, erosion of critical thinking, liability protection, and trust arose. Moreover, transparency, understandability of AI output and human oversight were seen as essential to mitigate risks and promote acceptance.

Discussion AI-enabled dosing tools have the potential to optimise dosing and improve patient safety, but adoption barriers remain. Successful implementation will require technically robust tools and careful alignment with clinical workflows and user expectations.

Conclusion Our study highlights the hopeful anticipation and complex challenges of introducing AI-enabled dosing into clinical practice. As AI inevitably becomes a part of healthcare, ongoing evaluation is essential to demonstrate value and promote adoption.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ While artificial intelligence (AI) can potentially optimise drug dosing, its integration into clinical practice remains complex.

WHAT THIS STUDY ADDS

⇒ This study provides qualitative insights into healthcare providers' perceptions of AI-based dosing tools, identifying key enablers and barriers to adoption. The findings highlight concerns about AI's suitability for complex cases that may question its value, its potential impact on critical thinking in the workforce, and the importance of transparent AI decision-making.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Understanding the end-user perspective can inform implementation strategies. Furthermore, there is a need for continuous real-world evaluation to establish value and drive clinical acceptance.

INTRODUCTION

Individuals are a complex blend of different phenotypic, genotypic and epigenetic factors—all of which influence their responses to drugs.[1 2] Despite these complexities, conventional dosing strategies overwhelmingly adhere to a one-dose-fits-all paradigm, failing to account for these individual variances.[1 2] This approach limits the safety and efficacy of drug therapies by overlooking real-world patient variability in terms of pharmacokinetics (how the body processes drugs) and pharmacodynamics (how drugs affect the body).[2] As a result, many patients may not experience the full therapeutic benefit of a treatment, while others may face an increased risk of adverse effects, underscoring the need for more personalised dosing strategies.

Tailored therapies or 'precision medicine' aims to better consider the unique factors influencing an individual's response to treatment. Precision medicine has profoundly impacted disease understanding and how individuals respond to therapies.[3] For example, advances in pharmacogenomics have expanded our understanding of how a person's genes affect drug response.[4] However, optimising dosing on factors such as genes, gender and concurrent medications is incredibly complex, requiring sophisticated data processing capabilities to derive informed dosing decisions. The advancement

of artificial intelligence (AI) and machine learning capabilities is now enabling the ability to incorporate complex data into actionable insights, including medication optimisation.[5] One innovative example is CURATE.AI.[6 7]

CURATE.AI was originally developed to optimise and personalise chemotherapy doses, using an individual's dose–response data and leveraging a phenotypic response surface correlation to predict ideal dosing specifications.[6 7] This approach enables clinicians to tailor chemotherapy regimens based on real-time patient responses, offering a more dynamic and precise method for dosing. Early clinical testing of CURATE.AI in the treatment of metastatic prostate cancer and immunosuppression in liver transplant has shown promise.[7 8] In these studies, CURATE.AI provided real-time, personalised dose adjustments using only a few data points, enabling faster achievement of therapeutic targets while minimising toxicity. Its effectiveness, coupled with the fact that it does not require population-level data for training, has shown its utility in clinical practice. Ongoing work is now exploring its capabilities in chronic disease management.[9]

While such tools are promising, adoption challenges are common and must be carefully identified and addressed.[10] The Unified Theory of Acceptance and Use of Technology (UTAUT) model, a widely used framework in the health technology evaluations, suggests that four core constructs determine users' behavioural intentions and subsequent use patterns: performance expectations (eg, improves dosing accuracy), effort expectancy (eg, the level of training required to use it), social influence (eg, institutional endorsement) and facilitating conditions (eg, infrastructure supporting the technologies use).[11] Access to electronic data, the cost–benefit trade-off of technology, data management and clinical guidelines on AI use are only a few practical examples of factors influencing technology adoption, but less is known about AI-guided dosing-related factors.[12]

As AI-enabled dosing becomes more commonplace, it is important to understand the factors that might influence healthcare providers' acceptance and use. These insights can inform system design and support the development of effective implementation strategies. In our study, we sought to explore the application of AI-enabled dosing in outpatient care, specifically chronic disease management. Our study objectives are:

1. To gauge healthcare providers' perspectives on AI-guided precision dosing.
2. To identify barriers and enablers for adopting AI-guided precision dosing tools into clinical practice.

METHODS

We conducted a series of in-depth interviews to glean insights into healthcare providers' perspectives and receptiveness to AI-guided dosing, and the potential challenges associated with implementing it into clinical practice. During the interviews, we verbally introduced CURATE.AI as an example of an AI dosing decision tool. The introduction included a brief overview of its purpose, how it works and how it could be deployed. At the time of this study, CURATE.AI was being tested within the outpatient clinics at Alexandra Hospital, Singapore, although interviewees largely had no direct exposure to the tool.

Participants

A purposive sampling strategy was employed to select a diverse group of healthcare providers working at Alexandra Hospital who are involved in prescribing (eg, physicians) or dose titration clinics (eg, pharmacists, nurses), ensuring a broad representation of perspectives. Since AI-enabled dosing is not limited to a specific disease, we sought the views of different professional groups with varying degrees of experience, and a mix of ages and genders. Inclusion criteria were as follows: healthcare providers of any discipline with responsibilities in outpatient care and experience of medication management (ie, advisory roles, prescribers). Participants were initially approached via email with information on the study and the interview process. If agreeable, each participant underwent an informed consent process. Recruitment continued until no new topics emerged from the interviews. No participants declined participation.

Data collection

All in-depth interviews were conducted privately by JS (woman), a health services researcher and assisted by JMA (woman). Interviews were done face-to-face in a private room at the hospital or remotely through a Microsoft 365 Teams video call (Redmond, USA). Interviews were semistructured and guided by an interview guide (table 1). While interviewing, we introduced participants to CURATE.AI. Sharing this real-world example helped participants understand how an AI dosing decision tool could operate in practice. At the end of the interview, demographical information was collected from each participant (age, gender, profession, years of experience). Interviews were conducted in English between August and December 2023, and each interview lasted between 40 and 90 min. Interviews were audio recorded with participants' consent and transcribed verbatim for data analysis.

Theoretical framework

The development of the interview guide was informed by a literature search on factors that influence digital tool adoption in healthcare and the UTAUT framework.[11] The UTAUT framework is a well-established lens for examining technology acceptance and includes four key domains: performance expectancy (ie, the expected benefits of the technology, such as reduced side effects or improved dosing accuracy), effort expectation (ie, the ease of use, such as the level of training required, or the simplicity of the interface), social influence (ie, the degree to which individuals perceive that others expect them to use the technology, such as through managerial endorsement) and influencing conditions (ie, the

Table 1 Interview guide

Adapted UTAUT domains	Interview questions
Ice breaker/context question	► Can you tell me about your current role and responsibilities?
Performance expectancy	► What are your general thoughts on personalised dosing? Is there a need? ► Do you think AI-enabled dosing tools can benefit patients and clinicians? And in what ways?
Effort expectancy	► What support/training would you need to use an AI-enabled dosing tool? ► What are your thoughts on the feasibility of data collection and review?
Social expectation	► Who could be the potential users of this technology? ► Do you think there is a use case for AI-enabled dosing tools like CURATE.AI? ► How do you think patients would react to AI-supported dosing?
Facilitating conditions	► What would need to be considered in terms of implementation? ► What are your perspectives on current AI regulation?
Trust and risk	► Can you foresee any negative consequences of implementing this technology? ► Would you be willing to use such technology if implemented? ► Would you trust using an AI-enabled dosing decision tool?
Moderators	► Demographical data (age, gender, profession, years of experience)

AI, artificial intelligence; UTAUT, Unified Theory of Acceptance and Use of Technology.

expected technical and organisational support to use the technology, such as the availability of IT support). These domains are further moderated by individual factors, including gender, age, experience and voluntariness of use. Although this framework offers a robust structure to explore perceptions, facilitators and barriers, the original UTAUT does not explicitly include trust or risk as a core construct. However, rapid AI development has highlighted the importance of these dimensions in digital health adoption.[13 14] To better derive potential AI challenges, such as reliability, liability, transparency and control, we adapted the framework to include an additional 'trust and risk' dimension.

An initial draft of the interview guide was formed and then refined through further discussion among the project team. Finally, the interview guide was further iterated if new topics emerged during the interviews.

Data analysis

We analysed the data using a hybrid deductive–inductive approach.[15] Initially, a deductive approach was applied, using a modified version of the UTAUT framework to guide the development of a preliminary codebook.[11] With this initial codebook, JS coded the first two transcripts line by line, also identifying segments that did not fit into existing constructs. This allowed for the incorporation of inductively derived codes. Next, JMA coded the remaining transcripts using the preliminary codebook, developing the codebook iteratively as each transcript was coded. The second researcher (JS) then reviewed the coding and differences in opinion were discussed and reconciled between the coders. The final codes were organised into subthemes and themes and mapped to the adapted UTAUT constructs.[11] The qualitative process is reported according to the Consolidated criteria for Reporting Qualitative research checklist (online supplemental file 1).[16] Data were coded in Microsoft Office (Redmond, USA).

RESULTS

A total of 16 participants were interviewed, consisting of associate and senior consultants (n=9), a principal pharmacist (n=1), senior pharmacists (n=2), an advanced practice nurse (n=1), a nurse clinician (n=1) and senior staff nurses (n=2) (table 2).

Factors influencing technology adoption

A summary of the factors influencing technology adoption is mapped to the four UTUAT domains and the additional trust and risk perception domain in figure 1. Subsequently, further details on the influencing factors are discussed under each domain heading.

Table 2 Participant characteristics

Characteristic, n (%)	n=16
Females	11 (69)
Male	5 (31)
Age category, years	
21–30	4 (25)
31–40	10 (62)
41–50	2 (13)
Profession	
Doctor (specialties in gerontology, cardiology, rheumatology and general surgery)	9 (56)
Pharmacist	3 (19)
Nurse	4 (25)
Years of experience	
1–10 years	5 (31)
>10 years	11 (69)

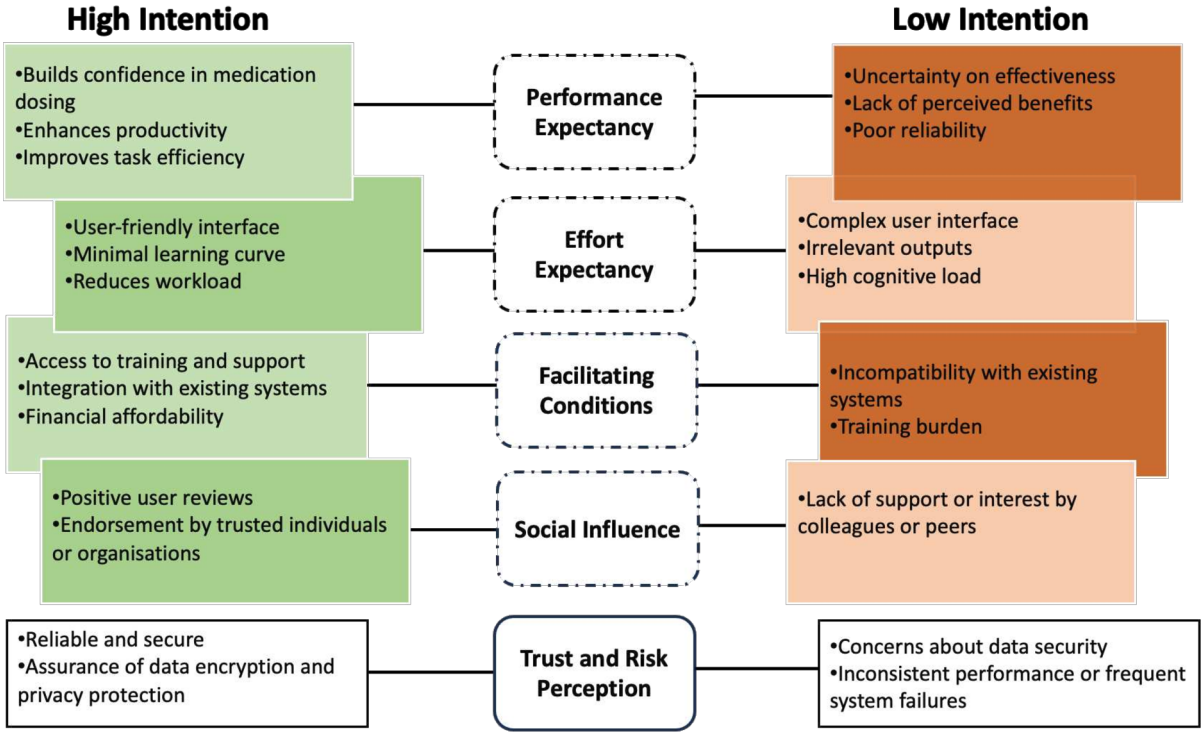

Figure 1 Summary of the key factors influencing low and high intention to use an artificial intelligence-enabled dosing decision tool, organised by the adapted Unified Theory of Acceptance and Use of Technology framework.

Domain 1: performance expectancy

Participants in the study offered diverse insights into the expected performance of AI-enabled dosing tools, emphasising that their effectiveness largely depends on the specific use case. Providers often operate under tight time constraints, an AI tool could play a crucial role in assisting with dosing decisions in this context, freeing up valuable time for clinicians to focus on other tasks. One participant reported, "I think maybe in polyclinics it might be helpful because the load is so fast and so high, and they only have a limited amount of time with each patient." [polyclinics refers to publicly run primary care centres] (Participant 09).

Some participants saw the tool as a virtual partner in care delivery. They likened it to having an on-call pharmacist or a decision-making assistant that could support clinicians and, in some cases, take over tasks traditionally performed by healthcare professionals. One shared, "AI can inform, maybe there is something abnormal in the liver function test and we should not increase the medication. So then the nurse can do that accordingly" (Participant 06).

Participants agreed that simpler cases, such as gout treatment or those seen in titration clinics (eg, anticoagulation) that have very structured dosing guidelines, were more suited for AI-enabled dosing tools. As noted by one participant, "I think simple cases does seem like a good way to start." (Participant 03). On the other hand, more complex cases, particularly involving elderly patients, were deemed too challenging for AI integration. Another participant remarked, *"In the elderly context… not sure about this AI thing." (Participant 08)*.

Another key theme was the potential for AI tools to improve safety and support better clinical practices. As exemplified by one participant, "It's like a psychic partner that you can have to actually, you know, make better informed choices in terms of prescribing for your patients" (Participant 02).

Additionally, participants foresaw benefits to gathering monitoring data when using the AI tool. One participant explained, "Actually to me, more data is always better because we can see the trends and treat better." (Participant 11). Another shared that patient education could also be beneficial, stating "But I think if the patients are engaged to do it for themselves it has another value of improving their self-management and self-efficacy." (Participant 01).

Domain 2: effort expectancy

Participants often emphasised the importance of system simplicity during discussions. It was deemed important to minimise the effort in using such tools and providing a user-friendly interface.

Some were uncertain as to how the tool would impact workload, with views ranging from scepticism that any benefit will be derived: "So I don't think it will reduce our load that much" (Participant 09) to belief that cognitive load could be reduced: "You know, AI is just to help you to deal with the multiple cognitive overloads." (Participant 13).

Overarchingly, the perceived impact on workload was highly dependent on how such a system would integrate with existing medical systems and workflows.

Computer-based alerts were identified by most participants as another potential source of increased effort. Interviewees discussed how excessive alerts lead to reduced responsiveness or 'alert fatigue'. As one participant shared, "We all get fatigue from the prompts." (Participant 13), while another reflected that some may see it as "Another thing that [they] need to check off the box." (Participant 07). These concerns highlight that appropriate set-up of alerts within EPIC software would be critical to ensure success.

Domain 3: facilitating conditions

Participants highlighted several key conditions necessary for the successful implementation of an AI-powered dosing decision tool. A strong emphasis was placed on data logistics, including the practicality of measuring and collecting diverse data types, the smooth integration of this data into electronic medical records, and the importance of timely data collection to ensure its usefulness. For example, one expressed "I think it's very rare to find patients that are diligent, uh, consistently diligent. [home monitoring]" (Participant 10). Another shared that certain conditions required more subjective assessment, making it hard to measure "What about things like behavioural management, that's very difficult to measure." (Participant 09).

Furthermore, institutional attitudes toward technological innovation and willingness to invest were identified as pivotal factors influencing technology implementation. One participant noted that "AH is a sandbox for trying new things." (Participant 02). However, uncertainties persisted regarding the cost implications of AI and how patients would be charged.

Finally, the availability and degree of training required were another facilitating condition that would influence implementation. As noted by one participant: "The amount of time it takes to train and understand should be less compared to the benefits." (Participant 13).

Domain 4: social Influence

Although there were varying degrees of acceptance, most anticipated that AI was an inevitability and expected they would need to work with it, as exemplified by one participant: "We are going to the future with a lot of AI assisting." (Participant 03).

Additional domain: trust and risk perception

Several reservations regarding AI-enabled dosing decisions were raised (figure 2). Participants shared that choosing the type and dose of medication is complex and requires skilled judgement, which may not be replicable with AI. Additional complexities, including variations in physician's dosing preferences, a lack of treatment guidelines, and the inability to account for 'human instinct' during dosing, were also discussed as challenges to an AI-enabled dosing decision tool.

If implemented, participants expressed a need for a comprehensive understanding of the system's functionality and the validation processes. Some suggested that elucidating the process behind dosing recommendations would foster trust and comprehension. Additionally, including human oversight was another critical factor in ensuring the system's safety; however, participants recognised that these steps alone wouldn't absolve liability concerns. They speculated on potential consequences if AI decisions were accepted or overridden, resulting in adverse outcomes. Other concerns encompassed the system's reliability, susceptibility to misuse and the risk of over-reliance impeding critical thinking.

Finally, from the patient's perspective, many felt that a clinician's use of an AI tool may negatively impact the clinician–patient relationship. For example, patients may question why they need to see a doctor if an AI tool is making the decisions, or they may lose confidence in a clinician's competence if the clinician depends on technology.

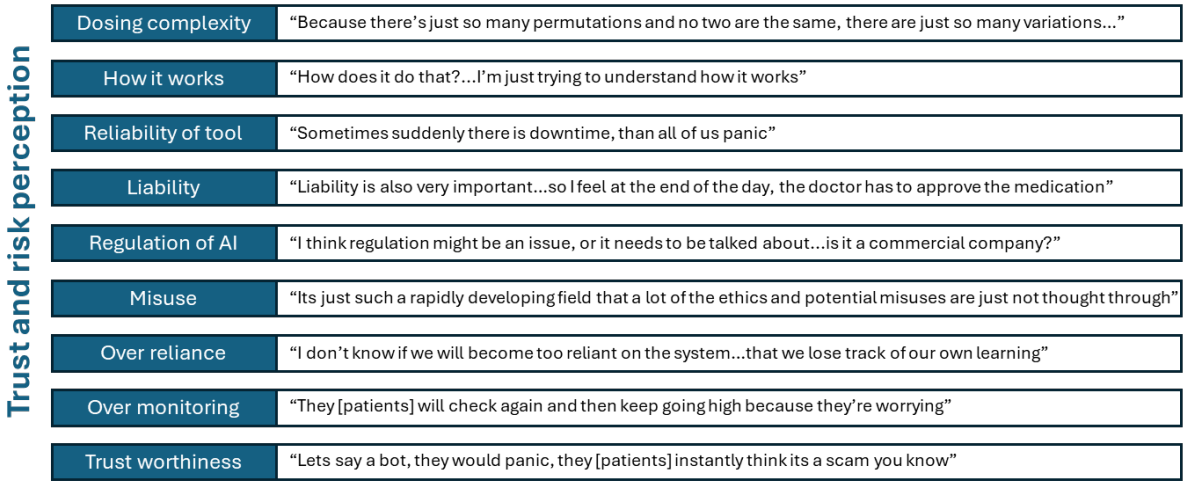

Figure 2 Examples of trust and risk perception factors influencing artificial intelligence (AI)-guided dosing use, organised by topic with example quotes.

DISCUSSION

Examining healthcare providers' perspectives on AI-based dosing tools reveals a mix of hopeful anticipation and recognised challenges. While healthcare providers acknowledge AI's potential to speed up decisions and enhance safety, they expressed concerns about AI's suitability for complex cases, erosion of critical thinking, liability protection and trust. Moreover, there was a prevailing emphasis on ensuring transparency and understandability of AI output and the need for human oversight to mitigate risks and promote acceptance. Although healthcare workers anticipate the integration of AI into healthcare, barriers remain. These findings underscore the importance of well-planned implementation and continuous evaluation to support adoption.

Participants expressed several expectations of AI, including saving time, supporting decision-making and improving safety by reducing blind spots and errors. Preliminary data suggest that AI-enabled decision support can generate such benefits,[17–19] but real-world implementation data are mixed. For instance, in radiology, AI integration into clinical workflows inconsistently impacts radiologists' performance and may lead to more errors.[20 21] Similar patterns may arise with AI dosing tools; thus, evaluating these systems in real-world scenarios is paramount. Another expectation was ease of use, including smooth integration with hospital systems. According to the Technology Acceptance Model, external factors such as system design are the first step in a three-stage process of influencing user behaviour.[22] While this finding is not novel, its consistent reporting in the literature underscores the importance of technology's ease of use to support adoption.[23]

Another insight from the participants was that the benefits of AI dosing tools would depend on the clinical context. Participants felt that AI might be more appropriate for simpler clinical cases rather than complex ones. This perception stems from concerns about AI's ability to consider the nuanced, intangible factors involved in complex dosing decisions. For example, doctors' subjective assessment of behavioural issues. Other factors, such as inconsistency in clinical practice due to a lack of clinical guidelines, the use of 'human' instinct in dosing and personal dosing preferences, are all difficult to embed in an AI system. These challenges might limit the widespread application of AI in clinical practice, raising concerns about AI's cost and overall value, a question already under debate.[24]

Concerns around trust, risk perception and liability were other prominent factors raised in interviews and widely debated in the literature.[25] Some feared that reliance on AI could diminish patient trust and critical thinking. Others questioned who would be accountable for errors from AI recommendations. Research into trust and AI is evolving, but factors such as transparency, reliability and social dynamics are thought to influence trust in these systems.[26] A holistic approach, including clear implementation plans, ongoing education and robust liability protections, is essential to foster confidence among healthcare professionals and ensure patient-centric care.[26] One promising solution is explainable AI models, such as Local Interpretable Model-Agnostic Explanations and SHapley Additive exPlanations, that could help healthcare professionals understand the rationale behind AI-generated recommendations and, in time, could improve trust and acceptance.[27–29] However, some caution that explainable models do not ensure true interpretability.[30] For instance, users may mistakenly assume that AI processes data such as humans do, leading to misinterpretation. These models may also oversimplify complex decisions; therefore, clinical complexities are uncaptured. Overall, more research is needed to ensure the reliability and effectiveness of explainable AI in clinical practice.[30]

While much research has focused on algorithm development and AI accuracy, our findings highlight the sociotechnical challenges and enablers of adoption. Our findings on clinical appropriateness, trust, explainability and workflow integration complement validation efforts and offer actionable guidance for developers and policymakers. Healthcare workers were generally open to tools that save time and improve safety, indicating readiness for adoption if systems are well designed and clinically relevant. However, they were wary of AI in complex clinical cases, questioning the trustworthiness of technology and accountability for errors. A phased rollout—starting with lower-risk clinical scenarios—may help build confidence and provide time to establish user guidelines. Finally, participants repeatedly stressed a need for transparency and ease of use. Involving users in the design process can improve the acceptability and relevance of technology.

Future work should focus on real-world implementation evaluations, capturing stakeholder experience, patient outcomes and workflow impacts. Furthermore, understanding different user experiences will clarify what supports or hinders adoption. Capturing patient perspectives is especially important to ensure these tools align with patient-centred care. Finally, improving AI explainability will build clinical trust through transparent decision-making.

Strengths and limitations

We conducted in-depth interviews with a diverse cohort of healthcare providers; however, we recruited participants from a single centre, which may limit generalisability. Selection bias is also feasible, with participants who are more technologically minded agreeing to be interviewed. Finally, we cannot rule out the influence of researcher bias. We reduced this risk by using a standardised topic guide during interviews and through regular coding discussions to ensure the reflection of participants' views.

CONCLUSIONS

Our study highlights the hopeful anticipation and complex challenges of introducing AI-enabled dosing decision

tools into clinical practice. While addressing concerns like data adequacy, applicability across clinical scenarios and usability, it is equally vital to acknowledge and respond to healthcare workers' apprehensions regarding AI's interpretability and integration. As AI-guided systems inevitably become a part of healthcare's future, real-world clinical evaluation is essential to demonstrate effectiveness and value and to foster acceptance.

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Competing interests DH (a coauthor) is a founder of KYAN Therapeutics, which is commercialising AI-based platforms. DH is also a coinventor of current and pending intellectual property filings pertaining to AI. All other authors report no conflicts of interest.

Patient consent for publication Not applicable.

Ethics approval This study involves human participant. Ethical approval was obtained from the National Healthcare Group, Domain Specific Review Board (NHG, DSRB 2019/01212). Participants gave informed consent to participate in the study before taking part.

Provenance and peer review Not commissioned; externally peer reviewed.

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