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Research article

AI in patient flow: applications of artificial intelligence to improve patient flow in NHS acute mental health inpatient units

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ABSTRACT

Introduction: Growing demand for mental health services, coupled with funding and resource limitations, creates an opportunity for novel technological solutions including artificial intelligence (AI). This study aims to identify issues in patient flow on mental health units and align them with potential AI solutions, ultimately devising a model for their integration at service level.

Method: Following a narrative literature review and pilot interview, 20 semi-structured interviews were conducted with AI and mental health experts. Thematic analysis was then used to analyse and synthesise gathered data and construct an enhanced model.

Results: Predictive variables for length-of-stay and readmission rate are not consistent in the literature. There are, however, common themes in patient flow issues. An analysis identified several potential areas for AI-enhanced patient flow. Firstly, AI could improve patient flow by streamlining administrative tasks and optimising allocation of resources. Secondly, real-time data analytics systems could support clinician decision-making in triage, discharge, diagnosis and treatment stages. Finally, longer-term, development of solutions such as digital phenotyping could help transform mental health care to a more preventative, personalised model.

Conclusions: Recommendations were formulated for NHS trusts open to adopting AI patient flow enhancements. Although AI offers many promising use-cases, greater collaborative investment and infrastructure are needed to deliver clinically validated improvements. Concerns around data-use, regulation and transparency remain, and hospitals must continue to balance guidelines with stakeholder priorities. Further research is needed to connect existing case studies and develop a framework for their evaluation.

1. Introduction

Due to rising costs and demand, healthcare services face significant challenges in improving care quality in a resource-efficient manner. Mental health illnesses are the second largest strain on healthcare resources in the UK as they are more prevalent and chronic than other illnesses [1]. The clinical management of mental health disorders has unique challenges. As the underlying causes and mechanisms of mental health disorders are not yet fully understood, prevention, diagnosis and treatment are not always accurate and effective. Assessments are often broad [2] as symptoms are not straightforward and overlap across multiple conditions [3]. The complex and often chronic nature of these conditions requires personalisation of care plans and a degree of flexibility [4]. A patient's subjective experience also affects their recovery and by extension influences treatment efficacy [5]. As a result, treatments that prove successful for one patient might not for another [6]. The challenges presented by the nature of mental health conditions are magnified by systemic inefficiencies such as staff shortages, service fragmentation and underfunding leading to suboptimal patient care [7].

Patient flow management is an integral part of healthcare. Patient flow can be defined as 'the ability of healthcare systems to manage patients effectively and with minimal delays as they move through stages of care' [8] with quality and patient satisfaction maintained throughout. With this growing demand for services in contrast to limited resources, the concept of focusing on patient flow to improve care has received increasing interest, 'especially in relation to reductions in patient waiting

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times for emergency and elective care' [1]. Poor patient flow has been shown to negatively affect patients, staff, and the overall quality of care [9]. Consequences of this include not meeting patients' individual needs [10] and overstretching staff which can lead to increases in medical errors, readmissions [11], dissatisfaction, prolonged patient length of stay (LOS) and worse health outcomes [12]. On the other hand, efficient patient flow alleviates the burden on staff, thus improving clinical safety and patient outcomes [8].

NHS Improvement (NHSI) has published various tools [13, 14] and reports to support care providers with patient flow such as "SAFER" [15], a practical tool to reduce delays in adult inpatient units, commonly used alongside "Red2Green Bed Days" [16]: a visual management system used to identify the time wasted and LOS during a patient's journey [8]. Although these traditional methods are useful, patients on mental health units still have a significant number of red days, with bed occupancy as high as 95%. There is also a large variation in the average LOS between hospitals, even for patients with similar illnesses. According to the 2018 census, the LOS in acute mental health units averaged 36 days [17].

This study focuses on the patient flow on inpatient mental health units, which provide care to patients with acute psychiatric illness. Inpatient admission has become increasingly reserved for treating severe mental illnesses (SMI) - an umbrella term encompassing schizophrenia, bipolar disorder, severe depressive disorder and psychotic disorders [18]. Whilst this study focuses on NHS related patient flow issues, generalisations can be drawn to other populations and global health systems. In particular, the solutions discussed can be considered in the context of other population and nation specific health needs.

Technological solutions such as AI are increasingly applied to healthcare settings, including purposes associated with patient flow. Medical data has been increasing in volume and complexity, exceeding the capabilities of current healthcare systems and professionals to extract all information in a meaningful way [19]. Personal health data now includes anything from demographics and medical notes to information generated from wearables or genetics testing. Moreover, vast amounts of medical data are progressively becoming digitised, with electronic health records (EHRs) being the most common investment within the global health information technology market [20]. AI is a disruptive pattern-recognition technology that can perform cognitive functions, such as problem-solving, decision-making and object recognition [21]. Machine Learning (ML), a commonly used type of AI, employs advanced statistical and probabilistic techniques to learn from data [22]. Table 1 explains the key terms used throughout this study. There are many possible general areas of AI implementation in healthcare (Figure 1). AI can could assist us in analysing medical information, with implications on improvements in clinical outcomes, as well as cost reductions, and advancements in research [23]. The possibilities for data-driven solutions in mental health are broad. AI presents opportunities to advance the understanding of the causes of mental health illness, improve detection and diagnosis, develop risk-based approaches, enhance decisions and help redesign services around the needs of patients [24].

The problems in patient flow and the need for improvement in mental health units have been identified in literature. Similarly, a significant amount of work has been put into investigating opportunities for AI in mental health or patient flow separately. However, little research has been done to explore applications of AI on mental health inpatient units to improve patient flow, showing an unexplored potential in this area.

1.1. Research aim

This paper aimed to devise a theoretical map showing the use of AI to improve patient flow in NHS acute mental health inpatient units and formulate recommendations for mental health trusts.

To achieve this aim, the following objectives were met:

1) Construct a map showing a visual overview of patient flow in acute mental health inpatient units.
2) Identify issues in the patient flow of acute mental health inpatient units.
3) Identify AI solutions that can be used to improve patient flow.
4) Establish which AI solutions could be implemented to improve the patient flow problems identified in mental health inpatient units.

2. Methods

The methodology of this study consists of a narrative literature review (NLR), interviews with mental health and AI experts followed by a thematic analysis. This study is a mono-method study that takes an inductive approach, seeking to enhance understanding of the subject matter of patient flow rather than to directly quantify it [25].

An NLR was conducted to synthesise relevant background knowledge and inform subsequent data collection. The NLR was subdivided into mental health (and related patient flow issues) and AI (and related potential solutions). The literature search was conducted in March 2020 to look for relevant publications from the last five years. OVID was used as the primary search engine to access Embase, Medline and HMIC. The selection of studies was based on the topic relevance, quality of the study and the inclusion criteria. Selection bias was limited by strict inclusion and exclusion criteria.

Semi-structured interviews with relevant experts were conducted after the NLR to collect qualitative data. Careful selection of participants is key to the success of inductive research [25] and as such, purposive sampling was adopted to ensure deliberate recruitment of experts [26]. A pilot interview with a management consultant, with experience in both AI and healthcare systems, was used to validate the interview structure and study design. Experts were recruited through various methods: LinkedIn, personal contacts, referrals, and the Imperial Alumni Network. Snowball sampling was used as interviewees were used to identify other potential interviewees [27]. AI experts were screened to ensure that they had proficient knowledge about AI along with specific knowledge of its healthcare applications. A list of core questions was developed based on the research objectives and literature review findings. Questions were designed to be open and non-leading, considering Kvale's [28] nine question types, and the semi-structured approach allowed flexibility to expand the scope of questioning according to concepts uncovered in previous conversations.

Table 1. Explanation of the key subtypes of Artificial Intelligence.

Machine Learning (ML)	A type of AI in which the system learns and improves with experience without having specified rules. Supervised learning is when the algorithm learns from the training dataset (e.g. Support Vector Machines (SVM), Random Forest (RF)) while unsupervised learning discovers the underlying information and patterns about data (e.g. clustering). The inputs and outputs are known in the supervised learning but only inputs are known in unsupervised [26]. Deep Learning has a neural network architecture (the most popular being a convolutional neural network (CNN)) that learns from multiple layers of data and is often compared to the human neuronal system [27]. These ML systems can learn and make predictions from datasets [28].
Natural language processing (NLP)	NLP organises unstructured text into structured, valuable text that is interpreted by a machine to extract information [29]. The basic function is to understand and analyse human language, examples include text prediction or information extraction [30]

Figure 1. General possibilities for AI in healthcare.

Interviews were recorded and individually transcribed. Transcripts were reviewed and coded using thematic analysis [29, 30]. Data analysis began during the interview period, as is common in qualitative research, enabling a process of iterative improvement [31] and progressive focusing [32].

Thematic analysis enabled the summarising of key features of the data and construction of a clear and structured report [29] and it is especially suited to applied healthcare research [30]. In line with our approach, data driven code generation (open-coding) was the first step in which interview transcripts were split amongst researchers and reviewed independently. The second stage, axial-coding, involved finding relationships and connecting codes. Finally, selective-coding allowed for the identification of high-level principal themes (Figure 2).

The proposed patient flow map augmented with AI solutions was formulated by analysing the knowledge acquired from the literature and interviews. Recommendations formulated for the use of AI to improve patient flow in mental health inpatient units were developed through a pragmatic approach, ensuring they are both feasible and beneficial, using knowledge gained throughout the research. Figure 3 summarises the methods used in this research project.

This study was granted ethical approval through the Integrated Application System, audited by the Imperial College Research Ethics Committee (Appendix A).

3. Results

3.1. Synopsis of the literature review - mental health

The literature search for studies done on the topic of patient flow in mental health inpatient units revealed 18,055 studies of which 72 were included in the final review using strict inclusion and exclusion criteria (Table 2). The literature provides a muddle of conflicting arguments around factors affecting patient flow and of those there are only a few shown to be significant in predicting how a patient will interact with inpatient mental health services.

The literature looking at patient flow in mental health were categorised with respect to the factors they identified as important to length of stay (LOS), service delivery, and risk of readmission (ROR), and their corresponding impact on patient flow. Any factors found to be of good predictive value were highlighted separately.

Within LOS, patient disease factors such as psychosis [33], and global assessment of functioning (an assessment of the severity of one's mental illness and how the symptoms may affect one's day to day activities) [34] were reported as important. With regards to demographics, age and gender were the biggest points of contention. A robust retrospective study concluded that age was not protective against increased LOS [35].

Regarding service delivery, there is some consensus with discharge-delaying factors, chiefly the arrangement of aftercare [36, 37]. However, there has been no literature published since to confirm this. In 2014, a

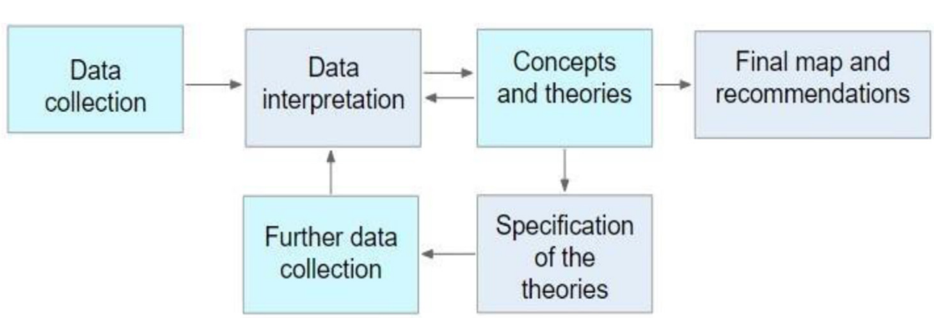

Figure 2. Steps taken to construct a theoretical map and recommendations.

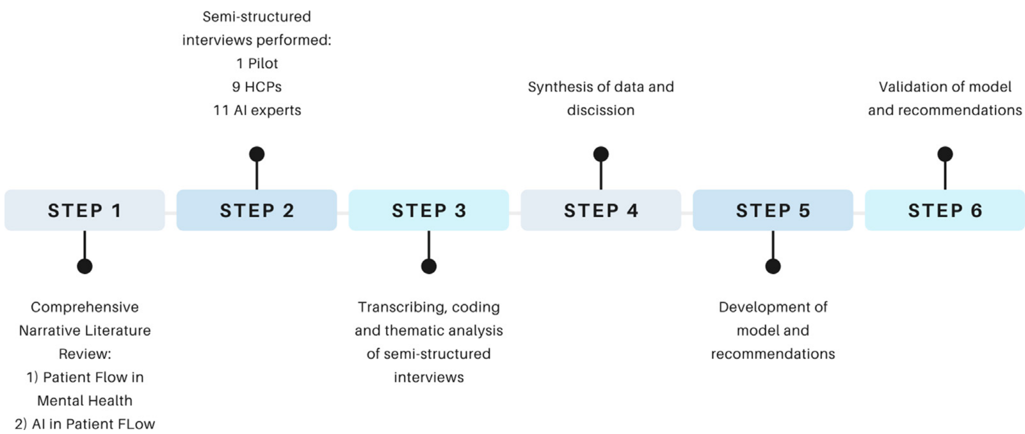

Figure 3. Summary of methods used in this study.

Table 2. The inclusion and exclusion criteria used for the mental health literature review.

Criteria type	Specification of the Inclusion Criteria	Specification of the Exclusion Criteria
Timeframe	last 10 years (2010–2020), articles older than 10 years for original source of data used in a newer study.	more than 10 year old (older than 2010)
Topic	Articles about the patient flow in mental health inpatient units (hospitalisation within a mental health context), articles on mental health patient characteristics, articles about mental health length of stay, articles about mental health readmission	Does not include patient flow, not a mental health inpatient setting (eg. community, social care), articles on patient flow unrelated to mental health, papers insurance based services, patient flow or patient length of stay or hospitalisation in the context of another department/service other than mental health inpatients
Type	qualitative and quantitative	Not published in a peer-reviewed journal
Journal	published in a peer-reviewed journal	articles not contributing any original work
Language	articles written in English	articles written in other languages than English
Availability	articles fully available through Imperial College London via institutional login	articles not fully available through Imperial College London via institutional login

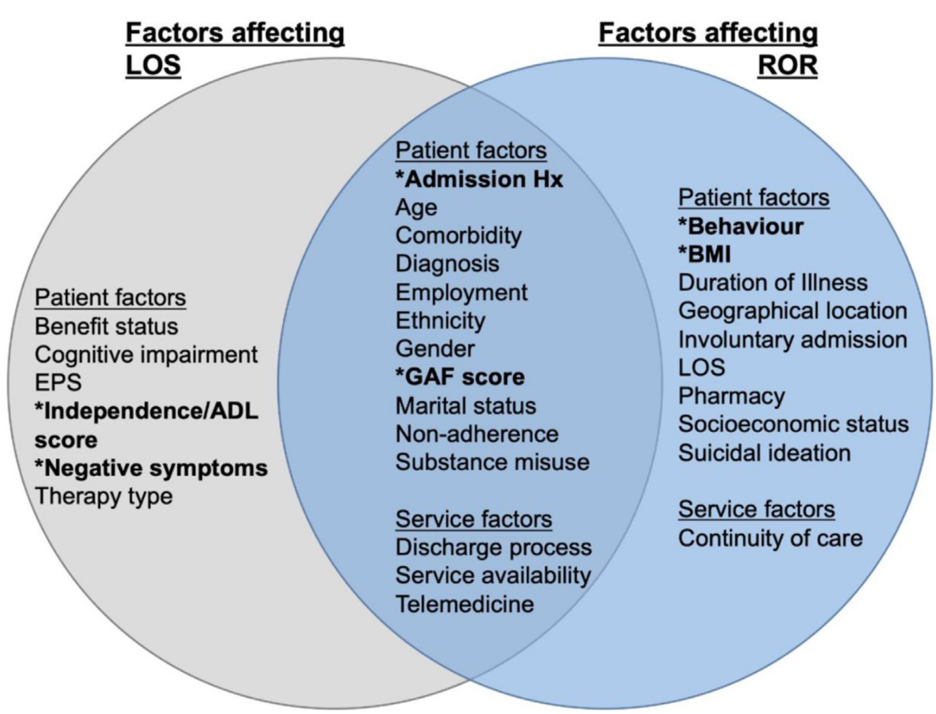

Figure 4. A venn diagram summarising the key factors identified. Those bolded with an ***asterisk** denotes validity as a predictor.

Table 3. Inclusion and exclusion criteria used in the AI literature review.

Criteria type	Specification of the Inclusion Criteria	Specification of the Exclusion Criteria
Timeframe	last 5 years (2015–2020)	more than 5 year old (older than 2015)
Topic	articles speaking about AI in patient flow or mental health/psychiatry or both, studies that evaluated the AI	doesn't include AI, not a clinical setting (eg. schools, community), mental health apps and other digital solutions that do not use AI, articles on AI unrelated to patient flow or mental health
Type	qualitative and quantitative	Not published in a peer-reviewed journal
Journal	published in a peer-reviewed journal	articles not contributing any original work
Language	articles written in English	articles written in other languages than English
Availability	articles fully available through Imperial College London via institutional login	articles not fully available through Imperial College London via institutional login (eg. conference abstracts)

small study (n = 62) by Southard, Neufeld & Laws found that telemedicine services reduced LOS significantly ($p < 0.001$).

Consistency was found in the reporting of history of previous admissions [36,38,39,], psychotic illness [36], and substance misuse [34, 40, 41, 42] as factors increasing a patient's ROR. The key factors identified in both LOS and ROR are outlined in Figure 4, bolded with an asterisk denotes its significance as a predictor. For a more comprehensive review, refer to Appendix B.

3.2. Synopsis of the literature review - AI

An NLR was also conducted to investigate the current use of AI for mental health patients in hospital settings and the use of AI in improving patient flow across departments [43]. 3,675 papers were identified and 75 were included in the final review using strict inclusion and exclusion criteria (Table 3). The number of papers specifically targeting the use of AI for patient flow in mental health units was limited.

The studies that looked into the use of AI for mental health have been categorised into three areas: diagnosis, prognosis and treatment and although a variety of outcomes were used, the impact of AI on patient flow was rarely measured in those studies. Some studies focused on developing triage and screening tools [44, 45, 46]. AI has also been applied to enhance our understanding of diseases [47], improve diagnostic accuracy [48], and even enable new diagnostic methods including novel biomarkers, such as DNA methylation [49]. In the field of prognosis, AI was used to improve accuracy and personalisation of predicting long-term outcomes such as severity [50] relapse, progression [51], and quality of life. For example Kautzky et al. [52] used 47 clinical and sociodemographic factors to predict treatment resistant depression using RF and 10-fold cross-validation (75% accuracy). Common methods in design of the predictive tools included analysis of EHRs [53] self-reported questionnaires [54] and hospital notes. For example, McCoy et. al. [55] used NLP to extract signs of sentiment from hospital discharge forms and found that it correlated with readmission and mortality risks.

Studies on AI in therapy aim to enhance decisions and personalise interventions to maximise likelihood of recovery and allocate resources efficiently. Most widely researched conditions include depression [56], bipolar disorders [57], schizophrenia [58] and substance misuse disorders [59]. For example, Koutsouleris et al. [60] used pre-treatment patient data to predict psychosis outcomes after 12 and 52 weeks with 75% and 73.8% accuracy respectively. Researchers were able to predict the risk of symptom persistence, non-adherence to treatment, readmission to hospital, and poor quality of life using factors such as unemployment, poor education, functional deficits, and more.

The review on using AI in patient flow revealed that so far, research has been done mostly in the emergency department setting, where AI is often used to predict various patient flow variables such as bed occupancy and rate of readmission [61, 62, 63]. The researchers aimed to utilise AI for efficient resource allocations, preventing avoidable admissions, reducing variation in LOS, and improving discharge [64]. Although some studies have already shown the potential of AI to improve patient flow, those solutions have not been investigated enough for use in mental health inpatient units.

There are however limitations of those studies and challenges in AI implementation. Although promising, many studies have limited generalisability and lack validations on large, external samples or fail to prove any impact on clinical outcomes [44]. Moreover, a lack of clear regulations and guidelines complicates development of AI models for healthcare [64] and can lead to ethical issues [65]. Implementation of a new technology may come at a great monetary cost and a great time disruption for health providers [66]. For a more comprehensive review, refer to Appendix C.

3.3. Interviews results

Thematic satiation was achieved as a total of 20 experts were recruited [67]: 9 mental health healthcare practitioners (HCPs) and 11 AI experts. One mental health interviewee was excluded based on their bias towards paediatric mental health. From the 8 mental health interviews, 247 codes were generated which were then sub-categorised into 45 components and 18 sub-themes. After data reduction, six themes were finalised (Table 4). From the 11 AI experts interviewed, 197 codes emerged from discussions. The codes were then sub-categorised into 33 components revealing 11 sub-themes and after data reduction, 5 themes were finalised (Table 5). The full description of results can be found in Appendix D, E and F.

3.3.1. Mental health interviews thematic analysis results

Interviewees broke the definition of patient flow into two categories. Firstly, the patient journey from the identification of a patient in the community followed through to discharge, and secondly, as an outcome metric that can be used for reductions in rate of readmission and LOS. Admissions to mental health inpatient units are either made voluntarily or involuntarily which is usually followed by assessments/triaging and diagnosis (where appropriate). Alternative treatment routes outside hospital admissions include intensive community support and home treatment. Problems identified with the pathways of patient flow included the use of the nursing model and community treatment order pathway which resulted in a shift in responsibility away from a traditionally doctor-led approach. The consultant model, nurse model, and stepwise model were identified as potential models of patient flow. There are merits of each, however inconsistent use of all three causes confusion and a lack of continuity of care. Measuring LOS as a patient flow metric was identified as unsuitable as it does not account for patient mix, and certain conditions can skew national benchmarks. Interviewees suggested it would be better to devise metrics around the delayed transfer of care. Staff shortages and risk aversion were uncovered as a main barrier to treatment leading to increased waiting times, reduced continuity of care, and adverse decision making which were related to problems in inpatient systems and services. Lack of funding has impacted both the inpatient and community care system resulting in an inappropriate skill mix, premature discharge, substance misuse, non-adherence, family

Table 4. Themes, subthemes and components extracted from the mental health expert interview thematic analysis.

Theme	Subtheme	Component	Example Quote
Current mental-health inpatient service and patient flow model	Structure and design	Care models used	"So it's starting with, like the emergency department or if people come in voluntarily or their sanction or through AMPs, and then they're triage and then if they've been decided to be admitted, they go through. If they've not been diagnosed, they go through diagnosis and prognosis. And then during the discharge, they have therapy, they allocate the beds, either on I believe there's multiple wards, so it can be acute, it could be a day Ward or it could be forensic Ward's."
		Service pathways	
		Key pathways	
	Patient flow	Definition	
		Institutionalisation	
		Revolving door phenomenon	
		Measuring/tracking	
		Important factors to consider	
Patient factors	Clinical Characteristics	Disease pattern	"I mean crisis presentations are mainly for people who have got personality disorder, patient with emotionally unstable personality disorder, with alcohol or substance misuse, they have got a history of self harm and have quite chaotic lifestyles. And so they get into crisis, a lot more. So most of the crisis, present presentations really to A&Es is people with personality disorder and substance misuse together. Those are the ones that keep presenting in crises."
		Impact of substance misuse	
		Adult comorbidities	
		Impact of patient disease of specific diagnosis	
	Patient characteristics and patient flow	Demographics affecting length of stay	
		Socio-economics affecting length of stay	
		Lifestyle factors affecting length of stay	
		Family effects on length of stay	
Problems with social care	Funding	Funding affecting social care	"I think it's really involvement of families really quite crucial when discharging patients as well. So involving families from quite early on that I mean, I think in London we struggle to there's many patients and families involved in patient care because quite often patients don't have, or they move away from families and have limited resources. But I think that's really good help if families are involved from early on when you're looking at inpatient discharge plans"
	Rehab	Availability of rehab	
	Community care delivery	Social/service workers/Family	
		Lack of care packages	
	Housing	Problems finding housing	
		Supported housing is a good investment	
Problems with clinical management	Problems with inpatient motioning	Scales for monitoring patients	"The problem with those rating scales is that if you do not do it yourself, different people do it. You can score it differently, because it's subjective. Yeah. They're not necessarily sensitive to change so quickly. So the rating scale used does not really work that way, but it's not sensitive to change especially quickly."
	Poor discharge planning	Early discharge increases rate of relapse	
		Reasons for poor discharge planning	
	Patient medical management problems	Treatment/therapy issues	
		Problems associated with comorbidity	
	Ward environmental problems /impact	Ward ambiance/atmosphere	
		Structural design	
	Clinical decision making and risks	Supportive housing is a good investment	
		Diagnostic challenges	
		Problems with clinical decision-making process	
		Clinical risk-taking impacting patient flow	
Problems with inpatient service and system	Lack of resources	Shortage of staff impact care	"Good patient flow means you've actually addressed those things but there is another side of patient flow which is about quality rather than speed. Literally just discharging someone the next day you may not achieve your target so then they might have to ... have a lot of risks and disabilities ongoing they might have to family they might've been a burden on the community they might come back in straight away to hospital."
		Lack of funding/services	
		Implications of bed usage/lack of availability	
	Patient record keeping	Use of patient notes	
		Records and information sharing	

(*continued on next page*)

Table 4 (*continued*)

Theme	Subtheme	Component	Example Quote
Mental health expert solutions	Service driven changes	Training	“You could look at a little bit more intrinsic in particular ward flow, length of stay and then match up, are there, is there a particular reason that there's a particular ward that's doing worse. They got less staffing, they got so you can pop all the get all that data maybe just for certain, can find a certain almost a handicap that some wards might have, it might be one ward that sector that they refer from, that's the sector that includes kind of hostels or, lots of places where there's a high rate of substance misuse, something like that. So you can just get some adjustments, so its like for like. And sync up the performances, erm, kind of different types of units and you could all so maybe get the prescribing patterns and I think a lot of consultants would feel monitored if you ask them how often they come to the ward or, that's the difficult part, the prescribe is easier to look at, because pharmacies and electronic prescribing would be useful.”
		Service design	
		Alternative clinical management approaches	
	Data/Tech driven	Data sources	
		Clinical decision support solutions	
		Operational solutions	

inability to cope, and subsequent readmission (described by the revolving door phenomenon). In inpatient mental health units, there is a severe shortage of beds, whilst in the community it can take up to 6 weeks to assign a social worker to a patient, resulting in delayed transfer of care. EHRs received mixed reviews from the mental health experts, however, a lack of integration was consistently reported as a barrier to information sharing. In addition, it was also found that doctors inconsistently both read and make notes, often not having access to them when needed. Interviewees highlighted the potential of AI solutions in predicting treatment responses, discharge date, and risk stratification. Opportunities also exist for AI to standardise diagnosis and enhance quality of administrative tasks, and for dictation softwares to reduce the time spent transcribing notes.

3.3.2. AI interviews thematic analysis results

Interviewees placed great emphasis on the need for large, clean data sets. EHRs were highlighted as a good data source however their main issue is their unstructured nature. Experts offered multiple solutions including predictive solutions (patient and back-end related), automation of tasks, diagnosis, therapy. and monitoring solutions. Successful implementation of AI would create value for four stakeholders: clinicians, patients, hospital trusts, and the NHS as a whole. Interviewees emphasised the importance that AI should be created as an assistive rather than a decisive tool. AI solutions need to be accessible and user friendly to encourage the uptake by HCPs. Additionally, AI can prevent avoidable mistakes from occurring due to human error and can also free up doctors' time from doing administrative work. Despite the promise, existing AI tools are far from perfect; interviewees pointed out three major challenges that AI models face: technical, regulatory, and humanistic. AI will take time and investment to reach a point of scalable integration with clinical services and requires significant supportive infrastructure upgrades across NHS organisations and additional training. AI regulation in healthcare is still underdeveloped and is yet to be perfected, and factors such as lack of trust and risk aversion can impede the adoption of AI.

4. Discussion

A general mental health patient flow map (Figure 5) was constructed using the information gathered from the literature review and expert interviews. This was then enhanced by mapping the solutions, uncovered in the literature review and interviews, onto the problem areas of patient flow, revealed in the literature review and interviews, to create Figure 6. A summary of all the discussion points can be found in Table 6.

4.1. Clinical decision support

The clinical management of patients on mental health wards has proven to be a significant challenge affecting patient flow. The overarching problems included slow and inaccurate decision making, inadequate availability of the right information at the right time, and an inability to target interventions to individuals’ needs. Although all those issues are interconnected, there are three main stages which were identified as crucial points to ensure smooth patient flow: assessment, treatment, and discharge.

4.1.1. Assessment

4.1.1.1. Triage. During triage, HCPs make decisions about discharge and admission based on their assessment of patients' needs and the medical resources available [68]. Clinicians need to take patient factors into consideration when deciding what the patient's needs are (both medically and socially) and whether patients are at risk to themselves, others or from others. The patient's needs will then need to be balanced with clinical capacity: what services can be provided for the patient and where

Table 5. Themes, subthemes and components extrapolated from the AI expert interview thematic analysis.

Theme	Subtheme	Component	Quote
AI Definition	Machine learning	NA	"AI would be something that uses some sort of machine learning, or monitors to gain insights into data that you wouldn't normally be able to gain from basic systems. I think it makes more sense to be talking about machine learning predominantly, because the techniques that you're talking about in terms of analysing workflows and that sort of thing. It will be machine learning based, and it's somewhat useful to stick to a particular term."
	Blackbox	NA	
	Natural language processing	NA	
Data	Patient	Structure	"The thing with psychiatry, the electronic patient record is like maybe arguably even more messy than in the electronic patient record of non psychiatric. There's even within electronic health records, you have a lot of unstructured data. So even the fact that you have an electronic record doesn't necessarily mean that it's useful."
		Collection	
	Source	NA	
Solutions	Automation	NA	"[You can] passively collect data from the patient's mobile phone, and [wearables], health trackers... and associate [data] like levels of physical activity, levels of social engagement (for instance, do they exchange lots of messages with their friends and family levels of use of different applications on the phone like social media apps,...), and then correlate those with the mood metrics. So it could be possible to monitor a patient passively without requiring any active [patient] effort and be able to determine when something's changing in their mental health state. By observing the patient's behaviour, we can identify changes in that can be indicative of something that requires help. And you could give them a much more lightweight intervention (for example) just remind them of an exercise they're supposed to do when they're having difficulties."
	Predictions (patient-related)	Prognosis prediction	
		Risk stratification	
	Human	Community monitoring	
		Digital Phenotyping	
		Monitoring patient progress	
	Therapy	Chat box	
		Personalised therapy	
		Engagement & Adherence prediction	
	Diagnosis	Audio/video diagnosis	
		Imaging biomarkers	
		Genetics biomarkers	
		Diagnostic decision support	
	Predictions (workflow related)	Length of stay prediction	
		Real time analytics	
		Decision support	
		Demand & Capacity planning	
		Discharge planning tools	
Challenges	Human	Scepticism about AI	"I think if you're looking at something that's going to be implemented in the real world and be useful, then external validation is very important. And there's a well documented decrease in the kind of performance of studies when you kind of move outside of the initial testing environment. So is important to show that does work in order to then be implemented. And there's a technical job or challenges with that, then there's the aspects of actually implementing that into healthcare and implementing that in a way that leads to proven clinical performance, and the importance of validating that with prospective clinical trials."
		Fear of being replaced	
		Supply-induced demand	
	Technical	Lack of validation	
		Technological limits	
		Lack of feasible data	
	Regulatory	Lack of guidelines	
		Ethics & Confidentiality	
	Operational & Logistics	Costs	
		Incoherence between trusts	
		Long implementation	
Implementation	Benefits	NA	"[AI model could] analyse written notes and provide some sort of kind of diagnostic support. The potential there is that you might have somebody who's maybe not that experienced, but they've picked up certain objective symptoms, and they reported them, they put together the clues to make that diagnosis."
	Stakeholders	HCPs	
		Patient	
		NHS	

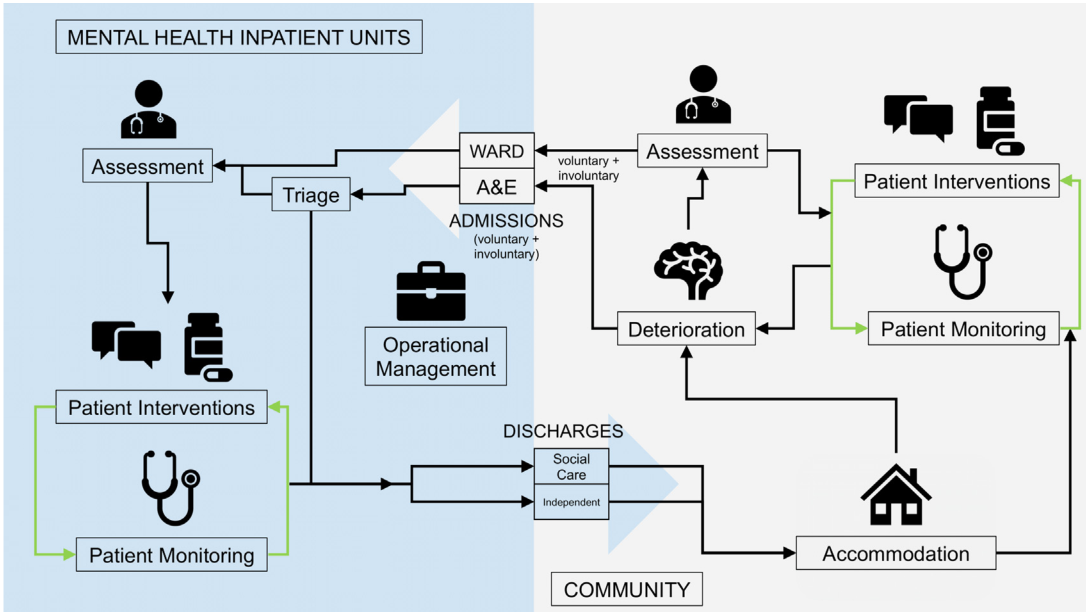

Figure 5. A map of the patient flow in a general mental health unit.

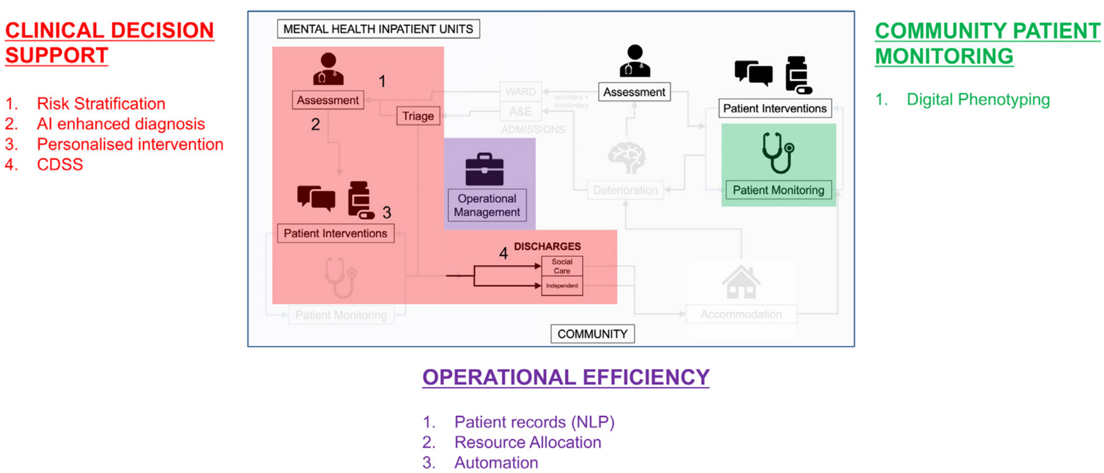

Figure 6. A map of the patient flow in a general mental health unit with possible areas enhanced with AI solutions.

the services can be best utilised [68]. Currently, triage is based on grouping patients by risk ("red, amber, green") and thus it's limited to a clinician's judgement and ability to associate the factors they know about the patient. According to the interviewers, while the current triage system is useful for risk-stratifying patients, decisions are often subjective and it can lead to admitting "low risk" patients who may be better managed in the community. Inappropriate admissions cause bed blocking [36]. The challenge in effective triage stems from the variability of mental health presentations. Patients who present with the same condition or even the same symptoms, often differ significantly based on their combination of personal factors, meaning they have different needs, risks, and prognoses and thus should be managed according to their personal circumstances. Patient demographics, medical history, social background, and substance misuse, amongst other factors, impact LOS, risk of relapse, readmission, and recovery [36, 40, 42, 69]. Interventions which are tailored to an individual patient's risk profile, can improve health outcomes [70]. AI's ability to process, connect and make conclusions from large amounts of data, can be used to risk-stratify patients according to their personal factors and needs. As highlighted in interviews and research [71], data-driven technologies can uncover correlations humans cannot, [71] and may thus be able to improve risk modelling of patients in ways we do not currently understand. As explained in the literature review, pre-diagnosis AI solutions have been shown to accurately differentiate low risk from high risk patients [72] even from self-reported screenings [45]. Patients could be asked to fill in a survey (e.g. using a digital chatbot), which may help reduce stigma as some patients are more likely to disclose personal details to AI-powered 'conversational assistants rather than to an actual clinician' [73]. Data from those can be linked with EHRs to provide scores for HCPs, which can be used in conjunction with the mental health stepped-care approach for deciding on a care pathway. Foley & Woollard [74] report that AI triage models could not only suggest the right intervention but also the right sequence of interventions. Low risk patients can be directed to other services or self-care, reducing the number of patients who need to be admitted. Those at high risk can be streamlined to interventions, as receiving care in a timely manner is essential in mental health, and such systems have already been modelled for psychosis [75]. These systems would provide timely information to the triage team (e.g. nurses, juniors) who will be responsible for the ultimate decision. Although it is not necessary to build the system around self-reported questionnaires, if it is, it's important to note that it would be dependent on patients' willingness to fill them in truthfully. Moreover, the value of the triaging solutions

Table 6. Summary of the important points highlighted in the discussion of the paper.

	Part of patient flow	Problem	Solution category	Solution details	The potential impact on patient flow
Patient clinical management	Triage	1. Current models for risk stratification for patients (e.g. "red, amber, green") are nonspecific and clinically subjective 2. Some personal factors may be difficult to illicit at triage due to time constraints or stigma about their private nature 3. Due to personal factors, mental health patients' clinical needs vary, even in those with similar conditions or presentations	Clinical decision support	1. AI's ability to process large amounts of data could enable the development of more accurate and objective models of patient risk. This would improve triage outcomes and reduce clinician-related variance 2. Automated systems (e.g. surveys/ chatbots) could save time and depersonalise collection of data, enabling a fuller understanding of the clinical picture to base decisions on 3. AI enhancements could change the nature of triage; becoming not only a broad risk assessment but also a highly specific clinical front-end, initiating intervention pathways to personally suit the patient	• Reduced admission load by filtering out low-risk patients who can be signposted to alternative care pathways, while targeting those with urgent or complex needs with earlier assessment and intervention • Improved front-end triage may allow faster transition to correct management pathways, leading to faster recovery andshorter LOS
	Diagnosis	1. Misdiagnosis is common and complicates later management 2. Subjective, slow decision making causes delays in treatment, especially when senior clinicians are unavailable e.g. weekends 3. Lack of clarity in disease classification e.g. distinct biomarkers. Mental health symptoms and conditions overlap which can impede progress through service pathways		1. Advanced diagnostic classification based on combinations of neuroimaging, blood samples and behavioural patterns could improve diagnostic accuracy 2. Accurate AI diagnosis algorithms could reduce reliance on consultant availability 3. In the future, novel diagnostic biomarkers and AI models could enhance understanding of mental health diseases, augmenting improvements in classification and service organisation	• Improved diagnostics may facilitate enhanced decision making on wards, leading to better, faster care. This would improve recovery, shortening LOS • Reduced reliance on senior clinicians empowers the rest of the team, reducing clinical variance in the system that could lead to poor and unpredictable flow
	Treatment	1. Current reliance on a trial and error approach for finding effective treatment regimens for individual patients. There are both short and long-term disability related benefits to delivering effective treatment first time 2. Many patients experience challenges with medication adherence, some due to inefficacy or adverse effects. Poor adherence to medications is a risk factor for preventable readmissions		1. AI treatment-response modeling could help predict a patient's suitability for a more quickly optimised treatment regimen 2. AI systems such as Clinical Decision Support Systems (CDSS) could enable clinicians to make better predictions of treatment adherence and side-effect profiles based on personal factors and treatment history. This would provide valuable information to factor into the individual's care plan	• Improvements in treatment decisions would speed up recovery leading to shorter LOS • Personalised treatment regimens would also mean decreased adverse effects that may jeopardise adherence, and thus lower rates of readmission
	Discharge	1. A lack of clinical outcome forecasting and a reliance on subjective clinical assessment or cohort metrics makes discharge planning challenging and imprecise 2. Non-clinical factors, chiefly aftercare arrangements, can further delay discharge beyond the point of medical optimisation		1. AI models such as CDSS can assist with predicting key treatment and recovery time-frames in order to effectively plan discharge timelines 2. AI models may also be able to help forecast what a patient's follow up and aftercare needs will be in advance, further streamlining discharge processes	• Delayed discharge was reported as one of the commonest reasons for extended LOS • Reducing delays through prediction improvements for both clinical and non-clinical outcomes could significantly boost planning capacity • Timely discharge means that patients are discharged when medically optimised, leading to less readmission and better outcomes
Community	Community Monitoring	1. Clinicians are limited to snapshots of patient data due to a lack of longitudinal patient monitoring 2. Systemic under-resourcing resulting in overstretched community services, which in turn makes deploying timely interventions challenging 3. Information gaps between community and inpatient teams may compromise continuity of care	Digital Phenotyping	1. Data science has an emerging role in modern industries, and AI with its ability to process large quantities of data is an important extension of this. With this processing capacity, data from both active (e.g. surveys or chatbots) and passive (e.g. wearable or social engagement data) monitoring can be used to provide dynamic digital profiles of patients' health needs, leading to better and more informed decision-making 2. The cost-effectiveness of digital monitoring may help under-resourced community services to function more efficiently, and target timely interventions according to health benefits or predicted deterioration risk	• Shared responsibility of patients across teams and settings necessitates improved teamwork and continuity of care • Equipping community teams with tools to enhance treatment and prevention and thus improving outcomes • Improved crisis prevention in the community could dramatically reduce admission and readmission rates

(*continued on next page*)

Table 6 (*continued*)

	Part of patient flow	Problem	Solution category	Solution details	The potential impact on patient flow
				3. Digital support systems can bridge the information gaps between different care teams, empowering shared management of patients and reducing changes post-discharge	
Operations	Patient Record Keeping	1. There are a number of issues with EHRs and how they are currently processed, including a. Lack of interoperability between providers due to confidentiality and technology challenges. Potential problems may arise when a patient is transferred to another service who are are unable to access the patient's full record b. Lack of structure within the notes making their contents hard to code and store as data points c. More time spent by clinicians typing up notes reduces their clinical time d. Shortage of clinical coders e. Due to lack of structure, missing data is hard to gauge and this can be to the detriment of patient care	Operational Efficiency AI systems	1. The use of NLP to extract, structure, and code information from free text has a number of potential benefits: a. Redesign of administrative systems across the NHS allows the opportunity to set up systems such that they are technically compatible, and can travel with patients b. Uses AI algorithms to extract, structure and code the data in a consistent way c. Saves clinicians' time through automated dictation and transcription, and predictive suggestions d. Clinical coding workload is dramatically reduced, and current staff may be well positioned for retraining to help run the new NLP systems e. With rapid and consistent coding, incompleteness in the data entry can be identified and corrected	• Automation of the manual coding process for extracting data from EHR entries would free up more time for HCPs to spend with patients, improving outcomes such as satisfaction for both HCPs and patients • Better organisation and availability of notes would support accurate decision-making leading to improved outcomes and potentially shorter LOS • Significant savings from automation of administrative tasks could be invested in flow improvements elsewhere in the trust
	Resource Allocation	1. High prevalence of staff shortages within mental health inpatient services 2. Bed shortages, exacerbated by current inability to accurately forecast their demand 3. Increasing demand		1. Data-analytics dashboards can be employed to provide high-quality, real-time patient and patient flow data, enabling clinical teams to effectively cover the same patient case load 2. AI models would enable data-driven demand forecasting (eg. using the discrete event simulation model). This can help wards pre-empt surges in demand and maximise their capacity 3. Streamlining administrative and often time-consuming backend operations would give staff more time to utilise their skill set in making patient centred decisions	• Equipping stretched teams with analytics tools to better manage their caseloads will reduce errors in demand predictions, allowing for higher supply-demand resource matching • Data-driven approaches enable demand forecasting for proactive capacity planning, as well as identifying bottlenecks in flow which could lead to improvements in system design • Allocating resources according to the demand would ensure that patients' needs are being met leading to improved outcomes, lower readmission rates and LOS
	System Design	1. Inappropriate division of job responsibilities (e.g. bed managers overseeing discharges) may be biased towards maintaining bed availability 2. Fragmentation of systems and lack of communication may result in issues in managing patient flow. For example, community clinicians are unable to admit patients to inpatient units despite clinical need, with other patients being admitted despite lack of clinical need, prolonging referrals		1. Systems could be redesigned around new technological capabilities and automation, such that some functions will be undertaken by other professionals or not at all; for example AI could enable efficient rota scheduling and diary management, AI virtual assistants could book patient appointments, automatically compose letters, and send patient reminders 2. Improved organisation of EHR, data sharing initiatives, and technological community monitoring could lead to improved continuity of care and better communication between inpatients and community services	• Automation could improve mental health inpatient unit efficiency and reduce errors • By reducing the administrative burden, AI solutions could streamline the workloads of HCPs, generating greater clinical productivity and relieve staff pressures

largely depends on the capacity of the system to provide appropriate level of care to patients following the initial assessment.

4.1.1.2. Diagnosis. Misdiagnosis is a common issue within mental health [76]. Although patients who are admitted to mental health inpatient units often already have a diagnosis, it is not uncommon for diagnoses to be inaccurate [77]. Interviewees agreed with the literature that diagnostic decisions are often subjective and slow [78], leading to delays in appropriate treatment delivery, longer LOS and poor outcomes. AI algorithms with superior diagnostic accuracy could reduce variation in the quality of decision making [79]. Accurate diagnosis means that appropriate treatment can be administered sooner, increasing the likelihood of recovery and thus improving outcomes and patient flow. Moreover, due to our limited understanding of mental health, there are as yet no clear biomarkers that could be used in clinical practice [74, 80]. In the future, AI could be used to analyse complex behaviour patterns, neuroimaging data, or blood samples [81] to enhance our understanding of underlying mechanisms of mental health, leading to better diagnostic classifications [82] and targeted therapies. For example, Li et al. [83] showed that it is possible to diagnose schizophrenia from fMRI scans, Ho et al. suggested a cheaper alternative of using functional Near-Infrared Spectroscopy to help understand the aetiology, diagnosis and treatment of depression [84], and Abbas et al. [85] used video analysis to diagnose autism. Technologically driven diagnosis for mental health conditions is still at an early stage, neuroimaging and genetic testing are not widely available and more research is needed but experts are confident in the future feasibility of such novel approaches to diagnose mental health illness [86]. Wurcel et al. [87] argued that reliable and accurate diagnostic tests lead to economic efficiency as they improve turnaround time, decrease the need for re-testing, and lower the waiting times, resulting in the driving down of operational costs and inpatient hospital stays.

4.1.2. Treatment

The trial and error approach [88] and inadequate treatment of mental health disorders lead to frequent readmissions and longer hospital LOS. Despite the popularity and tolerability of the selective seretonin reuptake inhibitor (SSRI) class of antidepressants [89], many therapeutic regimens, especially those for cases needing frequent admission, can often be ineffective and produce side-effects which may demotivate patients who then give up seeking help [90]. Penn & Tracy [91] reported an estimate that only 30% of patients take psychotropic medication as prescribed, potentially due to side effects. Treatment resistance is also common amongst patients admitted to acute mental health wards. Pharmaceutical and psychotherapeutic treatments are only effective for 30–50% of patients, and the optimal combination of each is unknown [92]. It is well recognised that there is significant individual variation in response to different medications, however the pharmacogenetics of such variation is poorly understood [91]. Providing patients with an effective treatment selection to start with can have positive outcomes on their health and quality of life. The STAR*D trial showed that patients who relapse with the first trial of an antidepressant experience significant reductions in work-related disability. In contrast, patients who relapse with subsequent treatment trials or strategies exhibit residual functional impairments [88].

AI could be used to predict a patient's response and adherence to treatment and thus be used as a treatment decision support tool. Patient data, such as neuroimaging data [93], demographic variables [94] and patient self-reported data [95] could be analysed with machine learning to predict how patients respond to treatment and thus allow clinicians to choose treatments that will most likely improve patient outcomes. A combination of data from different sources could allow for a personalised approach to mental health. For example, Lee et al. [88] conducted a meta-analysis of studies that use AI to identify predictors of therapeutic outcomes in uni/bipolar depression and founds that algorithms had an overall accuracy of 82% (95% confidence interval) but those which pooled multiple data types (e.g phenomenological patient features and neuroimaging or peripheral gene expression data) had significantly higher (93%) classification accuracy. Lim et al. investigated the five factors associated with depression with regards to its compatibility with the Schema Model, and found that neuroticism can exert direct and indirect effects on depression [96]. In the future, AI could support the field of pharmacogenetics which aims to identify biomarkers and genotypes that permit early identification of whether an individual will benefit from a given medication to justify the risks it entails.

AI can also predict if a patient is likely to engage in therapy or adhere to medications and suggest interventions that can increase adherence (e.g. reminders, contact with care teams, feedback, adherence based therapy, and contingency management) [97]. Behavioural interventions such as CBT (a form of psychological talking therapy) have been shown to have a significant impact, with some studies suggesting that they are more likely to reduce symptoms than SSRIs [98]. Digital solutions (eg. chatbots) and AI could be used to make therapy more accessible and personalised, however these solutions are more likely to have a direct impact in the community than on inpatient wards.

A possible way to incorporate treatment decision support into clinicians' workflow is through Clinical Decision Support Systems (CDSSs) - electronic systems with real time dashboards programmed to deliver recommendations based on data, scientific evidence, and the most-up to date guidelines [99]. CDSSs may be integrated into current hospital electronic systems or be used alongside them. Provided they are user-friendly and intuitive, they could be even visible on individuals' phones. Increased access to evidence-based information and real time data about patients could ultimately improve clinical management [83] and thus maximise the likelihood of recovery and optimise resource use.

4.1.3. Discharge

Current tools and metrics for discharge planning and prediction can be unreliable (e.g. lack of dynamic LOS), contributing to patients staying on inpatient units despite medical optimisation or being discharged too early leading to readmissions. Subjective clinical assessments, issues surrounding community services, and the absence of reliable clinical forecasting complicate discharge planning. Findings from both the literature and interviews suggest that there is an opportunity for AI to aid timely discharge.

Prognosis predictions are crucial in modern evidence-based medicine [100]. Currently on mental health inpatient units, predictions about patients' deterioration, recovery or crises are made by referring to group averages [92]. AI-enhanced prognostic tools could offer a more accurate and comprehensive approach to an individual patient's prognosis as they allow for the analysis of numerous factors including the patient's initial risk assessments and information gathered during their inpatient stay. For example, Mechelli et al. [51] analysed psychopathological data with AI to predict who will transition to psychosis. To help staff with discharge planning, accurate prognostic information could be integrated into CDSSs. Both junior and senior staff often do not have all the information required for a timely discharge (medical prognosis, social needs, care packages etc.) resulting in delays. CDSSs, apart from providing information, can also suggest the next required action in the care process (e.g. "send a plan to GP", "find a care package") needed to prevent readmission [101]. Moreover, experts suggest that based on AI prognostics, CDSSs could suggest timeframes in which patients should be followed-up after discharge. The post-discharge period is considered critical with increased risk of non-adherence, relapse, and rehospitalisation [102].

4.2. Problems in the community

Although social care factors are beyond the remit of ward staff, interview and literature findings both indicate that community care failings translate into poorer overall patient flow. Due to the disintegration of inpatient and community teams, monitoring is completely cut-off at discharge. Interviewees asserted that this discontinuity of care is a major issue, being able to do little for "revolving door" patients until they present again for inpatient admission. Ineffective rating scales based on currently attainable data, make community monitoring hard. Moreover, 'point in time' assessments can be inaccurate as mental health fluctuates over time [103]. Although funding and the complexity of mental health disorders ultimately underpin these problems, it is possible that technology could help bridge the gap between community and inpatient mental health services.

4.3. Monitoring solutions and digital phenotyping

Technological solutions can be useful in patient monitoring and data collection which could be integrated remotely into the clinical picture, offering a detailed account of the factors precipitating admission and diagnosis support. This would address clinician concerns over the lack of post-discharge feedback. 'Active data' collected with active involvement from the patient, for example completing surveys or contributing audio samples [104], can be collected by digital apps (e.g. MyCompass), and analysed with AI to then tailor services (CBT, chatbots) to the individual [105] with a by-product of further engaging patients in their recovery process. 'Passive' longitudinal data can also be collected from digital devices, via a range of mobile applications. The Beiwe app collects data from mobile sensors and phone usage, such as location and SMS logs, to monitor the state of schizophrenic patients [106].

Table 7. Recommendations for patient flow improvements on mental health units.

High priority recommendations	1. Prioritise operational efficiency solutions such as administrative automation with NLP to extract value from the existing systems and reduce costs 2. Implement risk-stratification and real-time data analytics to aid discharge, triage, and resource allocation 3. Engage stakeholders early, consulting representatives of clinicians, mental health trusts, and patients to ensure their concerns are addressed and solutions are user friendly
Implementation recommendations	1. Prioritise the development of AI solutions that are based on identified problems to increase adoption 2. Consider solutions that come from both private and public providers if they adhere to available regulatory, ethical and quality guidelines (e.g. CONSORT-AI, NHSX, and Medicines and Health Regulation Authority) 3. Engage with data-sharing initiatives for collaboration between trusts, increasing diffusion of this technology
Recommendations for the future	1. After further research, consider digital phenotyping as a possibility for community patient monitoring 2. Encourage the roll-out of technology training and engagement of clinicians with pre-existing training to increase technological literacy amongst HCPs 3. Consider adding new technological roles such as clinicial information officers to existing healthcare teams

Digital phenotyping is defined as the 'moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices' [104]. Onnela & Rauch [107] explored the use of smartphone-based digital phenotyping in monitoring behaviour and mental health. Smartphone-based data such as app usage, spatial trajectories (GPS), physical mobility patterns (accelerometer), and audio samples (microphone) were collected to develop 'precise and temporally dynamic disease phenotypes and markers to diagnose and treat psychiatric and other illnesses' [107]. Griffin & Saunders [108] investigated the use of digital phenotyping in psychiatric treatments, using naturalistic data from smartphone and wearable devices, using physiological metrics such as heart rate, respiratory rate, and sleeping patterns in conjunction with behavioural data. AI analysis of such an array of longitudinal input data could enable personal relapse risk modelling and subsequently, the ability to target early interventions in the community to most effectively prevent avoidable admissions, with an additional offering of self-monitoring functionality for the patient [108]. Integrating multiple sources of data presents a processing challenge, and such vast quantities of data require ML to analyse, correlate, and create baselines for different illnesses [109].

By combining all sources of data from digital phenotyping, higher level interpretation such as the "affect recognition" can be computed, which can then be used to explore correlations between digital phenotypes and mental health. EmotionCheck, a wrist-worn device, and other similar applications can generate data to help users predict and manage anxiety [110]. According to Dawson & Sapiro [111], generating large longitudinal psychiatric patient datasets would enhance better understanding of disease patterns to improve both the individual's care needs and the diagnostic frameworks that clinicians use. Those valuable digital data such as facial recognition and attention can help us capture and quantify behavioural measurements when patients are in their natural environment. With enough data, it may be possible to quantify diseases such as autism spectrum disorder. The large quantitative digital phenotyping data sets will allow for 'empirically derived, bottom-up descriptions of behaviour'. Therefore, an integrated system was proposed, where real-time data can be analysed by ML and used to personalise treatments [111]. Given the ubiquity of smartphones and wearables, digital phenotyping could be a novel approach to enhance monitoring, prevention, and understanding of mental health, whilst at the same time addressing the belief that the focus of psychiatry should be in the community. By better managing community mental health, the pressure on inpatient services may be relieved and subsequently streamline the patient flow.

4.4. Operational solutions

Operational and non-clinical issues with patient flow on mental health units have proven to be a significant challenge affecting staff and the quality of care delivered. Although many of those issues are interconnected, there are three main aspects which have a critical influence on patient flow and thus where opportunities for improvement are demanded: patient record keeping, resource management, and service design and delivery as a whole.

4.4.1. Patient record keeping

Whilst many hospitals are already using EHRs, they often suffer from usability issues. Firstly, EHRs lack integration resulting in limited interoperability and collaboration between providers. Secondly, EHRs can make administrative tasks time consuming. Record-keeping is conventionally done via free text, in various formats such as voice notes, handwritten or scanned documents [112]. Information about patients is typed into EHRs by clinicians in a process that can often take longer than the patient interaction [74]. Many mental health experts argued that EHRs lacked structure, standardisation, and uniformity in the data collected, with variations in medical abbreviations, and many involving spelling and grammar mistakes leading to 'information holes' with missing data pieces. Another consequence is that HCPs are unable to extract the relevant information, or are not reading the EHR at all.

NLP, a useful information extraction tool, aids in the structuring and coding of information stored in free text, such as that in EHRs. The first way in which NLP will be useful for mental health inpatient units is by providing digital, automated dictation services, replacing human typing. Secondly, when clinicians are typing notes, predictive text can increase the speed of data entry, structuring the notes automatically. Such solutions could reduce the administrative burden on clinicians and allow them to spend more time with patients. With NLP, clinical notes could become more standardized, organised, and easily available which would support clinicians in decision making.

4.4.2. Poor resource allocation

The under-staffing of both community and inpatient services was discussed as an operational challenge fueling issues within patient flow. Similarly, reductions in the number of inpatient beds available [113] and increases in demand [114] create a supply-demand mismatch and leads to suboptimal care (eg. patients being discharged too early leading to readmissions). Traditionally, hospital managers manage capacity and demand based on estimations and historical knowledge. Data driven applications could improve service planning and resource allocation through accurate prediction of demand [115]. AI and discrete event simulation technology could allow flow managers to make decisions about their resources based on accurate predictions. This would enable proactive preparation and achievement of optimal capacity before a demand spike. This information can be provided through real-time analytics dashboards - summary statistics of performance in real time which can be regularly reviewed by management to spot bottlenecks in patient flow and improve performance [116]. The tool can display high-level information such as "number of beds needed next month" but can also track beds and patients that are currently on units, with the potential to share data between hospitals and community facilities that could enhance collaboration [117]. Based on those, managers can decide how to best allocate staff, beds, and funding to meet the demand and prevent readmissions. Under-staffing cannot be solved directly with technology, however, AI solutions that reduce administrative burden on HCPs could improve efficiency.

4.4.3. System design

Interviewees flagged issues related to system design itself, for example inappropriate job responsibilities (e.g. bed managers overseeing discharges), control of activities (e.g. community consultants lack the power to admit), and a lack of collaboration (between crisis resolution and home treatment teams). Interviewees reported that the current systems design is associated with problems in pathway management (wrong patients being admitted, prolonged referrals and assessments, lengthy diagnosis and treatment processes), adding to a cycle of inefficiency.

Having the right workflow and team structure is crucial as inefficiencies affect patient care and team experience [118]. The first step in improving system design could be an analysis of activities and roles, and understanding which of those can be eliminated, reduced or raised. Systems will need to be redesigned around new technological capabilities, such that some functions will be undertaken by other professionals or not at all, with the introduction of automation and digital workflows to improve mental health inpatient unit efficiency. AI can enable efficient rota scheduling, through intelligent automation and NLP diary management [119]. AI virtual assistants, such as Amelia [120], 'could support medical staff by placing individuals on pathways, book appointments, automatically compose letters, and send patients reminders'. Through purely administrative applications, AI systems offer an opportunity to streamline the workload of HCPs, generating greater clinical productivity and operational efficiency, whilst simultaneously relieving some of the aforementioned staffing pressures. Although technology can be helpful, appropriate culture and management is necessary to address the problems with the design of mental health services.

4.5. Challenges & considerations for the proposed solutions

AI models require large amounts of high-quality data [121]. Crane & Bunn [122] highlighted the variation in EHRs, both geographically and within hospital departments. NHS England failed to meet their target of connecting EHRs across services by 2020 [116], resulting in fragmented EHR data. The recent NHS Digital Data Quality Maturity Index scores (2020) highlighted the national average for mental health services as 69.6%, the lowest of all the services. Questions have arisen over the consent process in mental health record sharing, specifically, due to patient mental capacity requirements for consent [74] and though informed consent is not strictly required for healthcare data processing under the GDPR Article 9 (2) [123], it could impact the completeness of available data sets. These findings stress how, currently, the available data in the NHS may not be of a high enough quality for successful data analytics and training of AI.

Interviewees and research [124] identified the issues with NHS culture (resistance to change, risk aversion) which could translate to resistance to systemic changes, such as the implementation of AI. Based on Martinez & Farhan [24] and Foley & Wollard [74], factors needed to tackle this culture and promote adoption are clear clinical responsibility, interoperability, clear information governance and guidelines, degree of transparency and interpretability, understanding of potential risks, usability and evidence of clinical effectiveness. A 'failure to change the skill mix of the end users of the new systems, or to enlist new individuals with the appropriate skills to manage the change' was cited by Wachter [125] as a reason for the failings of technology implementations in healthcare. According to Castle-Clarke & Hutchings [111], NHS experienced 'significant challenges with recruiting and retaining the workforce necessary to support digital change'. The MDT will need new roles, such as clinical information officers, to support clinicians and patients with the uptake of technology, ensuring that solutions are fit for purpose. Clinicians will need to understand how to optimise their technology-enabled workflows and evaluating the impact of technology will increasingly become a focus of quality improvement projects. Staff should be supported to understand the ethical and regulatory considerations; however, it is not expected for everyone to develop highly technical skills [23].

Lack of validation can cause the AI model to be flawed in drawing biased inferences [126]. External validation will have to become a regular practice before any implementation. Once the solution is implemented it has to be evaluated, by measuring its impact on health outcomes or performing a health economic analysis. According to the Department of Health and Social Care Code of Conduct [127], AI developers need to define the precise outcome and contribution of their AI solution.

There are ethical questions that are yet to be answered regarding data governance and the use of AI in mental health [128]. Interviewees highlighted these pitfalls with respect to language analysis or digital phenotyping. Ethical considerations around potential misuse, patient autonomy infringements, and transparency of AI models are crucial in mental health where data is particularly sensitive due to stigma and capacity implications [128, 129, 130]. The future challenge is to ensure transparency and comprehensiveness of models and datasets whilst still protecting confidential data and patients' privacy [131]. Special consideration needs to be given to ensure AI does not perpetuate discrimination and inequality at scale [24]. Meeting ethical obligations underpins public confidence and trust which according to Hall & Pasenti [119] 'will be vital to successful development' of AI.

In order to implement AI on mental health inpatient units, wider system and organisation actions will need to be taken, including information governance and culture change in line with ethical, regulatory, and evaluation frameworks.

5. Recommendations

This study aimed to devise recommendations for mental health trusts with a goal of improving patient flow on inpatient units, as outlined in Table 7. According to Hattula [132], it is important to identify which hospital trusts are the innovators and early adopters as they are technology enthusiasts who are likely to use new technologies first to gain competitive advantages. As the technology spreads through the diffusion curve, more and more trusts will utilise it [133]. NHSE [134] named seven mental health trusts as 'Global Digital Exemplars' of the second wave of digital transformation [24] who would fall into the 'early adopters' category. As such the recommendations are targeted at these trusts.

5.1. Study limitations

The NLR could have been affected by a selection bias in the 'author's interpretations and conclusion' [135] and does not allow for the critiquing of articles. As the review acted as a guide when devising interview questions, bias may have been carried forward. Due to the current COVID-19 pandemic, the selection of HCPs was limited. Various management and MDT roles crucial in patient flow should have been included. The mental health HCPs recruited were all based in different UK trusts so their understanding of patient flow may vary due to different systems and populations. Without necessary NHS ethical approval, EHR data could not be analysed. The lack of quantitative data prevented triangulation. A mixed-method approach of both qualitative and quantitative analyses would have further ensured the validity and credibility of the study [136]. Though the inductive approach is superior to the deductive approach, it is difficult to follow it perfectly as 'researchers cannot free themselves of their theoretical and epistemological commitments' [137]. Codes were generated based on the researchers' perceptions and understanding. The large volume of interviews conducted made it impractical to present all data collected, thus some data was reduced based on researchers' perception of relevance [138]. The recommendations were formulated using the general patient flow map and issues discovered in the interviews. As NHS Trusts differ in structure and performance, those are currently not generalisable. Due to the limited sample, only 2 out of the 17 key stakeholders identified were engaged in the recommendation formultion process, potentially limiting the quality of those.

5.2. Future research

Quantitative data from EHRs could be collected and analysed to confirm issues with the patient flow and triangulate findings from this study. To build on this research, various HCPs from the MDT should be interviewed. They could offer different perspectives and further information to aid a fuller understanding of patient flow inefficiency sources. This research topic was explored from a healthcare provider perspective. Further research should investigate the patient's perspective using surveys, interviews, and focus groups to map the patient's experience, identifying solutions based on patients' needs. Secondly, a trust specific case study would be beneficial to tailor the patient flow map and recommendations. A cost-effectiveness analysis should be conducted to evaluate the AI's algorithms' performance with respect to monetary cost. The results of these case studies and economic analyses could provide evidence for NICE and guide the implementation of similar solutions across the country.

6. Conclusion

This study explored the issues which affect patient flow, and thus clinical outcomes, on mental inpatient units and investigated the various AI solutions that could be implemented to address the problems. Interview findings highlighted the frustration of a fragmented system and deeper economic and socio-political impediments, as well as the practical reality of needing specific solutions to suit local service configurations. AI shows exciting potential to improve patient flow in three main areas: clinical decision making, operational efficiency, and monitoring. Whilst it is unlikely that technology will reduce the huge unmet demand for mental health professionals in the foreseeable future, AI models can help with demand prediction, increasing efficient resource allocation and workforce planning [74]. In the near future, AI could relieve pressure on mental health services by streamlining repetitive tasks, giving clinicians more time to spend on direct patient care and allocating resources effectively. The real-time data analytics systems supporting triage and discharge are already adopted in certain areas of healthcare. In the long-term, AI tools could enable improved delivery of preventive and personalised care, by opening up new avenues of data collection and analysis to enhance understanding of mental health conditions. More research still needs to be undertaken by engaging additional stakeholders and conducting case studies of specific trusts.

Declarations

Author contribution statement

Fatema Mustansir Dawoodbhoy, Jack Delaney, Paulina Cecula, Jiakun Yu, Iain Peacock, Joseph Tan, Benita Cox: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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No data was used for the research described in the article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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