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Cautiously optimistic: paediatric critical care nurses' perspectives on data-driven algorithms in low-resource settings—a human-centred design study in Malawi

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Abstract

Background Paediatric critical care nurses face challenges in promptly detecting patient deterioration and delivering high-quality care, especially in low-resource settings (LRS). Patient monitors equipped with data-driven algorithms that monitor and integrate clinical data can optimise scarce resources (e.g. trained staff) offering solutions to these challenges. Poor algorithm output design and workflow integration, however, are important factors hindering successful implementation. This study aims to explore nurses' perspectives to inform the development of a data-driven algorithm and user-friendly interface for future integration into a continuous vital signs monitoring system for critical care in LRS.

Methods Human-centred design methods, including contextual inquiry, semi-structured interviews, prototyping and co-design sessions, were carried out at the high-dependency units of Queen Elizabeth Central Hospital and Zomba Central Hospital in Malawi between March and July 2023. Triangulating these methods, we identified what algorithm could assist nurses and used co-creation methods to design a user interface prototype. Data were analysed using qualitative content analysis.

Results Workflow observations demonstrated the effects of personnel shortages and limited monitor equipment for vital signs monitoring. Interviews identified four themes: workload and workflow, patient prioritisation, interaction with guardians, and perspectives on data-driven algorithms. The interviews emphasised the advantages of predictive algorithms in anticipating patient deterioration, underlining the need to integrate the algorithm's output, the (constant) monitoring data, and the patient's present clinical condition. Nurses preferred a scoring system represented with familiar scales and colour codes. During co-design sessions, trust, usability and context specificity were emphasised as requirements for these algorithms. Four prototype components were examined, with nurses favouring scores represented by colour codes and visual representations of score changes.

Conclusions Nurses in the LRS studied, perceived that data-driven algorithms, especially for predicting patient deterioration, could improve the provision of critical care. This can be achieved by translating nurses' perspectives

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into design strategies, as has been carried out in this study. The lessons learned were summarised as actionable pre-implementation recommendations for the development and implementation of data-driven algorithms in LRS.

Keywords Data-driven algorithms, Paediatric critical care, Low-resource settings, Malawi, Nurses, Monitoring systems

Background

Although global paediatric mortality rates reached a historic low in 2022, most of these deaths happened in low- and middle-income countries, specifically in sub-Saharan Africa and Southern Asia, and they could have been prevented [1]. Although much attention has been paid to expanding access to care, ensuring quality of care is absolutely necessary to generate better outcomes, which includes paediatric critical care [2, 3]. Critical care, includes care in paediatric intensive care units (PICUs), high-dependency units (HDUs) and other critical care environments [4–6]. The care and treatment of critically ill children are challenging because deterioration can occur rapidly and suddenly, and signs of decline can be subtle [7, 8]. In these conditions, timely recognition of symptoms, paired with accurate and timely diagnosis leading to clinical action can be lifesaving. In low-resource settings (LRS), however, limited highly trained staff, scarce resources such as monitoring systems, and other specific contextual factors amplify the challenges of providing high-quality critical care [3, 9, 10].

Vital signs monitoring systems coupled with data-driven algorithms (Additional File 1: Definition data-driven algorithms and connection with AI), including artificial intelligence (AI) techniques, can be part of the solution. Such data-driven algorithms can, for example, facilitate the early identification or prediction of the deterioration of paediatric patients, even when specialised staff is not immediately available [5, 11, 12]. However, the development and clinical application of data-driven algorithms are not yet common in LRS. Barriers include reliability issues, skill shortages, complex workflow integration, poor user-friendliness, insufficient contextual alignment, and scarcity of monitoring systems and sensors [13, 14].

To develop vital signs monitoring systems with predictive features based on data-driven algorithms, it is essential to meet the needs of healthcare providers within their context, including nurses who play a central role in LRS. In this regard, human factors engineering (which focuses on optimising the interaction between people and systems [15]) and human-centred design (which prioritises user needs throughout the design process [16]) can facilitate the safe and effective development and adoption of data-driven algorithms in clinical practice. We applied those fields to comprehensively understand nurses' perspectives regarding the application of vital signs monitoring systems with predictive features in paediatric critical care in LRS. We used a continuos vital signs monitoring system specifically designed for LRS (hereinafter IMPALA system, see the "Methods" section). The study's end goal was to determine the type of algorithm, in terms of output, that nurses consider valuable to incorporate in the IMPALA system. Outputs considered included: deterioration, discharge, treatments or interventions, and diagnosis. Based on nurses' preferences, we aimed to generate a user interface design proposal for the monitoring system in question.

Methods

Study design and setting

This study is part of the project Innovative Monitoring in Paediatrics in Low Resource setting: an Aid to save lives (IMPALA project) (https://www.isrctn.com/ISRCTN71392921), which aims to develop an affordable, durable, robust, and easy-to-use paediatric continuous monitoring system for LRS.

This observational study integrated human factors engineering and human-centred design perspectives. Human factors engineering is defined as the formal study of people's interaction with their environment and a system [15]. Human-centred design is defined by the ISO 9241–210 standard as "an approach to systems design and development that aims to make interactive systems more usable by focusing on the use of the system and applying human factors/ergonomics and usability knowledge and techniques [16]." This study was carried out in four steps—step one: contextual inquiry (actively observing and encouraging workers to share their experiences while performing tasks), step two: semi-structured interviews, step three: prototyping, step four: co-design sessions. The research was conducted between March 2023 and July 2023 in Malawi at the HDUs of Queen Elizabeth Central Hospital (QECH) and Zomba Central Hospital (ZCH). This study was carried out in parallel with another IMPALA study, where the IMPALA system was used by research nurses only. Within the HDUs in both locations, there were two settings: the "clinical setting", where clinical nurses provided usual care, and the "research setting", where research nurses monitored patients using the IMPALA system. Children were always accompanied by guardians, individuals legally responsible for them [17]. Due to space constraints, the research setting was not physically separated from the clinical setting, and IMPALA systems were placed next to the same beds assigned to patients when admitted to the HDU.

QECH is the largest hospital in Malawi, with over 90,000 paediatric reviews conducted in the accident and emergency department annually, along with 26,000 paediatric hospital admissions to its 300 paediatric beds [18, 19]. After triage and stabilisation in the paediatric emergency department, patients are admitted to the HDUs in the nursery or the special care ward (Additional File 1: Floor plan of the HDUs in QECH and ZCH, Fig. S1). The two HDUs together accommodate up to forty patients. Patients in the HDU receive clinical care under clinical supervision, including physiological monitoring and nursing care, with access to oxygen provided via concentrators. There are 30 beds available, potentially shared among patients if needed. During this study, ten IMPALA systems were in use.

ZCH serves as one of the four central hospitals in Malawi, providing care to Zomba, a rural district in southern Malawi with an estimated population of 746,000 [20]. Patients are first triaged and stabilised in the emergency or the admissions room before referred and admitted to the paediatric HDU. The paediatric HDU comprised eight beds across two adjacent rooms within the paediatrics ward (Additional File 1: Floor plan of the HDUs in QECH and ZCH, Fig. S2). During this study, 11 IMPALA systems were available. In both locations, sharing beds is common, allowing for increased capacity.

Study population and eligibility criteria

The study recruited nurses working in the HDUs of QECH and ZCH for contextual inquiry, interviews, and co-design sessions. Both IMPALA research nurses, who handled the IMPALA systems, and clinical nurses, who did not directly handle the IMPALA systems, were included. Informed consent was obtained, and nurses signed the informed consent form in English or Chichewa. Inclusion criteria included being employed as a nurse with a valid nursing licence, fluency in English or Chichewa, and availability and willingness to participate in the study. A snowball sampling approach was utilised to recruit nurses while ensuring equitable representation in terms of gender, age, and levels of work experience. Recruitment ceased when data saturation was reached. Research nurses were included to provide insights based on their clinical experience, their knowledge about the IMPALA system (e.g. operational aspects and usability) and constant monitoring of vital signs. Clinical nurses were included to provide insights based on their experience in the clinical critical care setting, especially manual spot-check monitoring of vital signs.

Fig. 1 The IMPALA system (manufacturer, GOAL 3, The Netherlands)

IMPALA system

The IMPALA system (Fig. 1) is a vital signs monitoring system, manufactured by GOAL 3, a social enterprise based in the Netherlands. The IMPALA system is currently being tested and developed in the context of the IMPALA project. For this particular study, IMPALA system prototype 2.0 was used. The IMPALA system combines a simplified electronic patient record displayed on a wireless tablet (Fig. 1, right side) with a continuous monitor of vital signs (Fig. 1, left side). The tablet provides an overview of all patients using IMPALA systems in the ward, and allows for individual patient details to be accessed. Vital signs include heart rate and variability, respiratory rate, activity levels, oxygen saturation, and non-invasive blood pressure, which are displayed in real-time on the screen of the continuos monitor of vital signs. The monitor and its components comply with peripheral oxygen saturation (SpO_2), non-invasive blood pressure (NIBP), temperature, and electrocardiogram (ECG) related standards.

In order to assist in the provision of critical care in LRS, the IMPALA project also focused on researching the possibility of implementing an algorithm to assist clinical decision-making. The idea is that the output of the algorithm would eventually be displayed on the tablet. Given the clinical context and the data collected by the IMPALA system, it could be possible to generate algorithms for different purposes; including: predicting patient's deterioration, indicating treatments or interventions, making a diagnosis or indicating discharge. At the time this study was performed, different approaches to developing an algorithm were being undertaken, including machine learning, rule-based and traditional algorithms based on a snapshot of vital signs and clinical data.

Study procedures

Step one: contextual inquiry, observations of the clinical workflow

Contextual inquiry is a participatory field research method, it involves the observation and encouragement of individuals to express their work experiences while actively engaged in their tasks [21]. This method was applied to inquire about the workflow in QECH and ZCH HDUs, with the objective of gaining an in-depth understanding of how vital signs monitoring (manual spot-check or continuous) is conducted in the HDU and how nurses interact with other nurses, guardians and doctors. We aimed to comprehend how nurses make decisions to determine if and how data-driven algorithms could assist them in providing care. First, we focused on observing the workflow in the clinical settings at the HDUs in QECH and ZCH. Subsequently, we extended our observations to the research setting.

The first author (MR), a medical doctor, conducted structured observations at QECH and ZCH, covering day and evening shifts. This involved maintaining a regular presence over four weeks in April 2023, two–three times per week, with sessions lasting three to four h each. Observations continued until data saturation was reached. During this time, findings were continuously discussed with two researchers (DM, a Malawian social scientist, and LdM, a user experience (UX) designer). An observation manual (Additional File 1: Observation manual) was utilised to systematically and concisely document the clinical workflow, including the use of paper health records and medical devices, patient examinations, responses to deterioration, and communication of nurses with colleagues and guardians.

Step two: semi-structured interviews

Semi-structured interviews were prepared based on the results of the contextual inquiry. Interviews were conducted to (1) understand how nurses make decisions and prioritise critical patients in the HDU, and (2) explore nurses' perceptions of data-driven algorithms for critical care. The latter included nurses' general acceptability and intention to use data-driven algorithms; and which type of algorithm, in terms of output, is considered valuable to incorporate in a vital signs monitoring system for critical care in LRS. To ensure a thorough exploration, the interview guide was developed by a multidisciplinary team comprising social scientists, UX researchers, and clinicians (see Additional File 1: Interview guide). The interviews took place between April and May 2023, were audio-recorded, and transcribed verbatim. The interviews lasted 20–45 min and were conducted by an interdisciplinary research team consisting of a medical doctor (MR) and a Chichewa-speaking social scientist (DM) until saturation was achieved. The interviews were reported according to the consolidated criteria for reporting qualitative studies (COREQ) (Additional File 1: Consolidated criteria for reporting qualitative studies (COREQ)).

Step three: prototyping

Based on the results and analysis of the two previous steps (see results section), we chose to prototype the user interface of a hypothetical data-driven algorithm that would predict patient deterioration based on the vital signs data of the IMPALA system. The user interface, which would show the outputs of the algorithm, would be incorporated into the tablet of the IMPALA system. For this purpose, design objectives were identified and translated into components for a future interface prototype. Prototype components are elements or features aiming to address specific functionalities or aspects of the application of the algorithm. The concept of the data-driven algorithm based on the Paediatric Early Warning Score – Resource Limited (PEWS-RL) was then used to generate the prototype components. At least four design prompts were generated for each prototype component to discuss potential choices with nurses, during the co-design sessions. A UX designer (LdM) collaborated with a medical doctor (MR) to create the design prompts using the software program Figma (Figma, USA), which generates static screenshots.

Step four: co-design sessions

The co-design sessions used the prompts (step three) to co-design with nurses a user interface of the data-driven algorithm that would incorporate all components. In June 2023, four sessions were conducted involving 16 nurses, each participating in a two-h session. Each session began with a five-min introduction to familiarise nurses with the type of data-driven algorithm chosen for the co-design session, and the prototype components (step three). Design prompts were presented and subsequently, participants received a questionnaire (Additional File 1: Co-design sessions questionnaire) to rank different options of the components and justify their choices. Two moderators, a medical doctor and a biomedical engineer (MR and LC), led the discussion, covering all individual responses, putting emphasis on the comprehensibility of the prompts and how they could be integrated into a single interface. The session was closed with a general discussion about data-driven algorithms that could be valuable for critical care in LRS. All co-design sessions were recorded and transcribed verbatim.

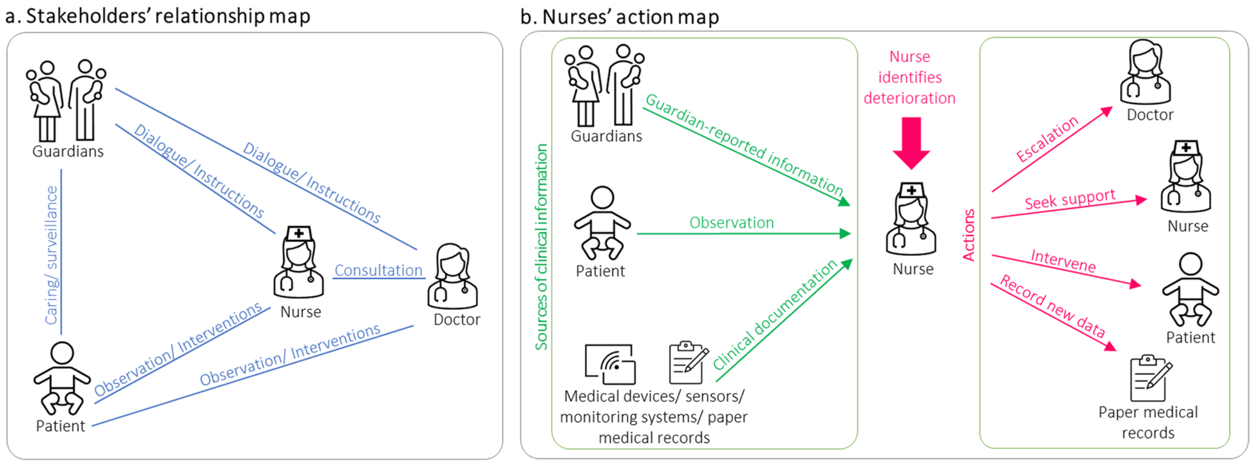

Fig. 2 Visual representations of the relationships observed in the high-dependency units of Elizabeth Queen Central Hospital and Zomba Central Hospital and the actions taken by nurses once they identify deterioration. **a** Relationship map between stakeholders caring for patients admitted to the HDU. Arrows and text in blue indicate the main type(s) of interactions observed. **b** Nurses' action map, response to deterioration. The green box on the left contains the means used to record/generate medical information (sources of clinical information) which is used by nurses. Arrows and text in green indicate the type of information used by nurses to identify deterioration. The red box on the right contains the different possible actions taken by nurses after identifying deterioration (arrows and text in red)

Data analysis

Qualitative analysis of the contextual inquiry, semi-structured interviews, and co-design sessions followed the methods outlined in Thomas et al. [22]. This analysis was conducted using principles of qualitative content analysis [23], and Atlas.ti software (version 8.4, Berlin, Germany) along with Microsoft Excel were used. The first author (MR) conducted data reading, sorting, labelling, and grouping into themes. Collaboration with KD, LM, and DM refined the identified themes through dialogue, resulting in a definitive code set that was considered to capture the essence of the data (codebook in Additional File 1: Codebook). For co-design sessions, qualitative and quantitative data from questionnaires and recordings were transcribed into a spreadsheet and analysed applying inductive qualitative content analysis principles. MR and LM independently reviewed the data, identifying patterns to generate themes, which were subsequently discussed within the research team (DM and KD).

Results

Step one: contextual inquiry—observations of the clinical workflow

Observations were conducted in HDU settings with five nurses from ZCH and three nurses from QECH. In the clinical setting, nurses performed manual spot-check monitoring only. In the research setting, research nurses used the IMPALA system to continuously monitor vital signs. Here, we describe the key observations considered for the interviews and co-design sessions. Other observed stakeholders included patients, guardians, and medical doctors who came in contact with the nurses observed (Fig. 2a depicts the stakeholders and their relationships).

In QECH, the nurse-to-patient ratio ranged from 1:10 to 1:13 during the daytime but increased to between 1:15 to 1:20 at night due to fewer nurses available. In ZCH, the nurse-to-patient ratio ranged from 1:5 to 1:7 (1:7 to 1:9 at night). In both hospitals, clinical nurses conducted standard manual spot-check monitoring four times daily using several devices such as a wall-mounted monitor, two portable multi-parameter vital signs monitors, a handheld pulse oximeter, a thermometer, a sphygmomanometer, and a glucometer, serving approximately 30–40 patients in QECH and approximately 20 patients in ZCH. Data were recorded on paper files hanging from the beds, where vital signs, clinical observations, medical orders, and assessments were written in a predefined table. Significant deviations from normal vital signs were mainly identified during planned spot-check rounds, as confirmed by patient paper files. Although abnormal vital signs were consistently documented, immediate follow-up actions were not always observed. Monitoring frequency intensified for sicker patients, particularly those experiencing respiratory distress or unresponsiveness. Between manual spot-check control rounds, nurses spent time in the nurses' station or medicine room preparing medicines, keeping records, and attending to other administrative tasks, inevitably losing visual contact with patients in the HDU. The localisation of nurses' stations in both hospitals had limited or no direct view of the HDUs (see Additional File 1: Floor plan of the HDUs in QECH and ZCH). Whenever nurses were physically absent from the HDU, they relied on guardians to assess the patient's condition until their return to the ward. In both locations, as it commonly happens in LRS, wards have no independent rooms for critically ill children and the presence of guardians is constant. Guardians stay day and night by the bedside, when possible sleeping with their children in the same bed, but often sitting in chairs. In critical cases, nurses immediately proceeded with necessary interventions (e.g. cannulation and administering oxygen and medication) and contacted the doctor after carrying out these interventions. Figure 2b depicts the decision-making process of nurses based on different sources of clinical information and the different actions undertaken.

Research nurses only worked day shifts and monitored three to ten patients. There were occasions when the IMPALA system alarms were not muted, resulting in continuous alarms without follow-up actions. Additionally, although the IMPALA training program covered the use of the "trend display" feature, which provides historical vital signs, this feature was not consistently used by the research nurses.

Step two: semi-structured interviews

In total, 17 nurses from both locations participated in the interviews, whose ages ranged from 25 to 60 years. All nurses observed during the contextual inquiry were interviewed. Participant characteristics are shown in Table 1.

From the qualitative inductive content analysis, 48 codes were derived and grouped into four main themes: (i) workload and workflow, (ii) patient prioritisation, (iii) interaction with guardians, and (iv) perspectives on data-driven algorithms. Quotes linked to each theme and code are presented in Table 2. Among these, the theme "perspectives on data-driven algorithms" was most extensively discussed.

Workload and workflow

Nurses mentioned variable patient loads, ranging from eight to forty, depending on seasonal fluctuations, staffing and paediatric severity of illness (Q1). Clinical nurses indicated that they monitor vital signs every six hours but increase the frequency if necessary for deteriorating patients and depending on the severity of the condition. Nurses with more than five years of experience reported that they felt confident intervening before consulting doctors when there were changes in vital signs or responding to warnings from guardians (Q2).

Nurses at both hospitals underscored the challenge of low staff throughout day and night shifts (Q3). Understaffing resulted in nurses being responsible for more patients than initially intended, which limited the

Table 1 Overview of participant characteristics

Participant ID	Hospital	Gender	Experience (years)
Observed participants			
1	QECH	Female	> 10
2	QECH	Female	> 10
3	ZCH	Female	< 5
4	QECH	Female	< 5
5	QECH	Male	5–10
6	QECH	Female	5–10
7	ZCH	Female	5–10
8	ZCH	Female	< 5
Interview participants			
1	QECH	Female	> 10
2	QECH	Female	> 10
3	QECH	Female	< 5
4	QECH	Female	< 5
5	QECH	Male	5–10
6	QECH	Female	5–10
7	QECH	Female	5–10
8	ZCH	Female	< 5
9	QECH	Male	< 5
10	ZCH	Female	5–10
11	ZCH	Female	> 10
12	ZCH	Female	5–10
13	ZCH	Male	5–10
14	ZCH	Female	< 5
15	QECH	Female	> 10
16	ZCH	Female	5–10
17	ZCH	Female	5–10
Co-design sessions participants			
1	QECH	Male	5–10
2	QECH	Female	< 5
3	QECH	Female	> 10
4	QECH	Female	5–10
5	ZCH	Female	< 5
6	ZCH	Male	5–10
7	ZCH	Male	< 5
8	ZCH	Female	5–10
9	ZCH	Male	5–10
10	ZCH	Female	< 5
11	ZCH	Female	> 10
12	QECH	Female	> 10
13	QECH	Male	5–10
14	QECH	Female	5–10
15	ZCH	Female	< 5
16	ZCH	Female	5–10

ID identification, *QECH* Queens Elizabeth Central Hospital, *ZCH* Zomba Central Hospital

Table 2 Quotes from interviewed participants are listed according to the four main themes and codes

Theme	Code	Quotes		ID
Workflow and workload	Nurse to patient ratio	Q1	"It varies depending on the situation. Ideally, one nurse should have one patient. However, there are times when we have fewer nurses on duty, and we may have to take care of more patients. So, we share the workload."	8
	Tasks and responsibilities	Q2	"When I assess a patient and notice deterioration, it's crucial to take immediate action. If oxygen is deemed necessary, I administer it without awaiting a doctor's consultation. After the necessary actions, I can communicate to the staff."	6
	Staff shortages	Q3	"During regular shifts, there should be six nurses, but shortages are common. Today, only three of us are on duty."	7
Prioritisation	Clinical experience	Q4	"Apart from observing the patient's vital signs, we can often discern changes in their condition simply by looking at them. We are familiar with these patients and their guardians, and we can notice if a child's health has deteriorated compared to their previous state."	6
	Prioritisation elements	Q5	"If there are too many sick patients at the same time, we prioritise the ones we feel can survive."	3
	Clinical judgement	Q6	"Because of these educational differences, my approach differs from how others would respond to the same problem in the same patient. I wish there was a standardised approach. My reaction to the problem should be consistent with how other nurses would react, regardless of who is on duty."	17
Interaction with guardians	Guardian's involvement in care	Q7	'Guardians can provide assistance with feeding, and if the nasal gastric tube is not fitting correctly, we offer guidance to the mother on how to adjust it properly. The guardians' help and support have been invaluable in our efforts.'	11
	Guardian's knowledge	Q8	"Some guardians can quickly recognise when a baby is not feeling well, while others may find it challenging to notice subtle signs, like when a child is trying to communicate but has difficulty. Some guardians may call and report that their child is experiencing jerking movements, indicating a potential problem, while others may simply say that their child is doing well without mentioning any concerns."	11
Perspective on predictive algorithms	Baseline knowledge	Q9	"I've heard that prediction tools help predict whether a baby's condition will progress positively. This involves determining if there's a risk of sepsis or an impending infection."	1
	Support clinical decision-making	Q10	"When caring for a patient, certain parameters can be continuously monitored. If the reading exceeds a threshold, the system asks you to take a specific action. Without this automated system, you might overlook trends and miss crucial details."	6
	Preventive intervention and early detection	Q11	"I think these systems can be valuable. When a patient's condition deteriorates, it can quickly become an emergency. It would give us time to prepare by placing essential equipment at the bedside. This preparation means that if something happens, we can intervene quickly and prevent further deterioration."	7
	Trust, transparency and traceability	Q12	"We shouldn't just rely on them. We can also do our own assessment so that you can compare the results and see if the prediction is correct or wrong."	3
	Preferences—prediction option	Q13	"Typically, when patients experience changes in cardiac or respiratory rates, it takes us some time to notice. (…) In the case of children, their bodies can compensate up to a certain point. However, they might suddenly deteriorate, which is different from adults. For patients who are unwell or experiencing deterioration, or even those doing relatively well, we can infer their condition from these output from the algorithm, indicating whether the patient's health is declining."	6
	Preferences—location	Q14	"In terms of monitoring patients, it would be very useful to have technology that allows us to monitor patients outside the ward (nurses' station). We often face challenges when we are on break, and no one is available to watch patients. […] Therefore, it would be advantageous to have an overview of patient monitoring at the nurses' station."	2
	Guardians' involvement	Q15	"To avoid causing fear, it would be more reasonable to display a simplified score or lights instead of showing all the dangerous vital signs. While many guardians possess the necessary knowledge, we cannot be certain about everyone's level of understanding."	2

monitoring of vital signs, especially at night. Clinical nurses from both hospitals perceived a collective responsibility for all HDU patients, extending beyond the care of those specifically assigned to them during their shifts.

Patient prioritisation

When asked about how nurses prioritise patients, they emphasised the importance of clinical experience (knowing their patients and conducting quick assessments) and clinical judgment (applying their experience along with vital signs information) (Q4). Vital signs used to identify patient deterioration included heart rate, respiratory rate, oxygen saturation, temperature, and blood pressure. Other factors that nurses mentioned using for prioritisation include diagnostic tools like full blood count samples, patients' responsiveness and level of consciousness, and the "airway, breathing, and circulation" triage (ABC-triage).

Resource and staffing limitations were raised as issues that potentially lead to overlooking deteriorating patients. When multiple critically ill patients were present, and resources were insufficient to provide necessary care to all, priority was given to those with a higher chance of survival (Q5). In both ZCH and QECH, nurses consistently sought immediate help from colleagues, including those from other departments, during emergencies.

Several nurses considered that during their studies, they received insufficient prioritisation training. In some cases, they considered that this knowledge gap had not yet been addressed by other independent training programmes or clinical practice. Additionally, one nurse mentioned that when working in the ward, their colleagues had different levels of education and training, which influenced how nurses respond to deteriorating patients and how they make prioritisation decisions. She emphasised the need for a consistent intervention approach for patient deterioration among all nurses (Q6).

Interaction with guardians

According to the nurses, guardians, particularly mothers and grandmothers of the patients, are actively involved in the child's medical care, particularly when the nurses are not in the HDU. It is common practice for nurses to instruct guardians to recognise warning signs and alert them when necessary. Nurses adjust their explanations based on the guardians' knowledge and understanding of the situation, and some guardians can even assist with tasks such as changing probes (Q7). However, nurses consider that not all guardians comprehend the information provided and are consequently less engaged in medical care (Q8).

Perspective on data-driven algorithms

During the interviews, we observed that not all nurses had heard of data-driven algorithms; therefore, we provided examples, such as predictive algorithms. Although initially unfamiliar with the concept of "predictive algorithms", ten out of 17 nurses (59%) could define prediction and understood the concept of predictive algorithms after it was explained to them. Most nurses emphasised the potential benefits of data-driven algorithms, such as improving patient prioritisation, clinical decision-making, early detection of deterioration, and facilitating preventive interventions (Q9, Q10, Q11). They favoured algorithms for detecting patient deterioration and guiding treatment, emphasising the challenge of managing a high patient load and the potentially unnoticed deterioration of patients (Q13). Nurses highlighted the necessity for improved methods to monitor patients' real-time status, particularly from the nurses' station during intervals between spot-check rounds and overnight. They suggested that data-driven algorithms could contribute to addressing this need (Q14). Providing an overview of algorithm outputs for all patients via the nurses' station (e.g. utilising a tablet) or implementing alarms could enhance care optimisation according to them. Additionally, they underscored the potential of algorithms to standardise clinical practice by aiding nurses in making informed clinical decisions.

Nurses acknowledged the potential negative effects of algorithms providing incorrect outputs (mainly in terms of risks for the patients). They identified the main cause as issues with the algorithm's input, particularly incorrect monitor readings. They cited instances where sensors measuring vital signs, such as peripheral oxygen saturation and temperature sensors, malfunctioned or detached, resulting in inaccurate measurements.

Recognising the usefulness of algorithms and their potential for error, nurses emphasised the importance of relying on their clinical expertise to interpret algorithm outputs (Q12), for which they need to observe, interpret, and verify the output in light of the patient's condition and vital signs. Additionally, they underscored the importance of comparing the output of the algorithm and accompanying data with manual spot-check monitoring results and the patient's current clinical condition before considering interventions.

Regarding the preferred characteristics of an algorithm's output, the majority of nurses were inclined to accept colour-coded outputs and highlighted the importance of displaying the vital signs on the monitoring system, emphasising the need for explainable outputs. Almost half of the participants favoured a scoring system (i.e. a numeric scale) as the output of the algorithm based on a known score, such as the coma scale used to assess children's level of consciousness.

We asked about the impact of using a data-driven algorithm for guardians, as we observed that they worked with nurses to provide medical care to their children. Nurses had varying perceptions of how a data-driven algorithm could affect care when considering the current role of guardians. One nurse believed introducing a data-driven algorithm could enhance guardians' ability to recognise patient deterioration and help in providing care. However, another nurse expressed concern that such involvement could increase guardians' stress. To alleviate guardians' anxiety, nurses considered it necessary to minimise the information related to the algorithm's output on the tablet which remains visible to the guardian. For instance, nurses recommended showing a simplified score (just a number) or indicator lights (green-yellow–red) instead of a comprehensive score that also depicted vital signs out of range (Q15). All nurses unanimously agreed that guardians should not participate in data entry.

Step three: prototyping

Based on the results of the observations and interviews, we selected prototype components for a user interface of a hypothetical data-driven algorithm designed to predict the deterioration of paediatric patients using vital signs data from the IMPALA system. Additionally, we searched for a scoring system for deterioration known by the nurses in our context. The PEWS-RL is a scoring system that indicates the risk of deterioration based on one entry and is an adaptation of one of the most well-known scores specifically for LRS [24]. The hypothetical example used for prototyping is then a PEWS-RL-like score that would use continuous monitoring of vital signs and other manually entered data to determine the risk of deterioration. The information that hypothetically would be provided by the data-driven PEWS-RL score aligns well with the results of the contextual inquiry, interviews, and design objectives, and it is clinically relevant to critical care.

Three prototype components emerged: (a) risk representation, (b) representation of score input, and (c) representation of the changes in the score (Fig. 3 and Table 3). At least four design prompts were created for each component, to be used during the co-design sessions. The different design prompts are aimed at finding understandable and clear representations. They were also intended to explore the nurses' need to comprehend how the system generated the output and the factors leading to an increased score. The different

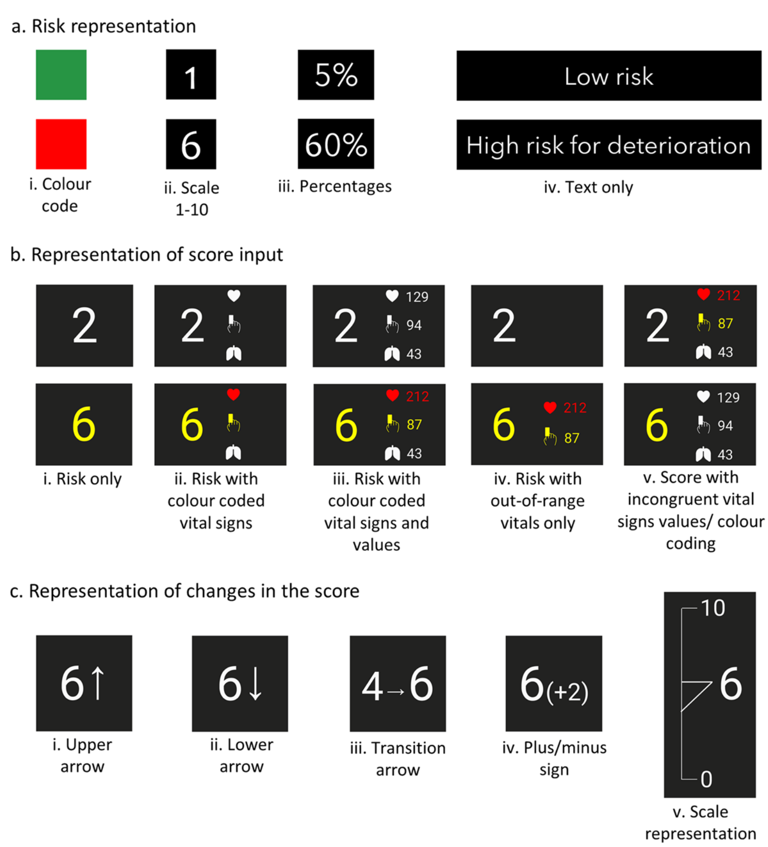

Fig. 3 Prototype components and the different design prompts explored during the co-design sessions

Table 3 Prototype components and refinement considerations are the foundation for the design prompts based on observations and interviews

Prototype component	Design prompts	Source
1. Risk representation Refinement considerations: Ensure swift data comprehension The presentation should be easily understandable and, preferably, intuitive Users should readily grasp whether the score indicates a high or low risk	We selected four prompts: **i. Colours**: Employing commonly recognised warning indicator colours (red, yellow and green) **ii. Number:** Providing a numerical score (0–10), aligning with standard health parameters **iii. Percentage:** Utilising a universal percentage scale (0–100%) **iv. Text**: Integrating descriptive text	Interviews and literature [25, 26]. The risk was determined to be a key aspect in the HDU workflow and for determining the chance of deterioration
2. Representation of score input Refinement considerations: Propose various solutions to achieve a balance between comprehensive information and simplicity	Five prompts were designed to illustrate different levels of explainability: **i. Score without background data:** providing the score without additional contextual information **ii. Score with an iconic representation of vitals with alarm indication:** incorporating icons to symbolise the status of vital signs and alarm indicators **iii. Score with numeric vital signs and alarm indication:** displaying numeric values of vital signs alongside alarm indicators **iv. Score with numeric vital signs of only the alarming vital:** highlighting numeric values for vital signs that contribute to the score that triggers an alarm **v. Score with incongruent vital signs values/colour coding:** displaying vital signs or colour codes that do not match the score presented	Interviews and literature [24, 27]. Participants expressed a desire for an understanding of the factors influencing the data-driven algorithm, deeming explanatory factors for risk necessary
3. Representation of changes in the score Refinement considerations: Use various change indicators to enhance the understanding of different cues	Five prompts were designed to represent patient deterioration: **i. An upward arrow:** indicating an increase in the score (presented to assess intuitive interpretation) **ii. A downward arrow:** indicating a decline in health (presented to assess intuitive interpretation) **iii. Previous and new scores:** displaying two scores simultaneously **iv. A score accompanied by a numerical representation:** showcasing the score change **v. A visual bar:** illustrating the current and previous score points	Observations revealed that the current way of working does not yet involve examining the patient's history to inform decisions, although nurses do acknowledge the significance of changes in health status

representations of changes in the score were designed to establish the most intuitive way to communicate changes in health state (especially deterioration). For each prototype component, refinements were identified (Table 3). Refinements refer to the iterative process of improving the design. The prototype components served as the groundwork for the co-design sessions (Table 3).

Step four: co-design sessions

In summary, we confirmed that the hypothetical data-driven PEWS-RL provided a solid foundation for further discussions and helped nurses focus on practical design issues and how they related to their clinical practice. For each prototype component, we presented the nurses between four and five design prompts (Fig. 3 and Table 3). Since the rankings carried out by the participants were difficult to interpret, we opted for an open discussion instead of a quantitative analysis.

Prototype component: risk representation

The nurses expressed familiarity with colour-coded triage systems and considered colour-coded scores (Fig. 3a (i)) more user-friendly than numbers (Fig. 3a (ii)). For example, they consider intuitive that red scores indicated "immediate attention" while green indicated "low risk". However, nurses confirmed the need for a score that would provide more detailed information than just binary classifications of "good" or "bad". For this reason, they favoured a colour scale representing different risk levels or combining numbers with colours to indicate the severity, thus providing better clinical insights. Regarding the numeric representation of the score, nurses preferred a one-to-ten scale (Fig. 3a (ii)). The second preferred option was percentages (Fig. 3a (iii)). Participants suggested that a text-based risk representation (e.g. 'high risk for deterioration') could reduce the need for interpretation and reduce variation in clinical responses caused by the different levels of education and training among nurses, which is a challenge also identified during the interviews (Fig. 3a (iv)).

Prototype component: representation of score input

Nurses were presented with five prompts that presented the factors that contribute or explain the risk displayed by the algorithm (Fig. 3b). They highlighted that if the algorithm's output is not accompanied by a clear explanation and indication of which data are behind the output (Fig. 3b (i)), it can be difficult for nurses to identify the source of the increased risk score and make the right clinical decisions. They highlighted the importance of viewing the individual vital signs contributing to the score, particularly when some vital signs were in alarming ranges and triggering alerts (Fig. 3b (ii–v)). Nurses voiced their need to understand why a score changed and to have access to the clinical information for them to corroborate clinically. They expressed that they would distrust the algorithm when vital signs did not align with the output (Fig. 3b (v)). These results corroborated the findings from interviews categorised under the theme "perspective on data-driven algorithms".

Prototype component: representation of changes in the score

Five prompts were used to explore the best way to represent changes in the algorithm's output (Fig. 3c). Each option combined a numerical value (representing the algorithm's output) with symbols or a graphic representation of a scale to illustrate the direction of the change in the algorithm's output. Symbols included arrows (↑, ↓, →, ←; Fig. 3c (i–iii)) and plus and minus signs (+, −; Fig. 3c (iv)). The third prompt ("4 → 6") was preferred by most nurses because it displayed both the previous and current scores and the direction of the change was clear to them. Nurses found this representation to enable them to clearly assess the child's progression. In contrast, nurses concluded that the first, second and fourth options ("6↑", "6↓", "6(+2)") were not intuitive. Prompt five, a graphic representation of a scale, was considered confusing and could not be interpreted, although during the discussion, the concept of representing scale was considered valuable.

The information gathered about the four prototype components was used to generate a single design proposal of the algorithm's interface, incorporating all components (Additional File 1: Final design proposal). This design will be used to develop an interface that will be incorporated into a new IMPALA system prototype, which will be the focus of future research.

General discussion about data-driven algorithms valuable for critical care in LRS

The last step of the co-design session engaged nurses in an open discussion to learn about their perceptions regarding a wider selection of algorithms. The following types of algorithms were discussed: algorithms that would (i) predict deterioration (as the example used for the co-design session), (ii) indicate treatments or interventions, (iii) diagnose, and (iv) determine the moment of discharge.

Deterioration prediction algorithms consistently emerged as the most realistic and helpful application. Nurses discussed the time delay in detecting early changes in vital signs and the compensatory mechanisms in children's bodies, which stop abruptly at a certain threshold, unlike in adults. Here, they suggested that a deterioration prediction algorithm could be valuable. When discussing discharge algorithms, nurses disagree on considering patient improvement or low risk of deterioration as the basis to indicate readiness for discharge. In response, nurses suggested integrating discharge and deterioration into a single algorithm. However, they acknowledged that ultimate responsibility for discharge decisions rests with doctors, so implementing a discharge algorithm would not directly impact their immediate decision-making. Nurses at ZCH identified an overlap between the potential positive effect of treatment and diagnostic algorithms, noting that delayed diagnoses in their current clinical practice result in subsequent delays in treatment. Consequently, nurses proposed combining treatment and diagnostic algorithms; however, they expressed scepticism about the reliability and functionality of these algorithms and insisted on the importance of human control alongside their use.

Discussion

To our knowledge, this is the first study to investigate nurses' perceptions regarding data-driven algorithms in Africa using a comprehensive and multidisciplinary approach. Contextual observations highlighted key challenges arising from scattered and insufficient monitoring equipment, physical configuration of the wards, shortage of nurses, and inconsistent decision-making practices. These challenges were corroborated during interviews. Nurses acknowledged the potential benefits of data-driven algorithms for HDU patient care but also expressed concerns about input accuracy, emphasising the need to use algorithm outputs in conjunction with clinical expertise rather than blindly following their outputs or recommendations. During the co-design sessions, nurses emphasised a preference for a clear, colour-coded and non-binary presentation of the algorithm's output. They found it necessary to understand which clinical data lead to a particular output and to be able to verify the clinical data on the IMPALA system, next to their own clinical observations. Finally, we generated a design proposal for integrating the interface of an algorithm into the next prototype of the IMPALA system (Additional File 1: Final design proposal).

Our study aligns with other reports from LRS, which have identified that the constraints on time and resources necessary for vital signs measurements were prominent factors affecting nurses' ability to provide comprehensive care and effectively prioritise patients [24]. In paediatric critical care settings, such as HDU wards, where clinical decisions can have life-saving consequences, continuous monitoring strategies supported by data-driven algorithms can be part of the solution; for example, by enabling early detection of deterioration and facilitating preventive interventions [5, 12]. In our study, nurses emphasised the added value of using data-driven algorithms to support patient prioritisation and improve clinical decision-making in critical care, similar to high-resource settings [28–31]. To our knowledge, no similar studies have been carried out in LRS, evidencing an important gap in scientific literature. The positive attitudes towards data-driven algorithms indicate a general acceptance of this new technology, consistent with prior research [30–33]. However, conditions must be met to make them appropriate for clinical care, especially in LRS. We describe the position of nurses as being "cautiously optimistic" about data-driven algorithms.

Algorithms, like the one analysed in this study, when implemented in medical practice, will change the workflow; for example, responsibilities, roles, scalation pathways, and communication among healthcare staff and between healthcare staff and patients/guardians. An adequate implementation plan would take these aspects into account before attempting to roll out such technology in a clinical setting [34].

This study highlights the importance of displaying the output of predictive algorithms by means of a simple, user-friendly and understandable design. This will allow nurses to appropriately act upon an algorithm's output. Viable design strategies include the application of colour coding to indicate when action is required. A colour-coding approach has been successfully implemented in various medical settings, e.g. emergency caesarean sections, and other triage tools for resource-limited emergency care, e.g. the WHO emergency triage assessment and treatment (ETAT) [25, 26]. Although colour coding can be a valuable design element for improving communication and decision-making in healthcare environments, it is essential to be compliant and respect current standards [35].

In our study's context, an essential feature to generate trust in a data-driven algorithm is to facilitate an explanation of the output (nurses need to understand how an output is generated and what it means), which aligns with the concept of "explainable AI" ("feature of an AI system that is intelligible to non-experts") [36]. Similarly, nurses need to understand which clinical data lead to a particular output, making it necessary to trace back which data was used by the AI system, this aligns with the concept of "traceability" ("ability to track the journey of a data input through all stages" until decision making) [36]. Explainability and traceability are two of the three elements of transparency [36]. Transparency enable nurses to validate the algorithm's outputs, identify potential errors, and make informed decisions grounded in their clinical judgment [37]. These elements should be embedded into the algorithm's design, for example, by providing an overview or easy access to relevant data, in our case vital signs data. They also need to be addressed during the implementation process, together with training programmes,

Table 4 Key pre-implementation recommendations for developing data-driven algorithms for LRS with illustrations from the present study

	Recommendation	Illustration from this study
1. Inquire about the type of algorithm to be developed	Get to know the context and potential end-users. Determine if data-driven algorithms could answer the needs of potential users. Consider that algorithms can have different aims, such as risk prediction, diagnosis, medication, or discharge. Involve the potential users early in the design process to investigate potential acceptance in the local context and improve the system's design and alignment with the clinical workflow. Consider user's specific requirements, preferences, and challenges on the ground	Analysis of the clinical context from clinical, design, and social sciences perspectives identified that an algorithm could assist in alleviating staff shortages and improving care provision. Interviews confirmed the users' perceived added value of algorithms for risk prediction in critical care
2. Foster trust in the data-driven algorithm	Fostering trust in data-driven algorithms depends on factors specific to the population. Researchers must, therefore, invest in identifying which factors enable or undermine trust. Different aspects such as actionability (ease of use, transparency, explainability), context specificity, and performance will probably be constant, but their interpretation and how to balance these aspects may vary depending on the users	Nurses working in critical care in LRS advocate for the primacy of their clinical expertise over a potential algorithm, independently of how good it is. In order to trust it, nurses found it necessary to be easy to use and capable of interacting to some basic degree with guardians. Nurses require outputs to be transparent and explainable, interpretable and actionable
3. Design actionable outputs	Design the outputs of the data-driven algorithm for specific purposes and tailor them to the context. Ensure that the output is actionable (understood as being able to act in response to the output). For example, the output facilitates clinical decision-making according to the accepted medical practices of the context. Hardware such as tablets and alarms can help address shortages in healthcare staff and suboptimal physical infrastructures	Analysing the workflow and working practices in a context with high patient-nurse ratios and where physical infrastructures do not provide an easy visual overview of patients allowed us to design the algorithm's output in a clinically meaningful way for nurses. It also provided us with insights into how technology can shorten distances between nurses and patients and provide a constant overview of the patients, for example, using tablets to display all the patients being constantly monitored and the output of the algorithm
4. Prefer minimal complexity and clarity	Simplify system complexity to accommodate educational variations among users. In doing so, avoid information overload. Providing different information layers may help simplify the system while making in-depth information available. Ensure clarity in distinguishing various aspects of your algorithm output by employing techniques like colour coding or visual cues	During the co-design sessions, nurses emphasised the importance of presenting the algorithm's output intuitively and simplistically, suggesting using color-coded scores, such as red to green, combined with numeric scales provided more detailed clinical information which is considered necessary for clinical decision making. This method enhanced understanding of which factors demand attention and facilitates interpretation of the algorithm's output, improving its applicability across diverse scenarios
5. Identify the most important aspects for designing tailored training programmes	Consider that providing users with comprehensive and customised training will define the adoption and success of a data-driven algorithm in clinical practice. Understanding aspects such as the users' responsibilities while using the algorithm and the changes in the clinical decision making that it can cause is necessary. Identify what is necessary for users for a correct interpretation of the algorithm's output and accompanying information, and how to communicate to other health professionals and guardians. Examine the role of guardians and determine if this needs to be part of the training provided to users. Consider, for example, if nurses need to be provided with information tools to be shared with guardians	Nurses expressed their need to have the right skills to interpret the algorithm, the capacity to critically interpret the results. They were already familiar with possible reasons why an algorithm could make mistakes (quality of input data). Training was seen as the means to achieve a coherent interpretation of the algorithm by nurses with different levels of education and training. Nurses confirmed that they would involve guardians in care while using such a data-driven algorithm (e.g. one that predicts the risk of deterioration) in clinical practice, aspect that we consider necessary to include in the plans for training nurses

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to acquire adequate new skills to adopt a critical care strategy that incorporates the use of a data-driven algorithm [33]. Training can help nurses recognise conditions that limit the performance of an algorithm, for example, when a score does not match the current vital signs, and help nurses interpret the algorithm for the particular case at hand, and decide the most appropriate follow-up clinical steps [38]. However, as previous human-factors research indicates [39, 40], explainability can be misleading and may not necessarily increase users' likelihood of following an AI prediction. It could even make it more challenging to identify incorrect predictions. Therefore, an in-depth assessment of explainability will need to be carried out in future research [40].

Training programmes should be designed for target groups with different levels of clinical expertise; for example, in our case, to address variations in familiarity with vital signs monitoring, data visualisations, and algorithms [24]. In our study, nurses acknowledged significant variations in their knowledge and competencies regarding specialised critical care, specifically limitations inappropriately interpreting vital signs trends and prioritisation. Other studies have identified these challenges, such as lacking training programmes for early critical care services in LRS [24, 41–43]. Another possibility is formally introducing the concept of data-driven algorithms in nursing study programmes.

Previously reported literature found that guardians' involvement in monitoring and medical care is crucial in LRS, including critical care settings [17, 44]. Observations and interviews indicated that nurses considered the involvement of guardians positive. Consequently, we argue that the guardians' role should be taken into account for both design and implementation and should be addressed in-depth in future research.

Limitations and strengths

This study was limited to two sites in Malawi, which requires considering the context before attempting to generalise our results. However, by including two different hospitals, with different urban and rural populations, and differences in resources available, we aimed to capture at least some of the variation between healthcare facilities in Malawi. The challenges generated by the lack of resources in these hospitals are common to countries in Sub-Saharan Africa. We focus on nurses as key users of vital signs monitoring systems, and we ensure to enrol nurses with different levels of expertise. However, future research needs to explore the perceptions of doctors, clinical officers, guardians, and other stakeholders who may utilise the technology actively or passively. Although the study provided evidence-based information to choose an appropriate algorithm to integrate into the IMPALA system and provided the first design prototype of the interface, several aspects still need to be researched, including the use of alarms to reflect the urgency of the algorithm's outputs (ongoing research). While choosing one hypothetical algorithm to carry out the co-design sessions may have limited the breadth of the co-design process, it facilitated the illustration and testing of fundamental design principles, informing the algorithm and interface development from a human-centred perspective. Despite these limitations, the study's focus on LRS contributes to filling a significant gap in existing scientific literature [28–31]. Furthermore, applying a human factors perspective and the methodological triangulation of contextual inquiry, interviews, and co-design sessions offered a comprehensive understanding of the potential of data-driven algorithms in paediatric HDUs in LRS and guided their development and implementation. Finally, the multidisciplinary approach allowed us to understand better the context and the significance of data-driven algorithms in critical care within LRS, and draw a set of general recommendations for the pre-implementation of data-driven algorithms in LRS (Table 4).

Conclusions

This pre-implementation and human-centred design study offers valuable insights into nurses' perceptions regarding data-driven algorithms for paediatric critical care in LRS, which we describe as cautiously optimistic. Nurses welcome data-driven algorithms but are clear about the superiority of their experience and clinical expertise. Acceptance of such a system depends on developing explainable and traceable systems. From a methodological perspective, we presented a research mechanism to explore and translate perspectives on the ground into development and design strategies. Our results are relevant for developing, designing, and implementing such algorithms and their accompanying software in various healthcare settings, but specifically for critical care within LRS. Most notably, the study demonstrates the genuine potential of data-driven algorithms in critical care environments in LRS, highlighting how contextual factors determine the effectiveness of these tools.

Abbreviations

LRS	Low-resource settings
HDUs	High-dependency units
AI	Artificial intelligence
IMPALA	Innovative Monitoring in Paediatrics in Low Resource setting: an Aid to save lives
QECH	Queen Elizabeth Central Hospital
ZCH	Zomba Central Hospital
UX	User experience
SpO2	Peripheral Oxygen Saturation
NIBP	Non-invasive Blood Pressure
ECG	Electrocardiogram
PEWS-RL	Paediatric Early Warning Score – Resource Limited
ABC-triage	Airway, Breathing, and Circulation-triage
WHO-ETAT	World Health Organisation – Emergency Triage Assessment and Treatment

Supplementary Information

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Additional file 1. 1 – Collaborators in the IMPALA study team. 2 – Definition data-driven algorithms and connection with AI. 3 – Floor plan of the HDUs in QECH and ZCH. 4 – Observation manual. 5 – Interview guide. 6 – Consolidated criteria for reporting qualitative studies (COREQ). 7 – Co-design sessions questionnaire. 8 – Codebook. 9 – Final design proposal.

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Authors' contributions
MR, KD, and MV designed, conceptualised and defined the methods in the study. MR, LdM, and DM did data collection, visualisation, and data evaluation. MR, LdM, and DM carried out the data analysis. MR, DM, LdM, LC, BB, AL, JL, NC, HvO, KR, MV drafted the manuscript and its final version. MV and KD supervised the study. All authors contributed to the article and approved the submitted version. All authors read and approved the final manuscript.

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Data availability
The data used to support the findings of this study are included within the article. Raw data (observational manuals, transcripts of the interviews, and the responses collected from the surveys during the co-design sessions) analysed during the current study are not publicly available due to confidentiality agreements but are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The study was approved by the College of Medicine Research and Ethics Committee (COMREC) at the University of Malawi on October 6th, 2022 (P.01/22/3552). The study adhered to the principles outlined in the Declaration of Helsinki and followed the guidelines set by COMREC for Health Research. Written informed consent was obtained, and nurses signed the informed consent form in English or Chichewa.

Consent for publication
Not applicable.

Competing interests
Two of the authors, LdM and BB, are affiliated with GOAL 3, a social enterprise. The remaining authors declare no competing interests.

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References

1. Levels and trends in child mortality - UNICEF DATA. Available from: https://data.unicef.org/resources/levels-and-trends-in-child-mortality-2024/. Cited 2024 Aug 13.
2. Calis JCJ, Bem RA, Chisti MJ. Editorial: pediatric critical care in low resource settings. Front Pediatr. 2024;8(12):1420688.
3. Kruk ME, Gage AD, Joseph NT, Danaei G, García-Saisó S, Salomon JA. Mortality due to low-quality health systems in the universal health coverage era: a systematic analysis of amenable deaths in 137 countries. Lancet. 2018;392(10160):2203–12.
4. Slusher TM, Kiragu AW, Day LT, Bjorklund AR, Shirk A, Johannsen C, et al. Pediatric critical care in resource-limited settings-overview and lessons learned. Front Pediatr. 2018;16(6):338287.
5. Diallo AH, Sayeem Bin Shahid ASM, Khan AF, Saleem AF, Singa BO, Gnoumou BS, et al. Characterising paediatric mortality during and after acute illness in Sub-Saharan Africa and South Asia: a secondary analysis of the CHAIN cohort using a machine learning approach. eClinicalMedicine. 2023;57:101838.
6. Bartlett ES, Lim A, Kivlehan S, Losonczy LI, Murthy S, Lowsby R, et al. Critical care delivery across health care systems in low-income and low-middle-income country settings: a systematic review. J Glob Health. 2023;1(13):04141.
7. Chapman SM, Grocott MPW, Franck LS. Systematic review of paediatric alert criteria for identifying hospitalised children at risk of critical deterioration. Intensive Care Med. 2010;36(4):600–11.
8. Ilangakoon C, Jones T, Innes K, Morphet J. Caring for deteriorating paediatric patients in the emergency department: a mixed method study. Australas Emerg care. 2020;23(4):252–8.
9. Vincent JL, Marshall JC, Ñamendys-Silva SA, François B, Martin-Loeches I, Lipman J, et al. Assessment of the worldwide burden of critical illness: the Intensive Care Over Nations (ICON) audit. Lancet Respir Med. 2014;2(5):380–6.
10. Van Zyl C, Badenhorst M, Hanekom S, Heine M. Unravelling 'low-resource settings': a systematic scoping review with qualitative content analysis. BMJ Glob Heal. 2021;6(6) e005190.
11. Massey D, Chaboyer W, Anderson V. What factors influence ward nurses' recognition of and response to patient deterioration? An integrative review of the literature. Nurs open. 2016;4(1):6–23.
12. Zaidi AKM, Ganatra HA, Syed S, Cousens S, Lee AC, Black R, et al. Effect of case management on neonatal mortality due to sepsis and pneumonia. BMC Public Health. 2011;11(SUPPL. 3):1–15.
13. Cossy-Gantner A, Germann S, Schwalbe NR, Wahl B. Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings? BMJ Glob Heal. 2018;3(4):798.
14. Ciecierski-Holmes T, Singh R, Axt M, Brenner S, Barteit S. Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: a systematic scoping review. NPJ Digit Med. 2022;5(1):162.
15. Beuscart-Zephir M-C, Elkin P, Pelayo S. Human factors engineering for clinical applications. Stud Health Technol Inform. 2006;124:685–90.
16. ISO 9241-210:2010 - Ergonomics of human-system interaction — Part 210: human-centred design for interactive systems. Available from: https://www.iso.org/standard/52075.html. Cited 2024 Oct 18.
17. Hoffman M, Mofolo I, Salima C, Hoffman I, Zadrozny S, Martinson F, et al. Utilization of family members to provide hospital care in Malawi: the role of hospital guardians. Malawi Med J. 2012;24(4):74.
18. Malawi population and housing census report. 2019. Available from: https://malawi.unfpa.org/sites/default/files/resourcepdf/2018%20Malawi%20Populati%20n%20and%20Housing%20Census%20Main%20Report%20%281%29.pdf. Cited 2024 Oct 18.

19. Morton B, Banda NP, Nsomba E, Ngoliwa C, Antoine S, Gondwe J, et al. Establishment of a high-dependency unit in Malawi. BMJ Glob Heal. 2020;5:4041.
20. Crehan C, Kesler E, Chikomoni IA, Sun K, Dube Q, Lakhanpaul M, et al. Admissions to a low-resource neonatal unit in Malawi using a mobile app: digital perinatal outcome audit. JMIR mHealth uHealth. 2020;8(10):e16485. https://doi.org/10.2196/16485.
21. Viitanen J. Contextual inquiry method for user-centred clinical IT system design. Stud Health Technol Inform. 2011;169:965–9.
22. Thomas BE, Suresh C, Lavanya J, Lindsley MM, Galivanche AT, Sellappan S, et al. Understanding pretreatment loss to follow-up of tuberculosis patients: an explanatory qualitative study in Chennai, India. BMJ Glob Health. 2020;5(2):e001974.
23. Erlingsson C, Brysiewicz P. A hands-on guide to doing content analysis. African J Emerg Med. 2017;7(3):93.
24. Sridhar S, Schmid A, Biziyaremye F, Hodge S, Patient N, Wilson K. Implementation of a pediatric early warning score to improve communication and nursing empowerment in a rural district hospital in Rwanda. Glob Heal Sci Pract. 2020;8(4):838–45.
25. Benazza N, Touzart L, Muszynski C, Gondry J. Impact of establishment of a color code in emergency caesareans in secondary health care maternity. J Gynecol Obstet Hum Reprod. 2019;48(4):261–4.
26. Mitchell R, Bue O, Nou G, Taumomoa J, Vagoli W, Jack S, et al. Validation of the interagency integrated triage tool in a resource-limited, urban emergency department in Papua New Guinea: a pilot study. Lancet Reg Health West Pac. 2021;1(13):100194.
27. Rakers M, van de Vijver S, Bossio P, Moens N, Rauws M, Orera M, et al. SERIES: eHealth in primary care. Part 6: global perspectives: learning from ehealth for low-resource primary care settings and across high-, middle- and low-income countries. Eur J Gen Pract. 2023;29(1):2241987.
28. Jocelyn Chew HS, Achananuparp P. Perceptions and needs of artificial intelligence in health care to increase adoption: scoping review. J Med Internet Res. 2022;24(1):e32939.
29. van der Meijden SL, de Hond AAH, Thoral PJ, Steyerberg EW, Kant IMJ, Cinà G, et al. Intensive care unit physicians' perspectives on artificial intelligence-based clinical decision support tools: preimplementation survey study. JMIR Hum Factors. 2023;10:e39114.
30. Ronquillo CE, Peltonen LM, Pruinelli L, Chu CH, Bakken S, Beduschi A, et al. Artificial intelligence in nursing: priorities and opportunities from an international invitational think-tank of the Nursing and Artificial Intelligence Leadership Collaborative. J Adv Nurs. 2021;77(9):3707.
31. Matthiesen S, Diederichsen SZ, Hansen MKH, Villumsen C, Lassen MCH, Jacobsen PK, et al. Clinician preimplementation perspectives of a decision-support tool for the prediction of cardiac arrhythmia based on machine learning: near-live feasibility and qualitative study. JMIR Hum Factors. 2021;8(4):e26964.
32. Alanazi A. Clinicians' views on using artificial intelligence in healthcare: opportunities, challenges, and beyond. Cureus. 2023;15(9):e45255.
33. Edzie EKM, Dzefi-Tettey K, Asemah AR, Brakohiapa EK, Asiamah S, Quarshie F, et al. Perspectives of radiologists in Ghana about the emerging role of artificial intelligence in radiology. Heliyon. 2023;9(5):e15558.
34. Chomutare T, Tejedor M, Svenning TO, Marco-Ruiz L, Tayefi M, Lind K, et al. Artificial intelligence implementation in healthcare: a theory-based scoping review of barriers and facilitators. Int J Environ Res Public Health. 2022;19(23):16359.
35. IEC 60601-1-8:2006(en), Medical electrical equipment — Part 1-8: general requirements for basic safety and essential performance — Collateral standard: general requirements, tests and guidance for alarm systems in medical electrical equipment and medical electrical systems. Available from: https://www.iso.org/obp/ui/en/#iso:std:iec:60601:-1-8:ed-2:v1:en. Cited 2024 Jan 4.
36. Ethics guidelines for trustworthy AI | Shaping Europe's digital future. Available from: https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai. Cited 2024 Aug 29.
37. Amann J, Blasimme A, Vayena E, Frey D, Madai VI. Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. BMC Med Inform Decis Mak. 2020;20(1):310.
38. Charow R, Jeyakumar T, Younus S, Dolatabadi E, Salhia M, Al-Mouaswas D, et al. Artificial intelligence education programs for health care professionals: scoping review. JMIR Med Educ. 2021;7(4):e31043.
39. Ghassemi M, Oakden-Rayner L, Beam AL. The false hope of current approaches to explainable artificial intelligence in health care. Lancet Digit Health. 2021;3(11):e745-50.
40. Amann J, Vetter D, Blomberg SN, Christensen HC, Coffee M, Gerke S, et al. To explain or not to explain?—Artificial intelligence explainability in clinical decision support systems. PLOS Digit Heal. 2022;1(2):e0000016.
41. Coyle RM, Harrison HL. Emergency care capacity in Freetown, Sierra Leone: a service evaluation. BMC Emerg Med. 2015;15(1):1–9.
42. Razzak JA, Kellermann AL. Emergency medical care in developing countries: is it worthwhile? Bull World Health Organ. 2002;80(11):900-5.
43. Amoateng-Adjepong Y. Caring for the critically ill in developing countries–our collective challenge. Crit Care Med. 2006;34(4):1288–9.
44. Marquer C, Guindo O, Mahamadou I, Job E, Rattigan SM, Langendorf C, et al. An exploratory qualitative study of caregivers' knowledge, perceptions and practices related to hospital hygiene in rural Niger. Infect Prev Pract. 2021;3(3):100160.

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