Can AI-supported Systems Help with Aftercare Planning? Opportunities and Challenges from a Clinical Perspective

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ABSTRACT

Ensuring optimal care post-hospitalization is a significant challenge for healthcare systems. Discharge management (DM) is crucial for continuing care, yet process-related issues persist. Artificial Intelligence (AI)-supported systems may address DM-related issues, but research on the needs of hospital staff is limited. This paper presents results from the first phase of a multicenter project aimed at developing an AI-supported system to predict aftercare needs and improve DM processes in German hospitals. We conducted an exploratory needs analysis using participatory methods (workshops, questionnaires and interviews) and defined suitable use cases. We observed a high level of interest in the proposed AI-supported system. However, participants expressed doubts about the effective implementation due to the current state of their hospital's digital infrastructure. The resulting use cases focused on the reception, processing and interpretation of "plausible" data. These outcomes form the basis for the further research and development with hospital staff and external developers.

CCS CONCEPTS

• **Information systems** → **Expert systems**; **Decision support systems**; • **Human-centered computing** → *Participatory design*; • **Computing methodologies** → Artificial intelligence.

KEYWORDS

Discharge Management, Artificial Intelligence, AI-supported Systems, Participatory Design

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1 INTRODUCTION AND RELATED WORK

Ensuring optimal and continual care for patients after a hospital stay presents a major challenge for the German healthcare system. Discharge management (DM) plays a key role in the process because it is responsible for the continuation of care and communication between various stakeholders, thus relieving the burden on patients and relatives and preventing readmission (Section 39 (1a) SGB V). A law and framework agreement was passed in Germany to ensure that patients receive continuous, needs-based care following hospital treatment, yet its implementation has shown that there are still interface problems between the stakeholders involved in DM [7]. There is a lack of recognition of increased post-inpatient care needs and deficiencies in the flow of information. DM often starts too late, is uncoordinated and inadequate [7, 10], which leads to unplanned readmission in 7.3% of cases [7]. In addition, delayed discharges for patients can lead to an increased risk of death, hospital-acquired infections, mental illness and reduced mobility as well as decreased activities of daily living. Delayed discharges mean additional stress for staff. They also lead to rising costs for the hospital [11].

1.1 Discharge management and the potential of AI support

There are several key issues which can impact a timely discharge. Delays may begin with incorrect documentation practices upon admission. Paperwork and administrative tasks - calls, emails and personal inquiries - take up a lot of time in everyday clinical practice. Conservative structures lead to a lack of transparency among stakeholders. Staffing shortages in DM are frequent and turnaround rate is high. Complex individual patient requirements like psychosocial needs or developments in social law entitlements can suddenly change the course of planning. Ultimately, these issues can lead to an extended (and thus costly) length of stay and interrupted care for the patient.

AI-supported systems can offer structure to clinical practice and have been used extensively in areas of prevention, diagnosis, novel drug designs and aftercare [4]. In this paper, we define an AI-supported system as a software with an integrated AI module, with the purpose of helping humans by providing them with expert recommendations and relevant information. In the context of nursing, AI-supported solutions have mainly been investigated in the fields of robotics and monitoring systems, even though the use of AI-supported systems is seen as a promising field of application [1]. Despite this research, AI-supported systems have not yet arrived in everyday clinical practice. Many regulatory, logistical and technical barriers exist [3, 17] and there are still open questions regarding ethical concerns [9], particularly with at-risk groups such as older adults [13, 15]. In general, evidence for successful implementation in clinical care is lacking [2]. As with medical decision support systems in general [14], these challenges are mainly due to the lack of interoperability and availability of high-quality data, data protection concerns and requirements for the explainability of results.

In principle, it is possible to determine a patient's need for follow-up care upon admission based on their (suspected) illness or symptoms. Indeed, recent studies report high predictive performance of patient discharges using machine learning methods [5, 6, 12], usually focusing on subsets of populations such as surgical patients. That being said, research on the relevance of an AI-supported system specifically for DM is still lacking in the context of German hospitals.

1.2 Participatory design – Involving the end users in the design and development of the system

Crucial considerations when developing digital technologies are the current and future needs of the end-user. The key feature of PD is the active "democratic" involvement of end-users and other relevant stakeholders in the design process. This ensures that the design is user-centered and meets the real needs and expectations of the users. PD is thus inherently collaborative, relying on the contributions of diverse participants. This collective effort helps generate innovative solutions and fosters a sense of ownership among stakeholders. By involving users in the design process, designers and developers also gain a deeper understanding of the context in which the product will be used. This helps in creating solutions that are more relevant, easy to use and effective. PD also intrinsically empowers users by giving them a voice in the creation of products that affect their (working) lives. This empowerment can lead to increased satisfaction and better acceptance of the final design. On the product/system development side, the design process itself is iterative, involving repeated cycles of prototyping, testing and refining based on feedback from users. This iterative nature allows for continuous improvement and adaptation as well as reducing costs by eliminating the need for extensive reworks in the later development and rollout processes.

Scientifically, PD is built upon several interdisciplinary fields, including human-computer interaction (HCI), cognitive psychology and social science. It is by itself a cornerstone of HCI, where the goal is to create interfaces and systems that are intuitive and user-friendly. Research in HCI shows that involving users leads to better usability and functionality. In addition, insights from cognitive psychology inform PD by highlighting how people perceive, learn and interact with technology. Understanding these cognitive processes helps designers as well as developers create more effective and engaging products. Last but not least, social science research emphasizes the importance of the social context and the user experience in design. PD draws on these insights to create solutions that are socially and culturally appropriate.

1.3 Designing and developing an AI-supported system for discharge management

The overall aim of the project is to develop an AI-supported system together with hospital staff which can i) predict aftercare needs upon admission using patient data and ii) assist in administrative and documentation processes. Such a system may help prevent longer hospital stays, post-inpatient care problems and allow more time for important patient consultations. The envisaged AI-supported system complements an available software solution for DM which is currently in use at the participating university hospital.

In order to prepare for the development and evaluation phases of the project, we carried out a basic need analysis using participatory methods (workshops, questionnaires and interviews) with hospital staff. We addressed the following questions to develop practical user-stories for our developers:

- What relevance do hospital staff see in AI-supported discharge management?
- What expectations do hospital staff have of an AI-supported system for discharge management?
- What are the potential concerns and risks from the perspective of hospital staff?

Our proposed system (see Figure 1) consists of three parts: a) an early prediction-system based on patient data to determine potential aftercare needs (trained with retrospective patient data from the participating hospitals), b) an optimized documentation system for employees and c) a virtual assistant (chatbot) for routine questions from patients and relatives. Using data generated during admission, diagnosis and treatment, aftercare needs can be predicted and readjusted interactively by the staff as well as partially automated by the system. The documentation assistant will provide text modules and automatic transmission of relevant patient data into required documentation. All this may enable more flexible transition processes. The virtual social worker (chatbot) can answer routine questions from patients and relatives, reducing the number of - potentially burdensome - calls for the staff.

Currently, several techniques and models are being tested, namely case-based reasoning (as our main entry point), regression models, decision trees as well as gradient boosting machines, support vector machines and neural networks.

2 METHODS

The study presented here is an explorative basic needs analysis with a triangular mixed-methods approach - as such it is not focused on generalizability (i.e. reliability or validity) in this early phase. The system will be co-designed and tested by hospital staff throughout the course of the project using PD methods. Staff working in DM at a German university hospital (total n=14) took part in workshops and questionnaires (subset n=8). Expert interviews were conducted

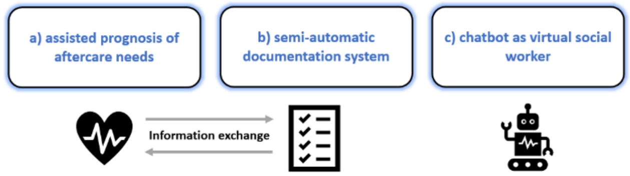

Figure 1: Functional modules of our AI-supported system for discharge management [Image created by the authors].

with doctors (subset n=3) and nursing staff (subset n=2). This study was approved by the responsible ethics commission and works counsel. All participants signed a declaration of consent.

Workshops and questionnaires took place between July and August 2023. Expert interviews took place between August 2023 and January 2024. A workshop consisted of 4 hours split into two 2-hour sessions. Interviews were 30 minutes long and questionnaires took approximately 15 minutes to complete. Workshop materials, transcribed audio recordings, interviews and results from the questionnaires were used to conduct a qualitative content analysis based on Mayring's method [8]. The theoretically deducted - ex-ante - categories used for the analysis encompassed (but were not limited to) the DM process including the admission and discharge plans, the staff roles and collaboration, the needs (e.g. documentation) and challenges pertaining to DM as well as the functions, concerns and acceptance pertaining to the AI system.

In the collaborative workshops we used several PD methods and techniques to engage users and stakeholders (based on narrative scenarios and user stories) to explore and communicate design ideas and user interactions where designers and users brainstormed, prototyped and evaluated ideas. Workshops began with a brief introduction to the project goals and a warm-up task on AI to assess the participants' baseline knowledge. Here, participants were asked to brainstorm about the following questions:

- What is AI from your point of view?
- What can AI do/what can't AI do?
- How can AI help you in your work?

We then gave a brief summary of how AI works and what our proposed system could look like. Participants were then asked to map indirect, direct and core stakeholders as well as processes relevant to DM. We then prompted participants to think about the benefits and concerns of using an AI-supported system to communicate with these stakeholders and to help in these processes. Ideas were collected via post-its and clustered according to category.

The workshops were followed by brief questionnaires to collect complementary quantitative descriptive data on the current status of division of labor according to task (i.e. documentation) or instrument (i.e. fax, computer), satisfaction with current DM processes, as well as expectations and ethical considerations regarding AI. Lastly, we conducted expert interviews to fill information gaps and gather insights from doctors and nursing staff. Insights gathered from all aforementioned tasks were used to develop the use cases presented in the results section.

3 RESULTS

An exemplary overview of participant ideas from the detailed mappings and from the clustering are shown in Figure 2. Questionnaires and interviews provided supplemental information that was not collected during the workshop process. Workshop materials, interview transcripts and questionnaire data were used to derive three new (hospital-specific) scenarios for an AI-supported DM system which were seen as particularly meaningful from the target group's perspective. The most frequently mentioned "pain point" in the DM process, which involves the reception, (further) processing and interpretation of "plausible" (patient) data, is at the forefront of each of the following use cases.

3.1 Use Case I – Plausibility and/or completeness check of data

- Problem/Challenge: Data in the clinical assignment ("Klinischer Auftrag - KLAU") serving as the basis for further processing of the DM case is transmitted incomplete, incorrect, or in some cases nonsensical.
- Extreme Example: The mandatory text field "phone number" is filled by the intake staff with the implausible string "1234" and then transferred to the primary system - this complicates or prevents further processing by DM depending on the case.
- Potential solution/Opportunity: The AI should subject the text fields to a) a plausibility check and b) provide a correction suggestion or - if not possible - display a prompt to the intake staff that can be directly adopted into the system.

3.2 Use Case II – System-related special case for plausibility check of telephone data

- Problem/Challenge: There are homeless patients who have no telephone connection and therefore no phone number.
- Extreme Example: The primary system does not have "codes" for such special cases, but a phone number still needs to be entered, as the form otherwise cannot be saved and processed correctly (the entry is made here by the intake staff analogously to Use Case 1 with the implausible string "1234").
- Potential solution/Opportunity: The system should a) recognize that such a (special) case exists and b) provide a note, a notification, or an alert for identical or analogous special cases to the further processing staff.

3.3 Use Case III – Intake or further processing staff who need to provide necessary data for case processing do not provide the said data at all or provide implausible data

- Problem/Challenge: Important data for processing the case, such as clinical or contact-related data, was not entered.
- Extreme Example: The corresponding departments did not enter the (nursing-related) "Barthel Index", which is difficult or impossible to obtain quickly by the DM staff.
- Potential solution/Opportunity: The system should a) periodically check whether its data is complete and b) provide feedback in the form of a "pop-up" to the discharge management staff and c) in the context of communication support,

preformulate a complete reminder/request email so that it can be sent directly to the "delinquent data providers."

3.4 Summary

In summary, the primary requirement for the AI system is to recognize the relevant pain points for case handling and provide reminders or suitable feedback for further processing to the handling staff. In addition to the above use cases, participants also mentioned further issues with multiple registrations of patients, the existance of several document versions (missing duplicate checks) and missing "up-to-date checks" of relevant documents in the course of the process (e.g. the current status of the patient's Barthel Index). Moreover, in addition to supporting communication with internal clinic departments, communication with patients or relatives should also be supported if standardized or frequent inquiries come in, which, although being "simple" to answer, result in a significant time expenditure for individual responses. Further general points, hopes and requirements that were mentioned singularly are listed below:

- Error avoidance and thereby shortening the (duration of) work processes/process steps, resulting in more "qualitative" time for the patient overall.
- Tracking of the work process ("Where do we stand, how far are we?").
- Assistance in clarifying responsibilities or forwarding documents to the right recipients.
- Support in demand planning and the selection of information relevant to the respective process step or respective handlers.
- Correct pre-filling of standardized documents by the system (including prescriptions) for review and quick approval by the handling person.
- Automatic documentation of processes and persistent storage of documents and materials.
- Fewer calls with generic inquiries from relatives (preferred solution: chatbot).
- Clear feedback: All relevant information should be clearly presented, e.g., in the form of a "management dashboard" (participant statement: "I sometimes feel like a detective").
- External interfaces, e.g., to support the search for suitable nursing homes.

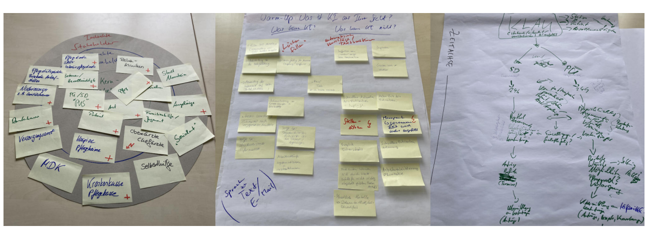

Figure 2: Excerpt from the workshop results [Image created by the authors].

4 DISCUSSION

We began our workshop sessions with an introduction to the project, warm-up session and a theoretical introduction to AI-supported systems. We wanted participants to have a foundational basis on the capabilities and limitations of AIs. While most participants understood the basic concepts of AI, only a select few had come in contact with commercial AI tools (i.e. ChatGPT). None of our participants had ever used an AI-supported system at work, although some reported optimizing their own workflows using digital tools like electronic signatures where allowed.

Our results from the stakeholder and process mappings as well as the clustering sessions confirmed that discharge planning is a complex and dynamic process, which can be exacerbated by the sectoral character of the German healthcare system, by administrative pitfalls and by lack of digital innovations to optimize workflows and facilitate patient engagement. That being said, our participants reported that an AI-supported system to predict aftercare needs and optimize workflows would be relevant for them, although they had doubts as to whether such a system can be effectively implemented due to the current state of the digital infrastructure at the hospital. In addition, developments in the situation or health of a patient as well as various structural and communication barriers can lead to further complications.

Regarding their expectations, our participants were interested in developing use cases that address current data management issues. Although participants had many ideas about how an AI-supported system could help them in clinical practice, their main focus was on solutions that do not necessarily require an AI. For example, many of our participants reported that improper or missing information from doctors or nursing staff can lead to organizational delays, not only because the information is missing, but because the case workers have to act like "detectives" in order to complete discharge documentation. Plausibility checks and automatic documentation as to who submitted what and when would be very useful in everyday practice.

The amount of documentation required in discharge planning was another issue reported by our participants. As an example, German health insurance companies each have their own set of documentation required for aftercare planning, which must be stored and retrieved for each case. This issue could be addressed with an "intelligent documentation hub" within the system where caseworkers can organize, share and collaborate with other stakeholders regarding relevant documents.

Alongside the pragmatism dominating the elaboration of use cases and pain points ("the main thing is that the solution works"), several fears or ethical concerns were expressed upon inquiry, primarily the fear of job cuts or extra work if the system supports an overly "efficient" process ("the saved time will somehow be filled by management again"). In the context of the relatives/patients chatbot module, concerns were raised that if the system malfunctions or is unavailable, relatives as well as patients would feel poorly "taken care of" and potentially discouraged by waiting loops. Additionally, the design of the consent declaration for the chatbot case remains unclear. Finally, concerns were expressed regarding data processing or possible data breaches, such as the system disseminating incorrect information - potentially also in connection with unauthorized access by non-entitled recipients.

In general, our results are in line with previous studies regarding barriers which impede implementation of AI in German hospitals [3, 17]. For our participants, these barriers included conservative structures, inadequate communication between stakeholders, tight budgets, existing data management practices and data privacy concerns. They were aware that there is a gap between what is expected from employees regarding professional digitalization and what hospital institutions can actually offer. Although they saw value in an early prediction system, they were mainly interested in conceptualizing an AI-supported system that mitigates data processing and documentation issues.

4.1 Conclusion

Our study used participatory methods to conceptualize a novel AI-supported system for prediction of aftercare needs and mitigating processes in DM. Discussions with potential end-users revealed structural, communicative and administrative challenges as well as scenario-related opportunities in a German university clinic.

Specifically, we observed that certain prerequisites in hospital information systems and communication between stakeholders need to be in place before an AI-based assistant tool can be practically and efficiently implemented into daily clinical practice.

4.2 Limitations

This study was conducted at a German university hospital with a small number of participants and therefore observes values and beliefs of a particular group and clinic specific workplace structures and climates. Ideally, AI-development methodologies should consider values of a wide array of subsets of users and large cohorts [16]. However, in the case of our study we observed that hospitals are in many ways their own worlds with specific structures and rules and that AI-supported systems and tools optimizing clinical and administrative tasks should be catered to specific needs of a hospital or even clinic.

Using PD in designing digital technologies has many benefits, but we also faced challenges, as the management of extensive user involvement (e.g. the work schedules of the clinical end users) was time-consuming and the management of the input from multiple stakeholders was complex (e.g. the balancing of diverse needs and opinions of different users) and required skilled facilitation. An example of this is the small number of returned questionnaires (8 out of 14, 57%).

4.3 Future research

Results of this study will be used to conceptualize workshops and interviews at a second German university hospital planned for summer 2024. Comparing results between these two hospitals will provide interesting insights on the role of preexisting digital infrastructures in effective aftercare planning. A questionnaire with patients and their relatives on interacting with an AI chatbot and ethical perspectives of using AI in aftercare planning is planned for fall 2024.

We have started the second stage of the project in parallel which focuses on compiling training data for the early prediction system, as well as developing the chatbot and documentation assistant. Prototype testing is planned for late 2024.

In stage three we will finally evaluate the accuracy of predictions and overall practicality of the new system and its accompanying processes in the field.

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