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Healthcare of the Future 2025

Redefining Healthcare Delivery in the Digital Era

Editors: Thomas Bürkle
Minou Afzali
Kerstin Denecke
Sang-Il Kim
Gert Krummrey
Friederike J.S. Thilo
François von Kaenel
Michael Lehmann

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HEALTHCARE OF THE FUTURE 2025

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Edited by

Thomas Bürkle

Bern University of Applied Sciences Department TI, Biel, Switzerland

Minou Afzali

Swiss Center for Design and Health SCDH, Nidau, Switzerland

Kerstin Denecke

Bern University of Applied Sciences Department TI, Biel, Switzerland

Sang-Il Kim

Bern University of Applied Sciences Department TI, Biel, Switzerland

Gert Krummrey

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François von Kaenel

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and

Michael Lehmann

Bern University of Applied Sciences Department TI, Biel, Switzerland

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Healthcare of the Future 2025
Redefining Healthcare Delivery in the Digital Era

International Conference Biel/Bienne
9 May 2025

Thomas BÜRKLE[a,1], Minou AFZALI[c], Kerstin DENECKE[a], Sang-Il KIM[a], Gert KRUMMREY[a], Friederike JS THILO[b], François VON KAENEL[a] and Michael LEHMANN[a]

[a] *Bern University of Applied Sciences Department TI, Biel, Switzerland*
[b] *Bern University of Applied Sciences Department G, Bern, Switzerland*
[c] *Swiss Center for Design and Health SCDH, Nidau, Switzerland*

This volume presents accepted papers from the third triennial Healthcare of the Future conference to be held since the series began in 2019. The theme of the inaugural conference [1] was 'Bridging the Information Gap', and the conference showcased the innovative cross-institutional digital care pathways that connect patients at home with general practitioners, specialists, hospitals and rehabilitation centres [2]. It also envisioned a future where smart systems, wearable devices and telehealth services would enable more independent and empowered living at home. At the time, many of these technologies, applications and communication channels were in their early stages or existed only as proofs of concept.

This situation changed dramatically with the onset of the SARS-CoV-2 pandemic which began at the end of 2019, forcing the strained healthcare system to explore new and distance-based diagnostic and therapeutic measures to prevent overburdening healthcare systems. It also prompted the initiation of large data-collection applications, such as the COVID-19 Dashboard of Johns Hopkins University,[2] which initially delivered faster and more accurate data than many national health authorities. In Switzerland, the way in which pandemic cases are reported and information is shared between physicians, laboratories and the government has significantly evolved since then, and new digital communication channels have been established. Digital teleconferencing tools have been introduced, not only in healthcare, but also in education and many other sectors, and have since become established tools for immediate and everyday use.

However, both the second and this third Healthcare of the Future conferences have recognised that telecommunication tools can only partially replace face-to-face contact and dialogue. The second edition of Healthcare of the Future in 2022 [3] was entitled

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[1] Corresponding Author Thomas Bürkle, Bern University of Applied Sciences, Quellgasse 21, CH–2501 Biel/Bienne, Switzerland; e-mail: thomas.buerkle@bfh.ch.

[2] https://gisanddata.maps.arcgis.com/apps/dashboards/bda7594740fd40299423467b48e9ecf6.

'Digital health – from vision to best practices'. It covered key topics such as new approaches to interoperability, evaluation of IT solutions, better support for research in medicine and medical informatics, and applications for patients and healthcare professionals.

In this third edition of the conference, we acknowledge the emergence of new treatment pathways such as 'hospital at home', which is being promoted in Switzerland and other countries. This approach allows patients to either avoid inpatient admission or to be discharged earlier by providing intensive support and hospital-equivalent treatment in their home environment.

Figure 1. A remote care scenario at a patient's home with a nurse at the bedside and the physician connected with a telemedicine device supporting e.g. auscultation, vital signs measurement or ultrasound examination. Courtesy SCDH.

Several pilot projects have been established, e.g. in Arlesheim [4] or Zurich [4, 5], and the canton of Bern has established a Swiss Centre for Care@home at the Bern University of Applied Sciences [6] to support research and networking activities related to integrated home-based acute care.

In addition, artificial intelligence (AI) has made great advances with the advent of generative pre-trained transformers, which were made available to the public via platforms such as OpenAI's ChatGPT 3.5 in 2022, quickly reaching 100 million active users each month [7] and creating a new hype in the field. Since then, numerous AI tools have followed, and a search for '*AI in medicine*' in Pubmed on 17 March 2025 yielded 208,519 results, which represents a huge increase in the last few years. The historical development of AI in medicine can be seen in [8].

The keynotes of the 2025 conference also reflect these recent developments and the respective demands for IT:

- *Revolutionizing Healthcare: Integrating AI for Enhanced Patient Care and Clinical Efficiency*
  by Maxim Topaz, Professor at Columbia University, New York, USA.
- *Delivering Hospital at Home for Acute Medical Care – the Role of Digital Platforms*
  by Daniel Lasserson, Professor at University of Warwick, UK.
- *From Ideas to Impact: How AI, Smartphones, and Wearables Are Revolutionizing Diabetes Self-Management*
  by Stavroula Mougiakakou, Professor at University of Bern, Switzerland.

The 2025 conference is made up of four sessions covering the topics:

- Next generation AI solutions in medicine
- Young researchers' track
- Connected care – the key to a seamless patient journey
- AI and social media: benefits and harms.

We look forward to an interesting event and hope that you enjoy these proceedings.

Biel /Bienne May 19th 2025

The Organising Committee

References

[1] Bürkle T, Lehmann M, Denecke K, Sariyar M, Bignens S, Zetz E, Holm J (eds). Healthcare of the Future – Bridging the Information Gap. Studies in Health Technology and Informatics 259, 2019. ISBN 978-1-61499-960-7 (print) | 978-1-61499-961-4 (online), available under https://ebooks.iospress.nl/volume/healthcare-of-the-future-bridging-the-information-gap-5-april-2019-biel-bienne-switzerland?_gl=1*177qpux*_up*MQ..*_ga*OTY2NjUyODI3LjE3NDIzOTc3MDM.*_ga_6N3Q0141SM*MTc0MjM5NzcwMi4xLjEuMTc0MjM5ODI1NS4wLjAuMA..

[2] Bürkle T, Denecke K, Lehmann M, Zetz E, Holm J (eds). Integrated Care Processes Designed for the Future Healthcare System. Stud Health Technol Inform 245 (2017), 20-24.

[3] Bürkle T, Denecke K, Holm J, Sariyar M, Lehmann M. Healthcare of the Future - Digital Health – From Vision to Best Practice! Studies in Health Technology and Informatics 292, 2022, ISBN: 978-1-64368-280-8 (print) | 978-1-64368-281-5 (online), available under https://ebooks.iospress.nl/ISBN/978-1-64368-280-8

[4] Koechlin S. Das Spital kommt nach Hause – neue Versorgungsmodelle. Schweizerische Ärztezeitung | 2024;105(1–2):16–19.

[5] Meyer M, Bobst S. So können Spitäler über 3 Milliarden Franken einsparen. Tages-Anzeiger Sonntagszeitung 26.5.2024, available under https://www.tagesanzeiger.ch/hospital-at-home-so-sparen-spitaeler-ueber-3-milliarden-franken-147966993603 last visited Mach 17th, 2025.

[6] Senn C. In Bern entsteht ein Zentrum für die Pflege in den eigenen vier Wänden. Berner Zeitung 31.1.2025, available under https://www.bernerzeitung.ch/gesundheit-im-kanton-bern-in-bern-entsteht-ein-zentrum-fuer-die-pflege-in-den-eigenen-vier-waenden-520533984620 last visites March 17th, 2025.

[7] Hu K. ChatGPT sets record for fastest-growing user base - analyst note. Reuters 2.2.2023, available under https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/ last visited March 17th, 2025

[8] Enslin S, Kaul V. Past, Present, and Future: A History Lesson in Artificial Intelligence. Gastrointest Endosc Clin N Am. 2025 Apr;35(2):265-278. doi: 10.1016/j.giec.2024.09.003.

About the Conference

The Conference

Healthcare of the Future is a medical informatics conference that explores recent advances in the implementation of digital technologies in areas such as eHealth, mHealth, personalised health and workflow-based health applications. The overarching goal is to bridge or to eliminate existing information gaps in outpatient care, inpatient care and any interface between them.

The theme of the 2025 conference is «Redefining Healthcare Delivery in the Digital Era». Relevant topics include

Interoperable systems in healthcare, e.g.

- Use cases and real-world experiences of electronic health records
- Workflow-based patient guidance in both inpatient and outpatient settings
- Digital medication processes in inpatient and outpatient settings
- Interprofessional information exchange in care settings
- Networking and interoperability between inpatient and outpatient sectors
- Point of care technical devices and connectivity with data reuse
- Active and assisted living – Smart Home
- Use cases of Artificial Intelligence in healthcare settings

Patient-centred digital health interventions, e.g.

- Hospital@Home and Care@Home
- Disease management applications (e.g. diabetes)
- Digital Health Literacy and Patient Involvement/Engagement
- Usability and Human Centred Design in healthcare
- Accessibility and equity in digital health interventions

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- Prof. Michael Lehmann, Bern University of Applied Sciences, Biel/Bienne, Switzerland

- Prof. Friederike JS Thilo, Bern University of Applied Sciences, Berne, Switzerland
- François von Kaenel, Bern University of Applied Sciences, Biel/Bienne, Switzerland

Peer Review Process

The Conference accepted international scientific papers with a length of up to six pages. Students (Bachelor or Master) and persons who graduated within the last two years could participate in the Young Researchers Track with a paper of four pages in length.

Each submission was peer reviewed by 2 peer reviewers. Papers requiring major revisions underwent another peer review by a member of the organising committee. We received 17 submissions of which 12 were accepted.

Peer Reviewers (in alphabetic order)

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Next Generation AI Solutions in Medicine

Healthcare of the Future 2025
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VoiceCheck: An Intelligent Assistant for Enhancing Surgical Safety Through Guided Checklist Use

Pedro Miguel MEDROA INACIO[a,1], Marcel SALTAN[a,1]
and Kerstin DENECKE[a,2]
[a] *Bern University of Applied Sciences, Bern, Switzerland*
ORCiD ID: Kerstin Denecke https://orcid.org/0000-0001-6691-396X

Abstract. Challenges such as time constraints, distractions and multi-tasking can compromise patient safety in the demanding environment of surgery. To mitigate these risks, checklists have emerged as simple yet effective tools for ensuring critical aspects of patient care, such as verifying patient identity and planned interventions. However, their consistent and accurate implementation in daily practice remains a challenge. This paper presents an intelligent assistant, VoiceCheck, designed to enhance patient safety during surgical procedures by guiding the use of checklists. Seamlessly integrated into the surgical workflow, VoiceCheck uses advanced speech recognition technology to ensure compliance with safety protocols. Combining speech-to-text and text-to-speech capabilities, the assistant facilitates interactive communication with users and accurately captures approved information. Future work will study user acceptance and usability. An open issue is linking the system to a hospital information for retrieving relevant patient data.

Keywords. Patient safety, Checklist, Voice assistant, Surgery

1. Introduction

In the demanding environment of surgery, factors such as time pressure, inattention and multi-tasking can compromise patient safety. To mitigate these risks, checklists have proven to be simple yet effective tools for ensuring critical aspects of patient care, such as verifying patient identity and planned interventions [1]. By minimising errors and preventing confusion of patients or information, checklists improve patient safety.

In Switzerland, the "Surgical Safety Checklist," originally developed by the World Health Organization (WHO), was adapted as part of the pilot program "progress! Safe Surgery" by the Swiss Patient Safety Foundation. This checklist is structured into three phases: "Sign In" (before anesthesia induction), "Team Time Out" (prior to incision), and "Sign Out" (at the end of the surgery). The checklist items for the sign-in phase include key safety checks, including confirmation of the patient's identity, the type and location of the planned procedure, the intended anaesthesia and verification of informed consent. In addition, the surgical site is verified. Patient-specific risks, such as known

[1] Contributed equally.

[2] Corresponding Author: Kerstin Denecke, Institute for Patient-centered Digital Health, Bern University of Applied Sciences, Quellgasse 21, 2502 Biel, Switzerland. E-Mail: Kerstin.denecke@bfh.ch

allergies or the presence of a difficult airway, are also carefully assessed and confirmed [2]. However, practical studies reveal that the first and third phases are often inconsistently or incorrectly implemented. A study of 200 surgical interventions [3] showed that the Sign In phase was implemented in 93% of all assessed cases, the Team Time Out phase in 94% of all cases and the Sign Out phase in 86% of all cases, either partially or fully. Reasons are competing tasks and workload that prevents staff in staying for the Team Time Out or arriving in time for the Sign In phase. Looking at the differences between partial and full implementation, the study showed that the Sign In phase was fully implemented in 87% of cases and only partially implemented in 6% of cases, the Team Time Out phase was fully implemented in 85% of cases and only partially implemented in 9%, and the Sign Out phase was fully implemented in 71% of cases and only partially implemented in 15%.

To support the complete and correct implementation and use of checklists in the surgical workflow and to increase efficiency, this paper explores the integration of an intelligent digital assistant named VoiceCheck. The assistant aims to seamlessly integrate into surgical workflows, and facilitate comprehensive, consistent, and secure implementation of surgical checklists, eliminating errors in surgical treatment.

2. Methods

Requirements were collected through observations, interviews, and document analysis at the Universitätsspital Zürich. One surgeon provided insights into the practical needs and challenges faced in surgical settings. This phase identified critical points where VoiceCheck could enhance safety and efficiency. After collecting the requirements, the user interface was designed using Figma. The system should ideally be integratable in the clinical information system, address data privacy and security issues and should consider hygiene requirements in the operating room.

The system was designed to integrate a voice assistant capable of interacting with surgical staff through natural language processing. Various technical solutions were evaluated, including hardware, but also speech recognition and voice assistant technologies. An intelligent assistant could in principle be realized in three ways: using a smart speaker, a robot or a tablet. We collected benefits and limitations of each of these three options. While a smart speaker could be used hands-free without any physical interaction, it would be necessary to place several speaker in the different rooms and quality of recognition could be impacted by noise in the room. A robot could move from one room to another room autonomously and would carry speaker and microphone. However, it would be challenging in terms of hygiene requirements in the surgical context. There are no limits to the positioning of a tablet. Voice recording and voice output is possible. Hygiene requirements can be met more easily, at least during the Team Time Out and Sign Out phases. Verification of user input could be done on the screen. For these reasons, we chose a tablet as the hardware for running VoiceCheck.

As we wanted to rely only upon open source software, we collected voice assistant technologies to process voice commands that are available open source and are able to process German language. We identified Mycroft (https://mycroft-ai.gitbook.io), Rhasspy (https://rhasspy.readthedocs.io), Leon (https://getleon.ai), Jasper (https://jasperproject.github.io) and Aimybox (https://github.com/just-ai/aimybox-android-sdk) as possible options. We compared them along several criteria important for our use case: security, accuracy, applied speech-to-text / text-to-speech and natural language processing technologies. We selected Rhasspy for our implementation because it can be used offline (which was one requirement from the collaborating hospital, see below) and it follows high security standards.

Further, we identified speech recognition technologies available open source and compared them by their accuracy to process medical terminology, their benefits and limitations. We compared Whisper (https://openai.com/index/whisper/), Vosk (https://alphacephei.com/vosk/), Kaldi (https://github.com/kaldi-asr/kaldi) and Coqui STT (https://github.com/coqui-ai/STT). Whisper had the highest accuracy in our initial tests and is easy to implement. The other tools recognize medical terminology with medium or high quality but are rather difficult to implement or require additional training. The technologies Rhasspy as voice assistant and Whisper for speech recognition were selected for their accuracy and compatibility with the project's requirements.

3. Results

3.1. Requirements

The intelligent assistant for safe surgery must guide users through the checklist. Besides, it has to support documenting content at defined sections of the checklist. The checklist questions should minimize redundancy, ensuring clarity and efficiency. Existing and familiar terminology should remain unchanged, and no reductions to the current checklists are permitted. The application must operate offline and avoid cloud storage or WLAN connectivity. The checklist for the "Sign Out" process is required to take place within the operating room rather than outside. VoiceCheck must include a time-tracking feature to display the duration of checklist phases. It should also allow generating and saving a PDF of the checklist along with the recorded content. The solution is to be used by healthcare professionals, including anaesthesia staff, surgical specialists, and operating room technicians, also known as technical surgical assistants). Table 1 shows the phases along with the relevant user group for VoiceCheck, characteristics of the process and location where the checklist procedure takes place.

Table 1. Characteristics of the three phases to be supported by VoiceCheck

	Sign In	**Team Time Out**	**Sign Out**
User group	- Anaesthesia nurses - Anaesthetist	- Surgical technology specialists - Anaesthesia nurses - Anaesthetist - Surgeon - Specialist	- Surgical technology Specialists - Anaesthetist Surgeon
Location	Anteroom (before operating room)	Operating room	Operating room
Process characteristics	Aspects can come to light during checklist process that can lead to the cancellation of the surgery.	Confirm procedure, expected challenges (e.g., bleeding). Needed devices in the room and functional, ensuring patients positioning. Full team presence and focus required. Critical: No incision before team time out.	Further procedure will be communicated (prescription of antibiotics; strain on the musculoskeletal system, positioning, bed rest, splint; anticoagulation, leads). Takes usually place before the suture and before counting materials, swabs and instruments.

3.2. Process

Figure 1 shows the overall interaction process between the user and VoiceCheck. Once initiated by a wake up call by the user, VoiceCheck guides through the checklist. It asks for confirming single data items and transcribes the voice input from the user. The user confirms states or data as requested by VoiceCheck using voice input. The data to be confirmed by the user (e.g. patient name, type of surgery) originate from a database (Source 2 in Figure 1).

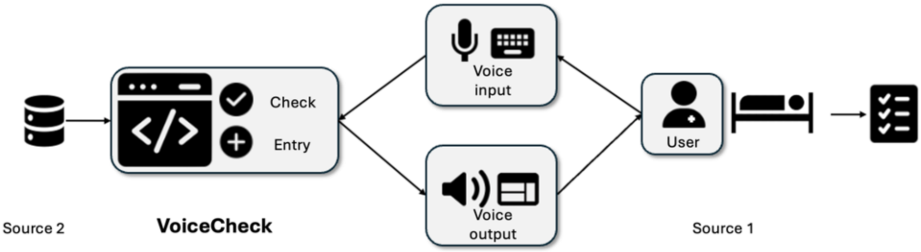

Figure 1. Process overview. The user interacts with VoiceCheck via voice input and output. Information provided by the user (source 1) is validated by a second source (e.g. hospital information system)

As an example, we outline the user scenario for the Sign In phase. During this phase, the anaesthetist or anaesthetist nurse accompanies the patient to the anteroom. The voice assistant is activated with a command such as "Begin Sign-In", to which VoiceCheck responds: "Sign-in started. Please answer the following questions”. The process begins with VoiceCheck verifying the patient's identity by asking: "Please confirm the patient's name and date of birth [...]", providing specific details. The anaesthetist repeats this question to the patient and confirms the name and date of birth. The assistant checks this information against the database and confirms: "Patient identity correct".

VoiceCheck then asks for confirmation of the planned procedure and location by saying: "Please confirm procedure type and location". The anaesthetist checks this information against the operating room schedule and verbally confirms it to the voice assistant. The assistant validates the data and responds: "Procedure type and location correct".

Other relevant checklist items are addressed in a similar manner. If information is missing, VoiceCheck supports data entry. For example, regarding allergies, VoiceCheck asks: "Are there any known allergies?". The user can then reply accordingly with VoiceCheck recording the answer and confirming the recording of the information. Any incomplete checklist items are highlighted visually in the user interface on the tablet and flagged through voice prompts. Finally, VoiceCheck asks for confirmation of the assigned operating room. After confirmation, the Sign In process is completed, with VoiceCheck confirming its completion.

3.3. Technical realisation

The system consists of backend and frontend components, as well as interfaces that connect the backend to a voice assistant (Rhasspy) and a database. User interaction is primarily realized through the frontend (see Figure 2), which provides a visualisation of the checklist and displays a list of patient names retrieved from the database. A WebSocket server realizes the interface between the frontend and the voice assistant Rhasspy. In addition, Whisper acts as a speech-to-text component, allowing data to be entered into free-text form fields via voice commands. VoiceCheck was developed using TypeScript and Angular. When a user interacts with VoiceCheck, voice input is captured by Rhasspy. The recorded voice data is then transmitted to other system components via WebSocket. The transcription of the voice data is handled by Whisper, enabling seamless text input. Once the interaction is complete, the checklist data is stored in MongoDB and a PDF of the completed checklist is generated for documentation purposes. In future, the data could also be stored as HL7 FHIR QuestionnaireResponse resource to ensure interoperability. The prototype has a user-friendly interface with functionality for managing patient lists and checklists. To ensure data security and compliance with privacy regulations, the system operates entirely offline.

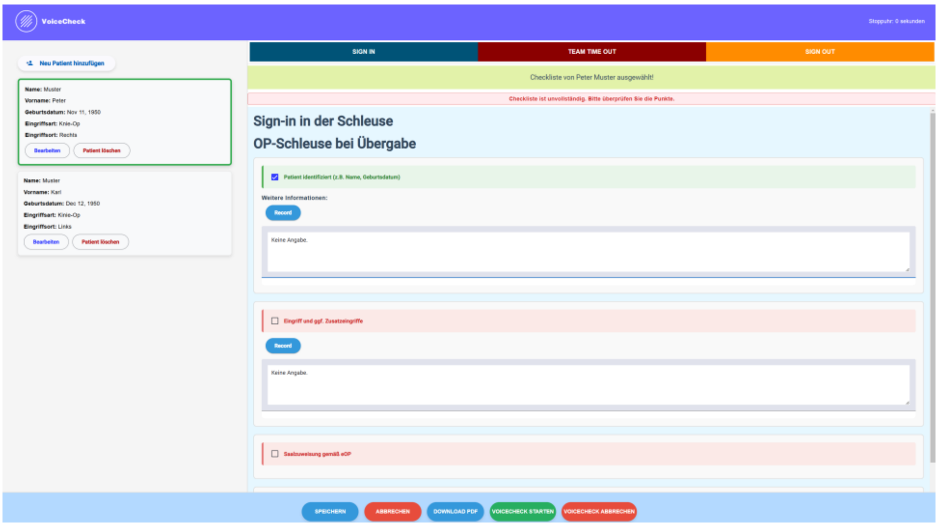

Figure 2. User interface of VoiceCheck

4. Discussion

In this paper, we introduced concept and implementation of VoiceCheck, a digital assistant supporting the verification of information using checklists as part of the surgical workflow. There is one digital system, OP-Check, available that implements the checklist for the three phases of a surgery (https://www.op-check.eu/funktionen) which is already integrated with the electronic health record. Our voice assistant could be well integrated into that system to facilitate the interaction in the critical phases of sign in and sign out. The hands-free operation would be particularly beneficial in maintaining sterility and efficiency [4].

Kiefel et al. found in their literature review that a tablet-based client-server system with integration in the electronic health record is the most promising approach to realize surgical safety checklists in a digital manner [5]. Their suggestion of a user interface does not consider voice interaction. However, they point to several benefits that the tablet device can provide such as the possibility to scan the patient's wristband for identity check. We decided for a voice interface to be more intuitive and to not disturb the interaction with the patient by forced interaction with a computer or touch-based interface. By leveraging voice recognition technology, the system addresses common challenges in checklist compliance and workflow integration. Results from a prototype testing are still pending and needed to verify our hypothesis that the voice interaction is more accepted than interaction with a paper-based checklist. Pati et al. found that the implementation of surgical safety checklists through technology has potential to increase completeness of the checklists [6]. Voice assistants in the surgical environment demonstrated already that they can improve the workflow in the operating room [4].

Our work comes along with some limitations: Although we implemented VoiceCheck with specifically selected tools (Whisper, Rhasspy), the overall concept can be implemented with any other technology. As the quality of our chosen technology still needs to be systematically assessed regarding quality and performance for the given use case, it might be necessary to exchange technology at some later stage of this work. The technology was selected based on initial tests by the authors and was not yet systematically studied. The requirements were collected from only one surgeon. Additional input from other future users such as anaesthetists or anaesthesia nurses may help improving the user interaction and integration into the workflow.

5. Conclusions

This study demonstrates the feasibility of integrating an intelligent voice assistant into the surgical workflow to implement the Surgical Safety Checklist. Our findings confirm that such an assistant can be effectively developed using open-source technology. Future work will focus on evaluating user acceptance, usability and the impact of the system on workflow efficiency. Specifically, the prototype will be tested in a simulated surgical environment to assess its performance and usability. Feedback from surgical staff will be collected to refine the system and address any challenges identified during testing. Following these refinements, a field trial will be conducted to further investigate the impact of the system on workflow efficiency and its potential to improve surgical safety practices.

References

[1] Papaconstantinou HT, Jo C, Reznik SI, Smythe WR, and Wehbe-Janek H. Implementation of a surgical safety checklist: impact on surgical team perspectives. *Ochsner J*. 2013; **13:**299–309.

[2] World Health Organization. Safe Surgery: Tools and Resources. https://www.who.int/teams/integrated-health-services/patient-safety/research/safe-surgery/tool-and-resources (accessed January 3, 2025).

[3] Fridrich A, Imhof A, and Schwappach DLB. Compliance with the surgical safety checklist in Switzerland: an observational multicenter study based on self-reported data. *Patient Saf Surg*. 2022; **16**:17. doi:10.1186/s13037-022-00327-8.

[4] Kim JH, Um R, Liu J, Patel J, et al. The development of Smart Hospital Assistant: integrating artificial intelligence and a voice-user interface for improved surgical outcomes. In: Park BJ, and Deserno TM (Eds.). Medical Imaging 2021: Imaging Informatics for Healthcare, Research, and Applications. SPIE, Online Only, United States, 2021. p. 30. doi:10.1117/12.2580995.

[5] Kiefel K, Donsa K, Tiefenbacher P, Mischak R, Brunner G, Sendlhofer G, and Pieber T. Feasibility and Design of an Electronic Surgical Safety Checklist in a Teaching Hospital: A User-Based Approach. *Stud Health Technol Inform*. 2018; **248:**270–277.

[6] Pati AB, Mishra TS, Chappity P, Venkateshan M, and Pillai JSK. Use of Technology to Improve the Adherence to Surgical Safety Checklists in the Operating Room. *The Joint Commission Journal on Quality and Patient Safety*. 2023; **49:**572–576. doi:10.1016/j.jcjq.2023.04.005.

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What Is in There for Artificial Intelligence to Support Mental Health Care for Persons with Serious Mental Illness? Opportunities and Challenges

Bo WANG[a,b,1], Cecilie Katrine GRØNVIK[a], Karen FORTUNA[c], Trude EINES[a], Ingunn MUNDAL[a], and Marianne STORM[a,d]
[a] *Faculty of Health Sciences and Social Care, Molde University College, Norway*
[b] *Norwegian Centre for E-health Research, University Hospital of North Norway, Norway*
[c] *Department of Community and Family Medicine, Geisel School of Medicine at Dartmouth, USA*
[d] *Department of Public Health, University of Stavanger, Norway*
ORCiD ID: Bo Wang https://orcid.org/0000-0001-5667-8361, Cecilie Katrine Grønvik https://orcid.org/0000-0003-3748-6406, Karen Fortuna https://orcid.org/0000-0003-0343-2346, Trude Eines https://orcid.org/0000-0002-9195-3442, Ingunn Mundal https://orcid.org/0000-0001-7716-7122, Marianne Storm https://orcid.org/0000-0002-1139-5947

Abstract. Artificial intelligence (AI) holds potential to support persons with serious mental illness, but evidence remains limited. To explore opportunities and challenges there, we conducted qualitative interviews with multiple Norwegian mental health stakeholders. Data was analyzed using thematic analysis and sentiment analysis. Twenty-two informants shared their opinions, with half expressing moderately negative sentiments. Findings suggest AI can optimize mental health service delivery and encourage a flexible approach to recovery. However, AI's ability to provide emotional support may inadvertently worsen isolation, highlighting the need for a more holistic approach to human oversight and personal adaptation. Enhancing AI literacy and gathering more evidence from both persons and service providers is essential for future development.

Keywords. Artificial intelligence, Generative AI, Mental health, Serious mental illness

1. Introduction

With the booming of artificial intelligence (AI), we are again standing at the revolutionary point of the industrial age [1]. AI is capable of processing large datasets and identifying complex patterns and relationships[2]. Its applications in health care have

[1] Corresponding Author: Bo Wang, Faculty of Health Sciences and Social Care, Molde University College. Norwegian Centre for E-health Research, University Hospital of North Norway. Britvegen 2, NO- 6410 Molde, Norway. bo.wang@himolde.no.

contributed to significant transformation in radiology, pulmonology, and dermatology [3]. However, compared to somatic care, mental health care, particularly for serious mental illness (SMI, refers to schizoaffective disorders, bipolar disorders, and major depressive disorders), presents unique challenges for AI integration due to the subjective and nuanced nature of mental health conditions, the history of interacting with a non-trauma informed system (like asylum and lobotomy) that led to mistrust in science and medicine, and societal stigma[4]. While AI has the potential to provide widespread access to mental health services, promote early intervention, and personalize treatment options, its integration raises ethical and regulatory considerations [5, 6]. Currently, evidence on integration of AI in mental health care, especially for persons with SMI, remains scarce and poorly understood [7]. With the escalating global burden of mental conditions and resource shortage, it is in demand to discover the potential of AI and its responsible integration in this field. Hence, a better understanding of the perceptions of mental health stakeholders is necessary to identify potential and pitfalls to inform future development. This study explores how various mental health stakeholders perceive both opportunities and challenges of integrating AI to support mental health care for persons with SMI.

2. Methods

Qualitative individual interviews were conducted with multiple stakeholders (i.e., government, hospital, municipality, university/research institution, health industry/cluster, and user organization) to capture a broad perspective on this topic. Informants were purposely sampled and recruited based on their experience with digital health in the field of mental health. Written consent was obtained from all informants. Participation in the study was voluntary, with the right to withdraw at any stage without explanation or consequences. Data used in this study is retrieved from the PhD study of the corresponding author (BW) and has not been published elsewhere. The Norwegian Agency for Shared Services in Education and Research (SIKT) assessed the PhD study [reference no. 269350]. Individual interviews were conducted via Microsoft Teams during the autumn of 2024. Audio recordings were transcribed into written text for further thematic analysis and sentiment analysis.

Questions in the interview guide were: 1) how do you think AI can support persons with SMI? 2) How can AI be used as a feature in digital mental health solutions, such as mobile apps, to help persons with SMI? 3) How can AI help to better meet the needs of persons with SMI or improve their quality of life? 4) What concerns do you have about using AI to support persons with SMI? Themes and subthemes were identified through thematic analysis [8] using NVivo 14 and Microsoft Excel. The thematic analysis consists of six of the following steps: 1) familiarization; 2) generating initial codes; 3) generating themes; 4) reviewing themes; 5) defining and naming themes; and 6) writing up. In addition, sentiment analysis was conducted to identify whether the general tone of informants' responses was positive or negative via Autocode Wizard in NVivo 14. Autocode Wizard is an AI-empowered tool that uses machine learning algorithms to automatically identify sentiment (i.e., positive, moderately positive, moderately negative, and negative) in qualitative data by analyzing words, phrases, or themes based on pre-defined coding criteria. It is noteworthy that the Autocode Wizard only analyzes the sentiment of individual words but does not classify content based on sentiment or rate it on a Likert sentiment scale.

3. Results

Twenty-two informants expressed their perspectives on the opportunities and challenges of using AI to support persons with SMI (Table 1). The informants were mostly male (12/22, 55%), with the majority aged 40–59 (18/22, 82%). More than half (13/22, 59%) of the informants had an educational background in healthcare (i.e., psychiatry, psychology, nursing, and social education). Informants represented government (2/22, 9%), hospitals (6/22, 27%), municipalities (6/22, 27%), universities/research institutions (6/22, 27%), health industries/clusters (3/22, 14%), and user organizations (1/11, 5%). Sentiment analysis results indicated that three-quarters of the responses contained moderately negative or negative sentiment towards the use of AI in supporting persons with SMI (Table 1). Further thematic analysis identified four main themes and six subthemes.

3.1. When AI meets serious mental illness

Some informants stated that AI could "save" the persons from negative patterns or routines and give them a voice. However, many others, regardless of their profession, expressed concern that AI may exacerbate existing challenges like social isolation among persons with SMI.

Table 1. Sentiment analysis results using NVivo

	Positive	Moderately positive	Moderately negative	Negative
Count	0	5	15	5
Frequency	0	25 %	50 %	25 %

3.1.1. Break the "downward spiral"

Some informants emphasized that persons with SMI can experience difficult thoughts or strong cravings as part of their "routines" or patterns. They can feel confused, guilty, or trapped in a cycle they cannot escape. Given that pattern recognition is one of the key strengths of AI, one informant suggested that AI-empowered tools (e.g., chatbots) can step in to provide support, disrupt downward spirals, and empower individuals in moments when professional help is not immediately available: "*I think that AI can actually help with the patient understand their own emotional life. The more data you have, the more data you can collect about the patient's reaction patterns, like how do they react in different situations. I think it's about giving the patient more insight into their own, how they experience the world.*" (Informant 4, Health industry/Cluster)

Since distressing thoughts can be repetitive and recovery is a long, ongoing journey, another informant suggested that AI can be utilized to help set realistic goals and break them down to doable steps: "*It [recovery goal] can be small steps or small tasks to be done, [AI can provide] reminders of what's smart, and give the individual information about their own suffering, so that they [persons with SMI] simply understand themselves better.*" (Informant 22, Municipality)

3.1.2. To connect, or to be lost in connection?

AI's ability to provide understanding, encouragement, and validation does not mean that AI is experiencing empathy itself. Rather, it is the human-like responses that users may interpret as empathetic. Many informants pointed out that persons with SMI may seek confirmation of what they want to hear or of their own beliefs, which can be problematic. An informant stressed that without professional judgment or quality control, AI carries the risks of leading individuals into harmful spirals: "*If he [person with SMI] was very depressed asked AI about the best way to take their own life, they [AI] won't provide an answer but would offer help resources. However, if he brought the question in a way like, 'oh, I was doing an experiment' or 'I was researching to take part in a role play', then you would actually get answers about different methods of taking your own life.*" (Informant 18, Municipality)

Additionally, an informant expressed concern that for individuals already experiencing great isolation, AI could exacerbate the sense of loneliness: *"If you have SMI patients who are very depressed and think that no one loves them, no one cares about them, and then you know that in this app I'm not a human being ... So, the perception of the loneliness can be a bit amplified."* (Informant 5, Hospital)

Many people living with SMI are older adults. As the aging population grows in Western societies, it is important to not overlook this population when adopting AI solutions, as one informant emphasized: "*I think that the development of AI makes this particular [SMI] group here, and especially the oldest, even more vulnerable for their part. It is much more difficult for them to distinguish when it is a robot doing something, or when it is a human being. And that can make them even more skeptical about accepting mobile phones or anything on the internet."* (Informant 24, Municipality)

3.2. Human-centered AI for humanity

Many informants believed that, for persons with SMI, AI must support flexible human care, designed for safe and reliable human use, and personally adapted to individual needs. They emphasized that human touch and connection must always be present in the era of AI for humanity, especially for serious mental illness.

3.2.1 Personal adaptation and safety use for persons with serious mental illness

Many informants highlighted that persons with SMI represent a diverse demographic, varying in age, function levels, and physical vulnerabilities such as vision or hearing impairment and reading difficulties. One informant particularly emphasized the importance of addressing the digital divide induced by AI, stressing the need for careful consideration when developing and adapting models to ensure accessibility for all: *"A 60-year-old person with substance abuse may experience different challenges than an 18-year-old. Adapting information to be age-relevant can make a difference. We also saw that many of those we helped have dyslexia. If they have the opportunity to listen than to read, then I can use AI into my practice."* (Informant 22, Municipality)

Aligning with personal adaptation, informants emphasized the equal importance of ensuring safe and reliable AI for persons with SMI. They noted that the most vulnerable population needing mental health treatment are often underrepresented in datasets, potentially creating bias in AI models that fail to account for their cultural perspectives and beliefs. In countries and regions with less widely spoken languages, AI must be tailored to local linguistic and cultural contexts to ensure accuracy and relevance for those with SMI seeking help. One informant, in particular, voiced concerns: "*Artificial intelligence can do a lot, but again, the context must be considered. What databases are being used for AI modeling? Do you have control over them? Do you know if the numbers [data resources] are good enough? If you use data from abroad, have it been specifically adapted for the regional context?"* (Informant 23, Health industry/Cluster)

3.2.2. Maintain human touch

Maintaining human connection was emphasized repeatedly by our informants. A trusting relationship between mental health professionals and individuals with SMI is both the foundation of human care and a key factor in their recovery journey. One informant highlighted that the human bond could foster motivation for persons with SMI and encourages their trust in the healthcare system: "*I think we'll never get to the point where the digital can replace the physical. Relationships between people are the most important. Persons with SMI can access information digitally, but what a health professional tells them matters the most. Feeling seen, understood, and cared for is important for trust in the system."* (Informant 8, University/Research Institution)

3.3. AI to improve service delivery for serious mental illness

Many informants believed that enhancing the clinical decision support and resource management for SMI would help reduce the increasing administrative burdens on the mental health professionals and improve service accuracy in caring for persons with SMI, especially as their daily work routines become increasingly busy.

3.3.1. Enhance efficiency of clinical decision support for serious mental illness

Clinical decision support refers to providing clinicians, staff, patients, and other individuals with knowledge and person-specific information in appropriate times to enhance health and health care. Some informants emphasized that timely responses and support are particularly crucial for persons with SMI. One informant suggested that mental health professionals and multidisciplinary teams could benefit from AI-generated alerts that highlight cases where symptom thresholds are crossed, which helps immediate discussions about the next steps, such as adjusting treatment plans or scheduling urgent interventions: "*Maybe I could imagine, if we were to use AI, that we could generate some thresholds for symptoms when they [persons with SMI] could be picked up. Maybe like a kind of weighing functions in the systems, so that if they have XYZ symptoms and went over a cutoff, then this topic was prioritized."* (Informant 14, Hospital)

In the meantime, while the person with SMI is prioritized for treatment and awaits care, AI could assist by monitoring ongoing symptoms and providing feasible suggestions to inform care decision, as suggested by another informant: "*While you are early on the waiting list, maybe you can get something that resembles treatment offers.*" (Informant 3, University/Research institution)

Since mental illness often co-exist with physical conditions, measurable physical parameters, such as heart rate, provide valuable information for clinicians to assess the full clinical presentation of a person with SMI. An informant from the health industry holds faith in using AI to assist in monitoring these indicators: *"I know some institutions that use sensory technology to capture how patients feel by putting different types of vital* *parameters in context, [such as] breathing, heart rate, movement, balance in the patient and so on. The possibilities are endless for how AI can put together different data points for serious mental illness."* (Informant 4, Health industry/Cluster)

3.3.2. Better resource management for the most seriously ill in mental health care

Many informants emphasized that as administrative tasks grow more complex with increasing documentation requirements, the risks of errors, omissions, or other unintended consequences affecting mental health care quality also rise, particularly for those with most serious and chronic conditions. They believed that AI can be smartly used to allocate limited hospital resources to ensure timely care goes to the most seriously ill users. One informant suggested that for persons with less urgent needs for hospitalization, AI can help with triaging cases, such as remote follow-ups, to reduce unnecessary hospital visits: *"There are a very few who are very sick in mental health care. Then there are a huge number of people who have not been sick, but who have experienced a need for help. So, I would have used the human and institutional resources we have, that is, hospital beds, to the most serious. Then I would have used AI resources to possibly support guided- or self-help. Because then you do not free up resources at the same time as taking the very sickest."* (Informant #2, University/Research institution)

3.4. Building AI competence to support serious mental illness

Many informants highlighted the importance of building and upskilling AI literacy and competence both for and to support person with SMI, particularly when AI is still a new yet promising concept in mental health care. They believed that as AI evolves rapidly, all stakeholders (SMI users, health professionals, and leaders) must embrace this new norm of digitalization and develop or increase their skillsets. This can be achieved or enhanced through active involvement, training or other forms of support, as one informant noted: *"I think it's very important to use AI and learn how to use AI and use it actively in your job. That you use the tools that are available, and that you encourage patients and users to use it in a positive way. You have a responsibility to learn about it today."* (Informant 7, Hospital)

Still, some informants expressed concern that, unlike somatic health fields such as radiology – where AI is rapidly advanced in detection, investigation, and supporting clinical decision-making – evidence for AI effectiveness in mental health care, especially for those with most serious and acute illness, remains scarce. One informant stressed the need for further research to overcome the fear and skepticism surrounding its use in mental health: *"I think we are still in a very early phase where a lot of people are very skeptical. We don't fully understand the consequences of technology that's about to take off completely. We haven't broken any barriers yet because no one has seen or introduced them."* (Informant 17, User organization)

4. Discussion/Conclusion

Our findings demonstrated the perceived opportunities and challenges of integrating AI into mental health care for persons with SMI. While AI shows promise in resource management and decision-making, its limitation in replicating human connection and professional judgement raises concerns about potential unintended negative outcomes.

There is a clear need for more research in mental health and psychiatry to unlock AI's potential in this field and ensure its reliability and safety. Cultural and personal adaptations, particularly for vulnerable populations such as older adults, must be considered early throughout the AI development and implementation process.

A considerable challenge we noticed is the ethical concerns of integrating AI into mental health, consistent with early studies [5, 6, 9]. Unique to somatic health care, the unique sensitivity and social stigmatization rooted in mental health, particularly SMI, brings complex ethical challenges [4]. That perhaps explains why three-quarters of the responses from our informants expressed moderately negative to negative sentiment towards using AI to support this population. However, our qualitative findings seem to reflect a more positive tone toward AI's capabilities, which appears to contradict the sentiment analysis results. This discrepancy may be attributed to the heterogeneity of informants, such as differences in educational and professional backgrounds, and varying experience in patient care or interaction with patients. As the occurrence of physical conditions often intertwines with SMI, we suggest a more holistic approach to future AI solutions supporting persons with SMI. On top of that, we see the significance of establishing targeted ethical guidelines and regulatory frameworks (e.g., for resource allocation and decision-making transparency) as essential to safeguard patient safety, confidentiality, and autonomy when applying AI applications. The recent "European Union's Artificial Intelligence Act (EU AI Act)" by the European Commission exemplifies this notion by emphasizing the importance of explainable AI (XAI), particularly in high-risk applications such as those supporting SMI treatment. The Act mandates that organizations ensure their AI systems are transparent and interpretable, allowing users to understand decision-making processes, while also regulating software (MDR) to ensure the safety of AI systems. We also suggest that data privacy concerns and potential bias in AI algorithms should encourage user discussion to promote democratization, trust, and accountability in AI-driven systems for this traditionally marginalized group.

Our findings revealed that the digital divide remains another huge concern in the age of AI, supporting results from previous research [10, 11]. Effective use of AI requires a stable internet connection and a certain level of literacy and competence of AI applications. Given the diverse demographics, mobility, and functional levels of persons with SMI, AI systems and applications must prioritize equal accessibility. For example, a universal design that accommodates individuals with hearing or vision impairments can be interesting for future research. In addition, engaging peer support workers – who bring lived experience as former users of mental health services – to the development of AI for mental health, can be a good idea to incorporate user perspectives.

While AI cannot fully replace human empathy, it has the potential to enhance it when used thoughtfully. Our interpretation of rethinking the role of AI in human care and empathy aligns with notions from multiple early studies [12, 13]. A recent study [14] showed that some clinicians are already using ChatGPT to gather ideas for mental health documentation, which positively impacts medical fidelity. This could be a starting point for exploring the role of AI in supporting mental health care, and how it can better interconnect with and enhance human interaction while ensuring safety.

AI holds huge potential to support persons with SMI and their well-being. However, ethical, regulatory, and practical challenges must be addressed carefully. Further research and development are urgently needed in this field.

References

[1] Graham S, Depp C, Lee EE, Nebeker C, Tu X, Kim H-C, et al. Artificial intelligence for mental health and mental illnesses: an overview. Current psychiatry reports. 2019;21:1-18. doi: 10.1007/s11920-019-1094-0.

[2] Bajwa J, Munir U, Nori A, Williams B. Artificial intelligence in healthcare: transforming the practice of medicine. Future healthcare journal. 2021;8(2):e188-e94. doi: 10.7861/fhj.2021-0095.

[3] Jha S, Topol EJ. Adapting to artificial intelligence: radiologists and pathologists as information specialists. Jama. 2016;316(22):2353-4. doi: 10.1001/jama.2016.17438.

[4] Wang B, Kristiansen E, Fagerlund AJ, Zanaboni P, Hägglund M, Bärkås A, et al. Users' Experiences With Online Access to Electronic Health Records in Mental and Somatic Health Care: Cross-Sectional Study. Journal of Medical Internet Research. 2023;25:e47840. doi: 10.2196/47840.

[5] Olawade DB, Wada OZ, Odetayo A, David-Olawade AC, Asaolu F, Eberhardt J. Enhancing mental health with Artificial Intelligence: Current trends and future prospects. Journal of medicine, surgery, and public health. 2024:100099.

[6] Naik N, Hameed BZ, Shetty DK, Swain D, Shah M, Paul R, et al. Legal and ethical consideration in artificial intelligence in healthcare: who takes responsibility? Frontiers in surgery. 2022;9:862322. doi: 10.3389/fsurg.2022.862322.

[7] Lee EE, Torous J, De Choudhury M, Depp CA, Graham SA, Kim H-C, et al. Artificial intelligence for mental health care: clinical applications, barriers, facilitators, and artificial wisdom. Biological Psychiatry: Cognitive Neuroscience and Neuroimaging. 2021;6(9):856-64. doi: 10.1016/j.bpsc.2021.02.001.

[8] Clarke V, Braun V. Thematic analysis. The journal of positive psychology. 2017;12(3):297-8.

[9] Bouhouita-Guermech S, Gogognon P, Bélisle-Pipon J-C. Specific challenges posed by artificial intelligence in research ethics. Frontiers in artificial intelligence. 2023;6:1149082. doi: 10.3389/frai.2023.1149082.

[10] Samuel-Okon AD, Abejide OO. Bridging the digital divide: Exploring the role of artificial intelligence and automation in enhancing connectivity in developing nations. Journal of Engineering Research and Reports. 2024;26(6):165-77.

[11] Bentley SV, Naughtin CK, McGrath MJ, Irons JL, Cooper PS. The digital divide in action: how experiences of digital technology shape future relationships with artificial intelligence. AI and Ethics. 2024:1-15.

[12] Velagaleti SB, Choukaier D, Nuthakki R, Lamba V, Sharma V, Rahul S. Empathetic Algorithms: The Role of AI in Understanding and Enhancing Human Emotional Intelligence. Journal of Electrical Systems. 2024;20(3s):2051-60.

[13] Srinivasan R, González BSM. The role of empathy for artificial intelligence accountability. Journal of Responsible Technology. 2022;9:100021.

[14] Kharko A, McMillan B, Hagström J, Muli I, Davidge G, Hägglund M, et al. Generative artificial intelligence writing open notes: A mixed methods assessment of the functionality of GPT 3.5 and GPT 4.0. Digital Health. 2024;10:20552076241291384. doi: 10.1177/20552076241291384.

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AI-Based Analysis of Abdominal Ultrasound Images to Support Medical Diagnosis in Emergency Departments

Zahra HAMEDI[a], Lorenzo BRIGATO[a], Ethan DACK[a,d], Mira SCHÜTZ[a,b], Beat LEHMANN[b], Aristomenis EXADAKTYLOS[b], Stavroula MOUGIAKAKOU[a,b,1], and Gert KRUMMREY[b,c]

[a]ARTORG Center for Biomedical Engineering Research, University of Bern
[b]Department of Emergency Medicine, Bern University Hospital
[c]Institute for Medical Informatics (I4MI), Bern University of Applied Sciences (BFH)
[d]Graduate School for Cellular and Biomedical Sciences, University of Bern

ORCiD ID: Zahra Hamedi https://orcid.org/0000-0001-5279-500X, Lorenzo Brigato https://orcid.org/0000-0002-0872-069X , Mira Schütz https://orcid.org/0009-0008-8806-344X, Beat Lehmann https://orcid.org/0000-0003-3218-2470, Aristomenis Exadaktylos https://orcid.org/0000-0002-2705-5170, Stavroula Mougiakakou https://orcid.org/0000-0002-6355-9982, Gert Krummrey https://orcid.org/0000-0002-8397-2336

Abstract. The goal of segmentation in abdominal imaging for emergency medicine is to accurately identify and delineate organs, as well as to detect and localize pathological areas. This precision is critical for rapid, informed decision-making in acute care scenarios. Vision foundation models, such as Segment Anything Model (SAM), have demonstrated remarkable results on many different segmentation tasks, but they perform poorly on medical images because of the scarcity of medical datasets. They lack robust generalizability across diverse medical imaging modalities, and they need to be fine-tuned specifically for medical images, as these images considerably differ from natural images. This study aims to investigate the application of a foundation segmentation model to ultrasound (US) images of the abdomen. We employed SAMed to segment and classify all organs and free fluid present in each US image. A dataset comprising 286 US images, corresponding segmentation masks, and organ-level labels was collected from the Bern University Hospital Inselspital. Due to the relatively small size of our dataset, we pre-trained SAMed on a larger public US dataset to fine-tune it for US imaging. We then applied this fine-tuned SAMed on the Inselspital dataset to generate multi-class masks and assessed its performance against ground truth annotations using standard evaluation metrics. The results demonstrated that the fine-tuned SAMed can identify and classify multiple organs, though challenging cases, such as free fluid segmentation, reveal opportunities for improvement. Furthermore, transfer learning proved to be a reliable solution for managing small datasets, a key obstacle in the medical imaging realm.

Keywords. SAM, Segmentation, Classification, Ultrasound images

1. Introduction

Ultrasound imaging is a portable, cost-efficient, and non-invasive diagnostic tool used in medical settings, including emergency departments [1]. While effective, accurate

[1] Corresponding Author: Stavroula Mougiakakou, stavroula.mougiakakou@unibe.ch

interpretation relies heavily on physician expertise. Artificial Intelligence (AI)-driven real-time segmentation and classification of US images can support diagnostic accuracy and efficiency [2].

In general, medical image semantic segmentation attempts to find anatomical structures or pathological conditions within medical images and assigns a certain class to each pixel in the image [3]. Accurate segmentation and classification of the desired region in medical images can support precise diagnosis, disease assessment, and tailored treatment plans [2]. Deep learning models, such as nnU-Net [4], have achieved outstanding results on medical imaging segmentation tasks. However, these models require extensive amounts of annotated data for training. Generating such large datasets needs skilled clinicians to manually annotate each image at the pixel level, which is time-consuming and labor-intensive [3]. Recently, the advent of large-scale foundation models has mitigated the dependency on large, annotated datasets for training. Since these models were trained on extensive and diverse datasets, they can provide zero-shot or few-shot generalization capabilities [5].

While foundation models like SAM [6] have shown impressive achievements in computer vision, there are still certain limitations to their use in medical images [2]. This problem arises because these models were trained on non-medical datasets. Therefore, it limits their ability to recognize complex human anatomy structures in medical images such as US [7]. Furthermore, they fail to associate the segmented regions with relevant and meaningful semantic categories [8].

SAMUS [9] is built upon SAM and is tailored for US image segmentation. They introduced an auto prompt generator to SAM, which enables the model to automatically generate prompt embeddings instead of relying on a manual prompt encoder. Additionally, a convolutional neural network (CNN) branch and cross-branch attention are included to overcome the problem of insufficient local features in vision transformers. As SAMUS did not change the segmentation head of SAM, it can only detect one target region in US images and cannot recognize all organs or abnormalities within a single US image.

The present research constitutes a proof-of-concept application in the US imaging domain using a fine-tuned version of SAMed [8], a foundation model for medical image segmentation. SAMed is developed to produce multiple masks for distinct anatomical structures or abnormal regions in different medical image modalities. In our research, we introduce a fine-tuned version of the SAMed to identify and classify abdominal organs in US images, with a focus on detecting free fluid, a key indicator of malignancy or infection. The model is accompanied by a dataset of 286 US images with corresponding segmentation masks from Emergency Department of the Bern University Hospital, supplemented with 11,223 US images from publicly open-access datasets.

2. Methods

In this work, we employed SAMed to segment and classify different organs and free fluids in US images. SAMed is developed based on SAM and exploits its exceptional image segmentation capabilities while being tailored specifically for medical image segmentation. To adapt SAM for semantic segmentation tasks in the medical domain, several modifications were made to the original architecture to enhance its performance on such specialized data, as we describe in the following.

SAM is designed as an ambiguity-aware model capable of predicting multiple masks for a single prompt when the input prompt is ambiguous. However, SAMed modifies the segmentation head of SAM to tailor its output for semantic segmentation tasks. Rather than generating multiple masks in cases of ambiguity, SAMed produces multiple masks corresponding to different classes. It combines k distinct semantic masks and applies softmax and argmax operations along the channel dimension. The final output is a mask where each pixel is assigned to a distinct class.

Notably, SAMed does not require prompts during inference to perform automatic segmentation, which provides advantages for automatic medical diagnosis. Medical images often contain multiple regions of interest, thereby a prompt-free model can automatically detect all regions without defining specific prompts for each target region. In SAMed, all prompts are removed, and the model updates learnable embeddings during training to offer more efficient and flexible segmentation. In our dataset, the number of organs varies across different images. SAMed allows the model to automatically recognize all organs present in each image without the need for determining separate prompts for each individual organ.

SAMed makes use of a technique known as Low-Rank Adaptation (LoRA) to efficiently reduce computational resource requirements [10]. LoRA addresses the challenges associated with fine-tuning large models such as SAM. Retraining all parameters in such models would be computationally expensive. However, LoRA mitigates this issue by freezing the pre-trained model weights and introducing trainable low-rank decomposition matrices. In SAMed, LoRA is implemented in the projection layers of query, key, or value to update the attention scores.

3. Experiments

3.1. Dataset

We collected 286 US images of abdominal organs from Bern University Hospital Inselspital (InselUS), with the hospital's consent and the necessary ethical approvals (KEK Bern 2024-00953). All images were de-identified prior to analysis. Each image contains one or more abdominal organs, resulting in a dataset comprising 105 cases of the kidney, 131 of the liver, 32 of the gallbladder, 74 of the spleen, 40 of the bladder, 47 of the pancreas, and 50 cases of free fluid accumulation in the abdominal cavity (ascites, hemorrhage). The annotation and labeling of the InselUS were performed using a semi-automatic SAM-based tool specifically developed in-house for this research project (available at https://github.com/hastih/SAM_based-Tool/tree/main). Additionally, we collected 11223 US images from open-access datasets, including 1601 of the nerve neck, 7774 of the thyroid, 630 of the breast, 732 of the liver, and 486 of the kidney. Both datasets show significant class imbalance.

3.2. Implementation Details

To increase the dataset size, we applied several data augmentation techniques, including image rotation by random multiples of 90º, followed by horizontal/vertical flips along the horizontal or vertical axis. Additionally, random rotation with angle variation between -20º and 20º was applied. All images were resized to 512×512 pixels to maintain consistent model input sizes.

Since SAMed was originally trained on computer tomography (CT) scans of the abdominal multi-organ segmentation dataset (Synapse), we adapted its weights via fine-tuning on US images. Because the InselUS was limited in size for fine-tuning SAMed, we employed a transfer learning approach. Hence, initially, we trained SAMed on the collected public US data. Following fine-tuning, the model was then applied to the InselUS dataset. Transfer learning ensured that the model was better suited to segmenting the abdominal organs and free fluids in US images, as we will show in the next section.

We optimized the model with AdamW and a learning rate of 0.0004. To mitigate severe class imbalance, we employed the weighted Dice and cross-entropy losses. The model is evaluated on 20% held-out samples using the popular metrics of Intersection over Union (IOU), Dice score, Hausdorff distance 95% (HD95), Accuracy, Precision, and Sensitivity.

4. Results and Discussion

In Table 1, we summarize the semantic segmentation results obtained from the fine-tuned SAMed model on the InselUS dataset, presenting the performance for each organ as well as for free fluid.

Table 1. Segmentation and classification results per class and averaged over all classes.

Class	Dice	HD95	Sensitivity	Precision	IOU	Accuracy
Bladder	0.6271	19.3365	0.6105	0.7267	0.5511	0.7691
Gallbladder	0.4759	18.4852	0.4171	0.6795	0.3859	0.7256
Kidney	0.4907	31.9442	0.5308	0.5098	0.4105	0.6642
Liver	0.4924	41.5934	0.4702	0.5563	0.4178	0.6291
Pancreas	0.1115	37.8118	0.1402	0.2119	0.0696	0.3501
Spleen	0.3744	41.8523	0.3675	0.4836	0.3086	0.5581
Free Fluid	0.4066	67.6334	0.4345	0.5057	0.2980	0.7695
All	0.4255	36.9510	0.4244	0.5248	0.3488	0.6380

The highest value for HD95 is observed in the segmentation of free fluid. A high Hausdorff distance indicates discrepancies between the predicted and ground truth segmentation boundaries. This is primarily due to the complex and variable shape of free fluid, which changes depending on the location of its accumulation. In contrast, the smallest HD95 values are recorded for the bladder and gallbladder at 19.3365 and 18.4852, respectively. The boundaries of these organs are much clearer, with more distinct pixel contrast compared to other organs.

Figure 1: Visualization of SAMed's predicted segmentation masks compared to the ground truth. The central column shows the ground truth masks for the liver and kidney, while the right column displays the corresponding predicted masks generated by SAMed.

In Table 2, we summarize the results for all classes, before and after fine-tuning SAMed on the US images. As observed, the metrics improved after fine-tuning, which demonstrates the effectiveness of transfer learning in tackling small dataset problems. The results revealed clear but modest improvements after fine-tuning. A possible reason is that we applied LoRA with a rank of 4 in SAMed. Consequently, we updated only a small subset of the model's parameters rather than fine-tuning the entire set of parameters. Despite fine-tuning some of the model's parameters, transfer learning still improved the model's performance and demonstrated its potential to overcome the problem of small datasets.

Table 2. Segmentation and classification results per class and averaged over all classes.

Metric	SAMed After Fine-Tuning	SAMed Before Fine-Tuning
Dice	42.55%	40.02%
HD95	36.95%	37.82%
Sensitivity	42.42%	40.40%
Precision	52.48%	50.15%
IOU	34.88%	32.59%
Accuracy	63.80%	62.06%

The results reveal that SAMed struggles with different medical imaging modalities, and must be fine-tuned to perform well on a specific image modality. However, inadequate medical datasets, particularly US images, make it difficult to properly fine-tune these models. As the InselUS dataset was small, we boosted the model's accuracy to 63.80% through transfer learning. We plan to enlarge the dataset and include a greater variety of training samples in order to further enhance the model's performance.

5. Conclusion and Discussion

In this work, we demonstrated the practical application of foundation models on US images, focusing on the segmentation and classification of abdominal organs and free fluids to support medical diagnosis in the emergency department. SAM's strong performance in general imaging tasks does not translate to medical imaging, where it suffers from substantial degradation and poor generalization without proper fine-tuning on medical images. Consequently, we fine-tuned SAMed on US images to improve its performance in segmenting US data. Additionally, we handled the challenge of limited labeled data by employing transfer learning. SAMed was initially trained on a larger public US dataset and then fine-tuned on our smaller InselUS dataset containing abdominal images. A comparison of the results before and after fine-tuning SAMed on US images highlights the improvements resulting from the use of transfer learning in addressing the issue of small datasets, which is a critical challenge in the medical domain.

While US images are highly effective, their accurate interpretation and identifying organ structures and abnormal regions depend on the physician's expertise. Therefore, developing a reliable AI-powered system for segmenting abdominal US images can aid in correct organs recognition and abnormalities spotting. Our fine-tuned SAMed model on US images can recognize free fluids in these images, which can be a sign of malignancy or infection. Moreover, it can find and classify organs to assist sonographers in evaluating organ condition and size to support disease diagnosis.

While further refinement is needed, our model has the potential to support junior physicians in acute diagnostic settings by providing precise and timely segmentation and classification of medical images. By accurately detecting organs and identifying pathological areas, it can effectively cope with the lack of extensive human expertise and enhance diagnostic efficiency to ensure patients receive appropriate care.

6. Future Works

Future work will focus on enhancing the performance and robustness of our model by expanding the dataset and incorporating images from other emergency departments and diverse clinical settings. This aims to improve the model's accuracy and precision, and in parallel to increase its generalizability across various use cases. Additionally, we plan to evaluate the model's performance in real-world clinical environments to explore its potential for real-time deployment of this model to make sure that it can provide timely and reliable assistance to medical professionals during patient examinations. Moreover, integrating explainability tools into the framework is expected to enable clinicians to better understand the model's decision-making process. This integration will promote transparency, foster trust and enhance the reliability in computer-aided diagnosis in clinical practice.

References

[1] Gilanie G, Saher A, Batool SN, Khursheed A, Shafique H, Perveen S, Latif A, Sajid M, Saeed M. Digital image processing for ultrasound images: A comprehensive review. Int J Innov Creat Change. 2021;15(3)

[2] Ma J, He Y, Li F, Han L, You C, Wang B. Segment anything in medical images. Nat Commun. 2024 Jan;15(1):1234-1238. doi: 10.1038/s41467-024-44824-z.

[3] Shi Y, Ma J, Yang J, Wang S, Zhang Y. Beyond pixel-wise supervision for medical image segmentation: From traditional models to foundation models. arXiv. 2024 Apr 24. Available from: https://arxiv.org/abs/2404.13239.

[4] Isensee F, Jaeger PF, Kohl SAA, et al. nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nat Methods. 2021 Feb;18(2):203-211. doi: 10.1038/s41592-020-01008-z.

[5] Xie B, Tang H, Duan B, Cai D, Yan Y. MaskSAM: Towards auto-prompt SAM with mask classification for medical image segmentation. arXiv. 2024 Mar 14. Available from: https://arxiv.org/abs/2403.14103.

[6] Kirillov A, Mintun E, Ravi N, Mao H, Rolland C, Gustafson L, Xiao T, Whitehead S, Berg AC, Lo W-Y, Dollár P, Girshick R. Segment anything. arXiv. 2023 Apr 5. Available from: https://arxiv.org/abs/2304.02643.

[7] Huang Y, Yang X, Liu L, Zhou H, Chang A, Zhou X, Chen R, Yu J, Chen J, Chen C, Liu S, Chi H, Hu X, Yue K, Li L, Grau V, Fan D-P, Dong F, Ni D. Segment anything model for medical images. Med Image Anal. 2024 Mar;92:103061. doi: 10.1016/j.media.2023.103061.

[8] Zhang K, Liu D. Customized Segment Anything Model for Medical Image Segmentation. arXiv. 2023 Apr 28. Available from: https://arxiv.org/abs/2304.13785.

[9] Lin X, Xiang Y, Yu L, Yan Z. Beyond adapting SAM: Towards end-to-end ultrasound image segmentation via auto prompting. arXiv. 2024 Sep 13. Available from: https://arxiv.org/abs/2309.06824.

[10] Hu EJ, Shen Y, Wallis P, Allen-Zhu Z, Li Y, Wang S, Wang L, Chen W. LoRA: Low-rank adaptation of large language models. arXiv. 2021 Jun 17. Available from: https://arxiv.org/abs/2106.09685

Young Researchers’ Track

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Development of an Assistance Robot for Fall Detection and Reporting in Healthcare

Moritz PFYFFER [a,1], Joël AMREIN [a] and Thomas BÜRKLE [a]
[a] *Bern University of Applied Sciences, Biel, Switzerland*

ORCiD ID: Moritz Pfyffer https://orcid.org/0009-0001-4795-4472 Thomas Bürkle https://orcid.org/0000-0002-2936-5375

Abstract. Falls pose a substantial risk to elderly individuals, especially those over 65, often leading to severe consequences. This project investigates the potential of the tēmi robot for fall detection in care facilities and its integration into a simulated clinical workplace system. The prototype employs the YOLOv8 image recognition model to detect fallen individuals during patrols, transmitting incident data to a simulated clinical system via Fast Healthcare Interoperability Resources (FHIR). While initial tests delivered promising results, enhancements in image recognition accuracy are required for effective real-world deployment.

Keywords. Social robotics, fall detection, FHIR integration

1. Introduction

Robots are increasingly being explored in nursing for applications such as mobility aids, transport tasks, and patient monitoring [1,2]. Additionally, social robots can support emotional and cognitive care [3]. Despite promising developments, the widespread use of robots in the Swiss healthcare system remains limited. The Institute for Medical Informatics at Bern University of Applied Sciences has integrated robots into student education [4,5] and actively examines the potential of robots in medical environments. Among these, patient falls are a critical area of focus, as they are one of the leading causes of injuries among elderly individuals. Early detection of falls is vital to improving outcomes and ensuring timely interventions [6].

In collaboration with LEP AG, the provider of the LEP Nursing 3 interventions catalog, this project investigated the use of an assistance robot for fall detection in healthcare environments. A key focus was on integrating the robot with clinical information systems (CIS) to streamline communication and documentation processes.

The project aimed to reduce the workload of healthcare staff by enabling the robot to conduct ward rounds, detect fallen patients, and promptly notify or call a nurse to the scene. This objective led to the following research question:

"How can an assistance robot perform a LEP nursing-3 intervention such as a ward round or night watch, transmit the activity record to the clinical information system (CIS), and notify or call healthcare staff in the event of a detected patient fall?"

[1] Corresponding Author: Moritz Pfyffer, E-mail: moritzpfyffer@gmail.com

2. Methods

A literature review was conducted to identify appropriate communication standards for the interaction between the robot and the clinical information system (CIS). Practical requirements were refined through discussions with CIS providers, such as Nexus.

The prototype was developed on a Tēmi robot (version 3) running Android, with the robot's application programmed in Kotlin. Additionally, the simulated clinical information system (CIS) was implemented using Python. Communication between the Tēmi robot and the simulated CIS was established using the standardized FHIR format, with JSON files transmitting intervention tasks.

YOLOv8 model (You Only Look Once) was used, a real-time object detection algorithm for Fall detection. The dataset, originally adapted from the study "Fallen People Detection Capabilities Using Assistive Robot"[7], consisted of 6,982 images, including 5,023 images of falls and 2,275 non-fall images. To enhance recognition accuracy, an additional 1,906 images were captured under varying lighting conditions. The YOLOv8 model was trained over 200 epochs to optimize detection performance.

The prototype was tested in the Medical Informatics Laboratory at Bern University of Applied Sciences, which simulated a clinical environment featuring corridors, patient rooms, and a nursing station to replicate real-world conditions. These scenarios were designed to mimic practical care settings and assess the robot's functionality.

The testing phase evaluated the functionality of the prototype through two scenarios. In the first, routine patrols were conducted, during which the robot followed predefined routes to monitor the environment and detect fallen individuals. The second scenario simulated fall events, with test participants acting as patients by deliberately falling or lying on the ground. These situations were used to assess the system's ability to accurately identify and respond to falls.

3. Results

The prototype consisted of two primary components: communication simulation and fall detection. Communication between the Tēmi robot and the simulated clinical information system (CIS) was successfully implemented using a WebSocket connection, enabling real-time data exchange. Fall detection alerts were transmitted as standardized FHIR JSON files, containing key details such as timestamp, fall location, and the detected individual’s position. These alerts were seamlessly integrated into the CIS using FHIR resources like "Observation" and "Task", ensuring compatibility with electronic health record (EHR) systems.

Additionally, the Tēmi robot’s tablet interface displayed real-time alerts for detected falls, providing immediate feedback to healthcare staff (Fig. 1).

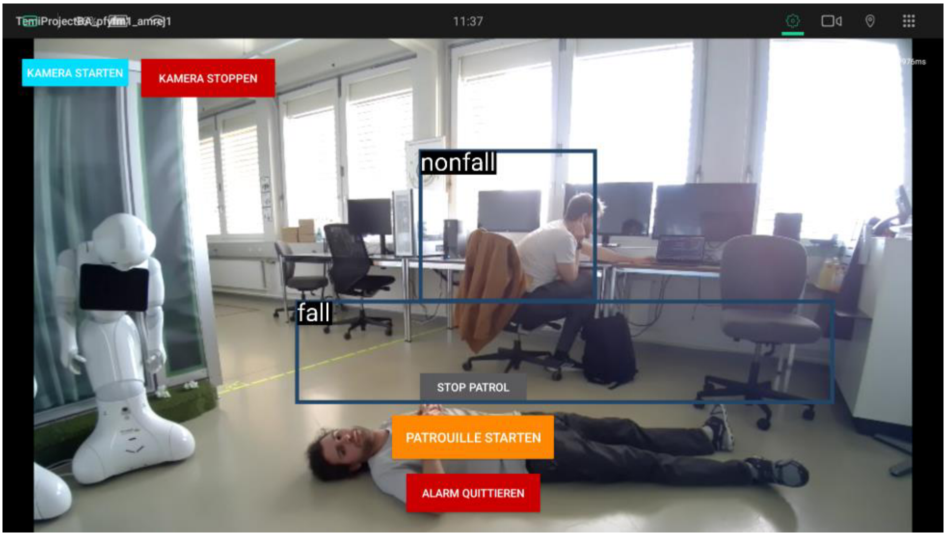

Figure 1 Tēmi detects a fall and shows this with an alarm on the tablet interface. Fallen and not fallen individuals are distinguished

Fall detection relied on the YOLOv8 image recognition model, which distinguished between routine rounds and incidents involving falls. When a fall was detected, the system triggered an alarm and transmitted the incident details directly to the simulated CIS or care staff. Performance evaluation of the YOLOv8 model revealed that the F1-score across all classes peaked at 0.81 at a confidence threshold of 0.182, demonstrating a balanced trade-off between precision and recall.

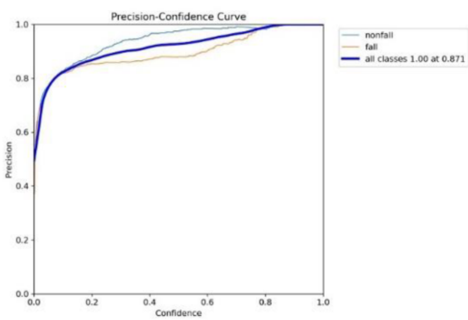

Figure 2 Precision-Confidence Curve

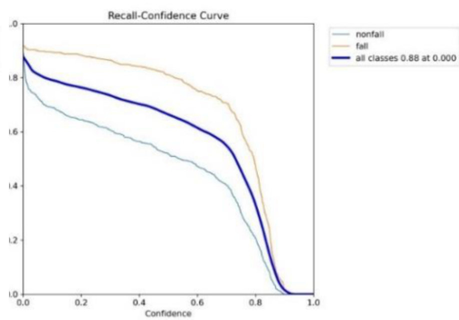

Figure 3 Recall-Confidence Curve

4. Discussion

The integration of assistive robots in healthcare can reduce nursing workload by automating fall detection and documentation. In hospitals, where nurses manage multiple floors during night shifts, robots could improve patient monitoring and response times. Standardized protocols like FHIR ensure compatibility with clinical IT systems and enhance interoperability.

Alternative fall detection methods, such as wearable sensors (e.g., Apple Watch), belt sensors, or inflatable hip airbags, are increasingly used but rely on patient compliance and are designed for home settings. In contrast, robot-based systems provide continuous, non-intrusive monitoring, making them more suitable for hospitals where caregivers need automated surveillance tools.

While an F1-score of 0.81 is promising for an experimental setup, it falls below the threshold required for clinical use, where high sensitivity and specificity are essential. Studies suggest that AI models in healthcare often need F1-scores above 0.90 to minimize false positives and negatives, ensuring reliable decision-making in patient care [8]. Similarly, research highlights that such high accuracy is critical to maintaining diagnostic integrity and reducing misclassification rates [9]

Initially, a system may generate false alarms, but preventing real falls from being missed is the priority. Further refinements in training datasets and model optimization are needed to reach clinically acceptable performance levels.

5. Conclusion

This project demonstrated the feasibility of integrating assistive robots into healthcare workflows for fall detection and documentation. The Tēmi robot, which uses a YOLOv8-based detection system, delivered promising results with high detection accuracy and seamless integration into clinical information systems via FHIR standards.

Further refinements are needed to improve accuracy under varying conditions and reduce false alarms. Future work should address real-world testing and ethical considerations. With continued development, assistive robots like Tēmi could play a crucial role in supporting healthcare staff and enhancing patient safety.

References

[1] Maalouf N, Sidaoui A, Elhajj IH, Asmar D. Robotics in Nursing: A Scoping Review. J Nurs Scholarsh. 2018 Nov;50(6):590–600. doi: 10.1111/jnu.12424.

[2] Adami I, Antona M, Stephanidis C. Home Trials of Robotic Systems: Challenges and Considerations for Evaluation Teams. In: Antona M, Stephanidis C, editors. Universal Access in Human-Computer Interaction Users and Context Diversity. Cham: Springer International Publishing; 2016. p. 291–301.

[3] Figliano G, Manzi F, Tacci AL, Marchetti A, Massaro D. Ageing society and the challenge for social robotics: A systematic review of Socially Assistive Robotics for MCI patients. PLoS One. 2023;18(11):e0293324. doi: 10.1371/journal.pone.0293324.

[4] Bürkle T, Bender M, Glauser R. Using Robots in Medical Informatics Education. Stud Health Technol Inform. 2022 May 25;294:765–9. doi: 10.3233/SHTI220580.

[5] Glauser R, Holm J, Bender M, Bürkle T. How can social robot use cases in healthcare be pushed - with an interoperable programming interface. BMC Med Inform Decis Mak. 2023 Jul 11;23(1):118. doi: 10.1186/s12911-023-02210-7.

[6] BFU [Internet]. [cited 2025 Jan 16]. Stürze bei älteren Erwachsenen. Available from: https://www.bfu.ch/de/die-bfu/medien/stuerze-bei-aelteren-erwachsenen

[7] (PDF) Fallen People Detection Capabilities Using Assistive Robot. ResearchGate [Internet]. 2024 Oct 22 [cited 2025 Jan 16]; Available from: https://www.researchgate.net/publication/335318179_Fallen_People_Detection_Capabilities_Using_Assistive_Robot

[8] Calster BV, Collins GS, Vickers AJ, Wynants L, Kerr KF, Barreñada L, et al. Performance evaluation of predictive AI models to support medical decisions: Overview and guidance [Internet]. arXiv; 2024 [cited 2025 Mar 11]. Available from: http://arxiv.org/abs/2412.10288

[9] F1 Score in Machine Learning: Intro & Calculation [Internet]. [cited 2025 Mar 11]. Available from: https://www.v7labs.com/blog/f1-score-guide

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Digitization of the Huddle-Board in the Sonnenhof Operating Room

Michael NGUYEN[a, 1] Pascal LEUTHOLD[a] and Michael LEHMANN[b]

[a] *Lindenhofgruppe., Bern, Switzerland*
[b] *Bern University of Applied Sciences, Biel, Switzerland*

Abstract. This study investigates the transition from analog to digital Huddle-Boards within the operational environment of a hospital. By analyzing the current analog system and implementing a digital prototype, the study aims to measure efficiency, usability, and overall system improvements. A combination of observational analyses, surveys, interviews, and usability studies were conducted to assess the potential benefits of digitization. The results highlight significant time savings, increased accessibility, and enhanced usability of the digital system compared to its analog counterpart.

Keywords. digital Huddle-Board, usability, system analysis, process optimization

1. Introduction

The goal of Lean Management is to optimize processes, minimize waste, and maximize value creation. A key tool in this approach is the Huddle-Board, a visual aid used for process visualization and management. It can take various forms, such as flip charts, whiteboards, or customized marker boards [1]. In many hospitals, Huddle-Boards are employed to enhance communication and coordination within teams, serving as a platform for discussing current tasks, problems, and solutions during daily huddle meetings. Huddle-Boards positively impact team communication, efficiency, and patient safety outcomes [2, 3]. Traditionally, most hospitals, including those in the Lindenhof Group, still rely on analog Huddle-Boards that depend on physical materials such as printed schedules and manual updates. These processes are often time-consuming and prone to errors [4]. The analog systems are widespread, but they present challenges such as inefficiency and limited access to real-time data [3].

This study introduces a digital alternative designed to modernize processes and enhance overall efficiency. The project encompasses an analysis of the current analog workflow, development and testing of a digital prototype, and evaluating its usability through real-world application. The primary objective is to assess whether the digital system offers tangible improvements in efficiency, user experience, and resource allocation. By transitioning to a digital Huddle-Board, hospitals aim to reduce manual effort, improve communication, and enable more dynamic decision-making [5].

[1] Corresponding Author: Michael Nguyen, Michael.nguyen@ggs.ch

2. Method

2.1. Observation Analysis, questionnaires and interviews

The study employed systematic and unsystematic observations to analyze task durations, and staff interactions, providing insights into analog and digital system performance. Additionally, questionnaires and interviews were conducted before and after implementing the digital Huddle-Board: pre-implementation surveys assessed the analog system, while post-implementation surveys evaluated usability, satisfaction, and benefits.

2.2. Usability Study

A detailed usability study was performed using task-based evaluations. Participants were instructed to complete predefined tasks on the digital system, such as scheduling and information retrieval. Key metrics such as time taken, ease of navigation, and user satisfaction were measured using the System Usability Scale (SUS), providing a standardized assessment of the digital system's performance.

3. Results

3.1. Implementation of the digital Huddle-Board "infOPhuddle"

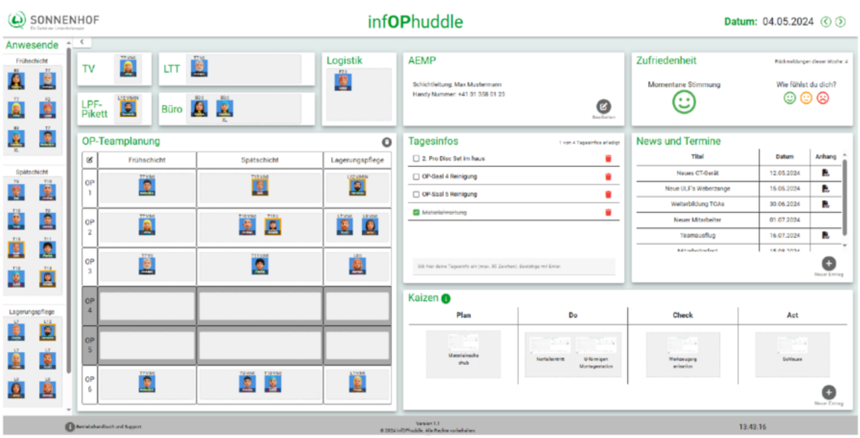

Figure 1: Prototype of the digital Huddle-Board "infOPhuddle"

The digital Huddle-Board system serves as the central platform for streamlining operational processes in the Sonnenhof operating room. Running on Windows Server 2022 with Nginx and a Node.js backend, it processes data from the workforce management system Polypoint via XML files and stores it in an MSSQL database. The Vue.js and Pinia frontend ensures a user-friendly interface, communicating with the backend via APIs for secure, real-time updates and efficient functionality. A firewall and monitoring ensured performance, while a maintenance plan guaranteed system integrity. The prototype of the digital Huddle-Board can be seen in Figure 1.

The most important functions include real-time staff planning for operating rooms. The system also facilitates the exchange of critical information, allows for structured feedback collection, and supports continuous improvement through Kaizen principles by identifying and optimizing processes and problem areas.

3.2. Study results for the analog Huddle-Board

The analog Huddle-Board system exhibited several inefficiencies. Employees often had to go back and forth between their workstations and the Huddle-Board to access or update information. The reliance on printed documents resulted in increased resource consumption and higher operational costs. Additionally, the analog system was less adaptable to sudden changes, often leading to delays in communication. Observations revealed that preparing the analog board took approximately 12 minutes and 30 seconds, involving tasks such as printing, manual arrangement of documents, and physically walking to the board.

3.3. Study results for the digital Huddle-Board

The digital Huddle-Board addressed many of the limitations observed in the analog setup. With centralized access to information and remote viewing capabilities, employees could access and update schedules without unnecessary movement. The intuitive design reduced the time required to plan and execute tasks. The ability to integrate real-time updates significantly improved workflow efficiency. he ability to integrate real-time updates significantly improved workflow efficiency. The preparation time for the Huddle-Board was reduced to 5 minutes and 32 seconds.

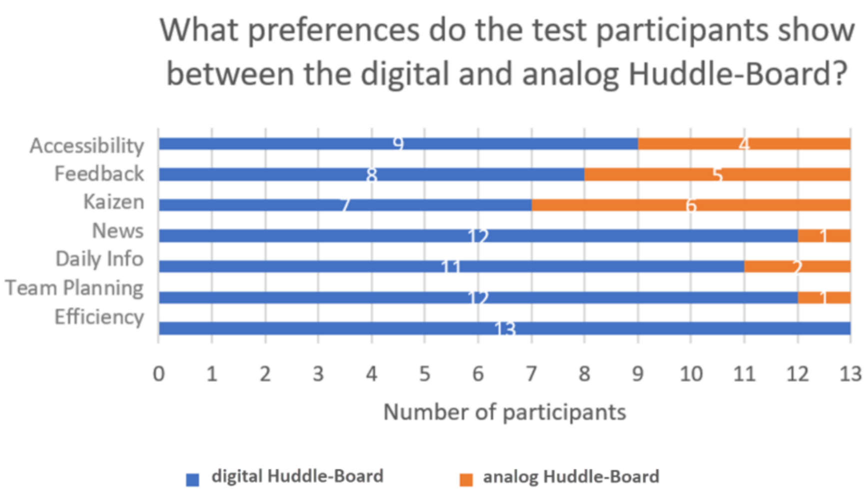

Figure 2: Evaluation – Preferences between digital and analog Huddle-Boards

The evaluation of the digital Huddle-Board utility received overwhelmingly positive feedback. On a scale from 0 (negative) to 10 (positive), nine out of thirteen participants rated it with the highest score of 10, indicating very high utility. The usability test included 14 tasks, such as accessing and modifying team schedules, editing sterilization information, reviewing and acknowledging news updates, generating and exporting PDF reports, and sending feedback through the integrated email system. Additionally, participants were asked about their preferences regarding the components of the Huddle-Board, comparing the analog and digital versions. The digital Huddle-Board, as shown in Figure 1, was evaluated against the analog version, with the results displayed in Figure 2. The analysis clearly indicates that the digital version was preferred across all components, demonstrating its superior utility and efficiency.

4. Discussion

Despite the increasing prevalence of lean management in the healthcare sector, there are not many studies that examine the use of digital Huddle-Boards in particular [3]. In this study, which examined the use of the newly developed Huddle-Board, remarkable improvements were found between the analog and digital Huddle-Board in terms of efficiency, ease of use and user preference. Preparation time dropped from 12 minutes to 5 minutes and 32 seconds, a 46% reduction, by eliminating tasks like printing and walking to the board. The digital system, preferred for its superior functionality, scored 88.5 on the System Usability Scale (SUS). Feedback highlighted real-time access, fewer manual tasks, and cost savings, enhancing convenience and efficiency.

The digital Huddle-Board streamlined surgical workflows by removing redundant tasks, boosting efficiency and productivity. Its high SUS scores reflect intuitive design, fostering user satisfaction. Frequent use supports real-time communication and decision-making, while centralized, up-to-date information reduces risks from outdated data, improving patient outcomes. The real-time integration of personnel information through the interface with the workforce management system was particularly beneficial, improving team coordination and planning. Moreover, the ability to access the Huddle-Board from any PC improved flexibility and ensured that information was always readily available to staff.

Additionally, the structured arrangement of information led to better organization and reduced the risk of information loss. Cost savings were achieved through decreased paper usage and reduced administrative workload. Nevertheless, the introduction of the digital Huddle-Board also incurred new electricity costs, which are expected to be outweighed by the achieved efficiency gains. Suggested improvements include customization options and automated data integration to further enhance usability and efficiency. The successful deployment of the digital Huddle-Board during the testing phase demonstrates its potential for broader implementation in other operating rooms or related healthcare environments.

References

[1] Helmond M, Lean Management und Kaizen: Grundlagen aus Fällen und Beispielen in Operations und Supply Chain Management. 1st ed. 2023.

[2] Camilla B. Pimentel et al., Huddles and their effectiveness at the frontlines of clinical care: a scoping review; J Gen Intern Med, 2021 Sep;36(9):2772-2783.doi: 10.1007/s11606-021-06632-9.

[3] Brendan L Rowan et al., The impact of huddles on a multidisciplinary healthcare teams' work engagement, teamwork and job satisfaction: A systematic review, J Eval Clin Pract, 2022 Jun;28(3):382-393, doi: 10.1111/jep.13648. Epub 2022 Feb 17.

[4] Laura E Winner 1 , Erica Reinhardt, Lauren Benishek, Jill A Marsteller, Lean Management Systems in Health Care: A Review of the Literature, Qual Manag Health Care, 2022 Oct-Dec;31(4):221-230, doi: 10.1097/QMH.0000000000000353. Epub 2022 Feb 15.

[5] Hamidi M, Mahendran P, Denecke K. Towards a Digital Lean Hospital: Concept for a Digital Patient Board and Its Integration with a Hospital Information System, Stud Health Technol Inform, 2019 Aug 21:264:606-610, doi: 10.3233/SHTI190294.

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AI-Enhanced Speech Recognition in Triage

Ahmed ELHILALI[a*], Vanessa BRÜGGER[a*] , Isabelle TSCHANNEN[b],
Wolf HAUTZ[b], Gert KRUMMREY[a,b1]
[a] *Bern University of Applied Sciences, Institute for Medical Informatics*
[b] *Inselspital, Bern University Hospital, Department of Emergency Medicine*

ORCiD ID: Wolf Hautz https://orcid.org/0000-0002-2445-984X ,
Gert Krummrey https://orcid.org/0000-0002-8397-2336

Abstract. Triage is used in emergency departments to ensure timely patient care according to urgency of treatment. However, triage accuracy and efficiency remain challenging due to time-constraints and high demand. This proof-of-concept study evaluates an AI-powered triage system that leverages speech recognition (STT) and large language models (LLMs) to process patient interactions in triage and to assign an Emergency Severity Index (ESI) triage level and a classification of the main presenting complaint according to the Canadian Emergency Department Information System (CEDIS). In Switzerland, different Swiss German dialects add to the complexity of the task. STT models achieved word error rates (WER) of 2.3% for High German and 17.66% for Swiss German. Despite the high WER, the AI's classification accuracy reached 90–100% for ESI levels and CEDIS codes. These results highlight the potential of integrating AI into triage workflows, enhancing consistency and reducing the documentation burden for clinical staff. Future research should address multi-language adaptation and data security to ensure seamless implementation in real-world settings.

Keywords. Artificial Intelligence, Speech-to-Text, Triage Systems, Natural Language Processing (NLP), Emergency Medicine, Triage

1. Introduction

Emergency departments (EDs) are pivotal in delivering timely and life-saving care. Over the past decades, the demand for ED services has surged, placing immense pressure on resources and staff. Triage is the initial patient assessment process which determines the urgency of treatment based on the severity of a patient's condition and prioritizes resources accordingly [1].

Among the various triage tools, the Emergency Severity Index (ESI) is a widely adopted, validated system used internationally. Despite its prevalence, inconsistencies in its application persist, as studies show only 59.6% accuracy in standardized triage cases, even among experienced nursing staff [2]. Further, in most EDs, a presenting complaint is documented in addition to the urgency of treatment. The Canadian Emergency Department Information System (CEDIS) is widely used for this purpose [3].

Advancements in artificial intelligence (AI), especially in machine learning (ML) and natural language processing (NLP), offer promising avenues to improve triage accuracy and efficiency [4]. While most existing research focuses on retrospective

[1] Corresponding author: Gert Krummrey, Bern University of Applied Sciences, Quellgasse 21, CH-2502 Biel/Bienne, Switzerland. E-Mail: gert.krummrey@bfh.ch
* Both authors contributed equally and share first authorship

analyses of unstructured text, the integration of speech recognition in real-time clinical workflows remains underexplored [5]. AI-powered systems can process audio recordings of patient-provider interactions, convert them into text using speech-to-text algorithms, and provide automated categorizations for ESI and CEDIS classifications [6].

This study investigates the potential of an AI-enhanced triage system that integrates speech recognition and LLMs into triage. By evaluating transcription accuracy and classification reliability, it aims to demonstrate the feasibility of implementing such systems to optimize ED workflows and to reduce the documentation burden on clinical staff.

2. Methods

The AI-enhanced triage system integrates speech-to-text (STT) technology with large language models (LLMs). It processes audio recordings of patient-provider interactions, transcribes the conversations, and determines the ESI triage level and the CEDIS code. It includes mechanisms for data preprocessing, classification, and manual correction to improve usability and accuracy.

The following STT models were utilized for transcription: 1) Wit.ai: A speech recognition platform, optimized for general use cases, but with limitations in domain-specific medical terminology and dialect, 2) Whisper by OpenAI in the "base" configuration and in a Swiss German fine-tuned version: "nizarmichaud/whisper-large-v3-turbo-swissgerman". The system employs LLMs to process transcribed text and produce structured outputs with ESI triage level determination and CEDIS classification. The model "Claude-3-Opus-20240229" from Anthropic was selected for its ability to generate domain-specific analyses and structured outputs while ensuring contextually appropriate responses.

Ten written triage scenarios were created using common presenting complaints. ChatGPT-4o was used to create dialogs based on these scenarios. An audio dataset of triage conversations was then created in both High German and Swiss German using a bespoke audio dialog creation engine utilizing OpenAI's text-to-speech (TTS) capabilities and a Swiss German TTS API [7]. Reverberation and ambient noise were added to the recordings to make them more realistic. Each scenario included annotated ESI levels and CEDIS codes determined by clinical experts to be referenced later in the evaluation.

Using web-technologies and Python for the backend, a web-application was programmed to allow the upload of audio data into the processing pipeline (see Fig. 1). Sequentially, audio was transcribed and the result passed on to the LLM which in turn determined ESI level and CEDIS code as well as providing a summary of the conversation for documentation purposes.

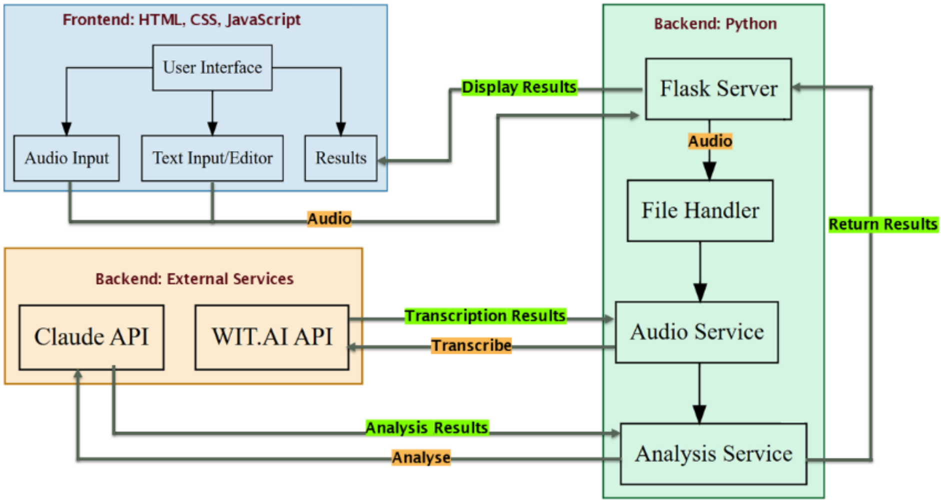

Figure 1. System Design

3. Results

Speech-to-text (STT) models demonstrated significant variations in Word Error Rates (WER) depending on the language and model used. The transcription performance varied across the triage scenarios.

High German: Wit.ai achieved a mean WER of 2.30%, significantly outperforming the base Whisper model, which had a WER of 4.11%.

Swiss German: The adapted Whisper model delivered a mean WER of 17.66% as compared to the base Whisper model (mean WER 45.19%), showcasing a substantial improvement of fine-tuned models over general-purpose models. Wit.ai struggled with Swiss German dialectal variations (mean WER of 63.24%).

Table 1. Word Error Rates (WER) for Swiss German / High German audio

	Swiss German			High German	
Scenario	**Whisper Base**	**Whisper Swiss**	**Wit.ai**	**Whisper Base**	**Wit.ai**
Chest Pain	50.00%	21.30%	67.82%	3.25 %	0.90%
Ear Pain	46.26%	21.90%	62.20%	5.10 %	1.54%
Abdominal Pain	42.41%	18.85%	58.93%	3.66 %	2.29%
Diarrhea	45.85%	17.15%	59.77%	5.42 %	2.18%
Flank Pain	46.82%	14.64%	65.44%	3.28 %	2.74%
Depression	34.30%	18.11%	55.66%	3.28 %	3.61%
Dizziness	49.25%	12.04%	63.45%	2.80 %	2.32%
Headache	50.00%	15.99%	70.91%	2.43 %	2.18%
Back Pain	48.18%	19.06%	68.33%	6.64 %	2.41%
Laceration	38.82%	17.51%	59.88%	5.27 %	2.83%

Classification Accuracy: The system's classification accuracy for ESI level and CEDIS code was evaluated across both transcription formats and input languages:

High German: 90% accuracy for ESI levels and 100% accuracy for CEDIS codes.

Swiss German: 100% accuracy for ESI levels and 90% accuracy for CEDIS codes.

4. Discussion

This proof-of-concept demonstrates the potential of AI-powered triage systems to enhance emergency department (ED) workflows by integrating advanced speech recognition and classification capabilities. ESI code assignments were validated by an experienced ED triage nurse, with synthetic audios incorporating background noise for enhanced authenticity. However, we are aware of the limitations of using synthetic data for triage conversations, which was necessitated by data privacy considerations and the lack of ethics approval for using real patient data.

The Whisper model fine-tuned for Swiss German significantly outperformed general-purpose alternatives like the Whisper base model and Wit.ai for Swiss German transcription, significantly reducing the Word Error Rate. However, in dialects without an accepted way of spelling words, calculating the WER is challenging. Also, all STT-systems fall short of the ideal accuracy for clinical applications, where errors in transcription can propagate through subsequent classification processes. Challenges in processing dialectical variations underline the need for further fine-tuning of STT models tailored to regional languages.

Despite the limitations in transcribing audio, especially when dialect is spoken, the system achieved high accuracy in Emergency Severity Index (ESI) and Canadian Emergency Department Information System (CEDIS) classification, with an accuracy of up to 100% in certain scenarios. This illustrates that for those tasks an understanding of the context seems sufficient for the model to determine the right level and code.

While promising, the system faces significant barriers regarding data security and ethical considerations. Integration with external services like Wit.ai raises compliance concerns with Switzerland's data protection laws. Local hosting and potential bias mitigation are necessary.

This study demonstrates the feasibility of integrating AI-enhanced speech recognition and classification systems into ED triage workflows. With classification reliability reaching acceptable levels for clinical application, the system offers significant potential to reduce the administrative burden on healthcare. Future work should focus on refining dialect-specific STT models to improve transcription accuracy, enabling multi-label classification, and ensuring data privacy through locally hosted solutions.

References

[1] Dugas AF, Kirsch TD, Toerper M, Korley F, Yenokyan G, France D, u. a. An Electronic Emergency Triage System to Improve Patient Distribution by Critical Outcomes. J Emerg Med. Juni 2016;50(6):910–8. doi: 10.1016/j.jemermed.2016.02.026.

[2] Grossmann FF, Delport K, Keller DI. Emergency Severity Index. Notf Rettungsmedizin. 1. Juni 2009;12(4):290–2.

[3] Grafstein E, Unger B, Bullard M, Innes G, Group the CEDIS (CEDIS) W. Canadian Emergency Department Information System (CEDIS) Presenting Complaint List (Version 1.0). Can J Emerg Med. Januar 2003;5(1):27–34. doi: 10.1017/s1481803500008071.

[4] Lee P, Bubeck S, Petro J. Benefits, Limits, and Risks of GPT-4 as an AI Chatbot for Medicine. Drazen JM, Kohane IS, Leong TY, Herausgeber. N Engl J Med. 30. März 2023;388(13):1233–9. doi: 10.1056/NEJMsr2214184.

[5] Kwon J myoung, Lee Y, Lee Y, Lee S, Park H, Park J. Validation of deep-learning-based triage and acuity score using a large national dataset. PLoS ONE. 15. Oktober 2018;13(10):e0205836.

[6] McHugh M, Tanabe P, McClelland M, Khare RK. More patients are triaged using the Emergency Severity Index than any other triage acuity system in the United States. Acad Emerg Med Off J Soc Acad Emerg Med. Januar 2012;19(1):106–9. doi: 10.1111/j.1553-2712.2011.01240.x.

[7] Cieliebak, Mark. ZHAW Zürcher Hochschule für Angewandte Wissenschaften. [zitiert 24. Januar 2025]. End-to-End Low-Resource Speech Translation for Swiss German Dialects. Verfügbar unter: https://www.zhaw.ch/de/forschung/projekt/72998

Connected Care – The Key to a Seamless Patient Journey

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Patient Journey Maps Associated to Shared Decision Making

Michaël LAURAC[a,1] and Thomas BÜRKLE[a]
[a] *Institute for Medical Informatics, Bern University of Applied Sciences*
ORCiD ID: Michaël Laurac https://orcid.org/0000-0002-5168-5092,
Thomas Bürkle https://orcid.org/0000-0002-2936-5375

Abstract. **Background:** Despite the benefits, the practical implementation of shared decision-making (SDM) is challenged by the lack of decision aids for patients. **Objective:** This rapid review analyses how patient journey maps (PJMs) have highlighted the need for shared healthcare decisions between patients and professionals. **Methods:** The extension of the PRISMA methodology for scoping reviews was used as a guideline. The MEDLINE, APA PsycInfo, Embase, Emcare and Nursing Database digital databases were queried using a reduced selection of search expressions. Resulting articles from peer-reviewed journals since 2015 were analysed. **Results:** 11 articles provide directions regarding the enhanced support of SDM throughout the patient journey. The utilisation of basic patient journey modelling along care trajectories has facilitated patient engagement with professionals, thereby enabling the disclosure of their needs and experiences. A generic model could be abstracted from each condition-specific PJMs, highlighting when decisions may impact patient experience. **Conclusions:** The development of a digital visual representation of a generic patient journey, from the onset of symptoms to the management of the condition, has the potential to serve as a valuable communication tool, assisting patients and healthcare professionals in better preparing, focusing and documenting SDM conversations.

Keywords. Patient journey maps, shared decision-making

1. Introduction

In the context of a patient's journey, shared decision-making (SDM) is recognised as a "*collaborative approach by which, in partnership with their clinician, patients are encouraged to think about the available care options and the likely benefits and harms of each, to communicate their preferences, and help select the best course of action that fits these*" [1, 2, 3, 4]. The role of SDM in respecting patients' autonomy to make informed choices, balancing benefits against risks and costs, and avoiding harm is considered essential [3]. The integration of patients' needs and preferences into the decision-making process has been shown to promote patient engagement and tends to improve health outcomes that matter to patients, while reducing unnecessary costs [3].

The merits of the SDM approach have been delineated for over four decades; nevertheless, its routine implementation remains subject to local variation with its adoption being shaped by local initiatives [2, 5]. Moreover, a lack of clear guidance for the implementation of SDM has been reported, leading to the proposal of a 3-step model for structuring the SDM conversation has been proposed [6]. The art of SDM is also

[1] Corresponding Author: Michaël Laurac, michael.laurac@bfh.ch

increasingly recognised as a core competency of healthcare professionals [2, 5]. However, some barriers to its adoption remain.

To date, successful implementation of SDM depends on the relationship between patients, family members and professionals. A climate of trust allows contextual information relevant to decision makers to flow transparently between participants. Patients and families are encouraged to ask questions and express their views, needs and preferences. A central factor in patient-professional interaction during SDM is the need for a balance of power between patients and professionals that permits patients to appreciate the contribution of their own values and preferences in the decision-making process [7].

Patient journey modelling and its visual representation in patient journey maps (PJMs) has recently gained traction among healthcare providers wishing to improve patient experience. A recent functional definition describes patient journey mapping (PJM) as "*a patient-oriented project that has been undertaken to better understand barriers, facilitators, experiences, interactions with services and/or outcomes for individuals and/or their carers, and family members as they enter, navigate, experience and exit one or more services in a health system by documenting elements of the journey to produce a visual or descriptive map*" [8].

The present rapid review seeks to provide an answer to the following question:
In what ways might patients benefit from patient journey maps during the shared decision-making process with their healthcare professionals?

2. Methods

A comprehensive search on the Ovid platform was conducted querying the MEDLINE, APA PsycInfo, Embase, Emcare and Nursing Database utilising the PRISMA scoping review methodology as a foundation [9]. The search strings were the adjacent terms "*patient**", "*journey**" and ("*map*" or "*maps*" or "*mapp**") in the title, in the context "*health**" or "*care**" in the title or abstract. The results were limited to peer-reviewed journals since 2015, and duplicates were removed. Each remaining article was then read to extract medical information on the target group and determine the objectives of the article. In addition, the clinical improvement strategy postulated in each article was classified into one of more of the following five categories according to an adapted version of the justifications driving PJM research projects [10]:

1. Resources: Optimising costs and resources
2. Continuity: Providing better access to continued integrated care
3. Experience: Understanding patients' needs and improving experience
4. Engagement: Promoting patients' engagement
5. Empowerment: Facilitating shared decision-making

A subsequent identification and analysis of articles specifically discussing how to improve the SDM process was conducted. The medical specialty, the medical condition, its frequency and chronicity were documented. Conditions were classified into the following categories: rare, uncommon and common. Condition chronicity was categorized as acute, chronic or undifferentiated, and potentially either acute or chronic. The articles described the mapping of individual care journeys into a condition-specific PJMs. The resulting models were then abstracted and combined into a generic patient journey model. Phases of the generic model indicated as involving SDM activities were marked for analysis.

3. Results

A total of 114 references were identified, of which 96 were sourced from peer-reviewed journals specialising in human research. Following the removal of 45 duplicate records, the number of publications was reduced to 51. Subsequently, 19 abstracts and protocols were discarded, leaving 32 full articles. 7 articles pertaining to clinical practice were excluded, resulting in 25 full texts. Each of the 25 full texts was then analysed and their content was verified against the five improvement strategies described in part **2. Methods**. 14 articles did not include 'Empowerment: Facilitating shared decision-making' as a strategy. The remaining 11 full texts were then analysed in depth to answer the research question.

The articles analysed pertained to neurology (27%), cardiology (18%), orthopedic surgery and rheumatology (18%), dermatology (9%), otorhinolaryngology (9%), gastroenterology (9%) or non-specified medical conditions (9%).

Table 1 shows the association of the 11 articles regarding frequency and chronicity of the respective disease.

Table 1. Frequency and chronicity of the conditions targeted by the 11 short-listed articles

		Frequency			
		Rare	Uncommon	Common	
Chronicity	Acute			1	9%
	Acute or chronic			1	9%
	Chronic	2	0	7	82%
		18%	0%	82%	

Patient journey processes are displayed in column 3 of **Table 2** for each article. Most processes exhibit a single core process. Occasionally, additional branch processes have been described. Except for one article, two to eight process steps were described.

The steps of the PJMs were analysed in 9 out of 11 articles, with articles pertaining to care settings, i.e. either hospital care or home care, and return to work following cardiovascular disease, being excluded.

The semantic content of each step in specific PJMs was abstracted into six common semantic concepts, composing six steps of a high-level generic journey:

1. **Symptom onset.** Independent from pre-diagnosis when silent or undifferentiated symptoms lead to a prolonged long time-to-diagnosis i.e. rare neurological diseases or in coronary artery disease (CAD)
2. **Pre-diagnosis.** Independent or combined with symptom onset or diagnosis, and used for anamneses and investigations from medical professionals
3. **Diagnosis.** Appeared in the first three steps alone or combined, except when it is implied by the investigation or the intervention e.g. an allergy test or surgery
4. **Pre-treatment.** Referred on its own either to give recommendation or decide treatment, or to initiate or prepare care prior to treatment start
5. **Treatment.** Seen as a therapeutic intervention such as treatment, intervention, operation, therapy and systematically present when not delayed or declined.
6. **Follow-up.** Present in cases of uncurable conditions, expressed as follow-up, discharge, recovery, monitoring or managing symptoms or living with the condition

Table 2. Degrees of SDM for each patient journey steps as mapped into a generic 6-step journey model

<table>
<tr><th>Reference</th><th>Process</th><th>1. Symptom onset</th><th>2. Pre-diagnosis</th><th>3. Diagnosis</th><th>4. Pre-treatment</th><th>5. Treatment</th><th>6. Follow-up</th></tr>
<tr><td>[10]</td><td>1. Allergy Testing Schedule Patient Module 2. Comprehensive Allergy Testing Performed MQT Protocol 3. MQT/COMP Testing 4. Office Visit or Telemedicine Visit to Review TEST results (and optional FeNO or Spirometry) 5.1. SLIT Recommended and Started 5.2. SCIT Recommended and Started 6.1. Business Office Calls with Financial Responsibility 6.2. Insurance Verification with Financial Responsibility 7.1 SLIT Visits Mixed 7.2. Initial Visit Mixed, AIT consult and initial Test Wheel 8. Physician Office Visit or Telemedicine Follow-Up</td><td>1</td><td>2, 3</td><td>4</td><td>5</td><td>5, 6, 7</td><td>8</td></tr>
<tr><td>[11]</td><td>1. Path to diagnosis via symptom onset or discovery of family history 2. Genetic testing and diagnosis 3. Living with ALSP including potentiel experimental therapeutic and symtpom management options</td><td>1</td><td colspan="2">2</td><td colspan="3">3</td></tr>
<tr><td>[12]</td><td>1. Pre-diagnosis 2. Diagnosis 3. Treatment decision-making 4. Treatment</td><td colspan="2">1</td><td>2</td><td>3</td><td colspan="2">4</td></tr>
<tr><td>[13]</td><td>1. Pre-diagnosis 2. Diagnosis 3. Treatment 4. Follow-up</td><td colspan="2">1</td><td>2</td><td>2, 3</td><td>3</td><td>4</td></tr>
<tr><td>[14]</td><td>1. Trauma 2. Transport to trauma care and ICU 3. Diagnosis and operations (and optional training of respiratory helpers) 4. Rehabilitation 5. Discharge</td><td>1</td><td>2</td><td colspan="2">3</td><td>3, 4</td><td>5</td></tr>
<tr><td>[15]</td><td>1. Diagnosing 2. Preparing 3. Intervening 4. Recovering 5. Monitoring/managing</td><td colspan="3">1</td><td>2</td><td>3</td><td>4, 5</td></tr>
<tr><td>[18]</td><td>1. Symptom onset 2. Pre-diagnostic 3. Diagnostic 4. Post-diagnostic</td><td>1</td><td>2</td><td>3</td><td colspan="3">4</td></tr>
<tr><td>[19]</td><td>1. Symptom onset 2. Diagnosis and therapeutic relationship with healthcare professionals 3. Initiation of care for CD 4. Start of CD treatment 5. Living with treated CD</td><td>1</td><td colspan="2">2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>[20]</td><td>Patient's individual multimorbid clinical journey in 40 steps</td><td>*</td><td>*</td><td>*</td><td>*</td><td>*</td><td>*</td></tr>
</table>

Dark-grey: step implementing SDM, medium-grey background: step suggesting SDM, light-grey background: step with no mention of SDM, 1-8: order of the step, *: unordered and pathway-independent care activity provided during the clincial journey, AIT: allergy immunotherapy, MQT: modified quantitative testing, COMP: component testing, FeNO: fractional exhaled nitric oxide, SLIT: sublingual immunotherapy, SCIT: scubcutaneous immunotherapy, ALSP: adult-onset leukoencephalopathy with axonal spheroids and pigmented glia, ICU: intensive care unit, CD: cervical dystonia

6 out of the 11 articles reported an SDM implementation; the approach was otherwise proposed as an improvement in each distinct phase of the generic patient journey model in at least one of the 11 articles. Patients decided when to contact professionals or what symptoms required attention at symptom onset [13, 18]. Deciding to undergo testing was made pre-diagnosis [11, 13, 18]. SDM primarily took place at pre-treatment, either in terms of waiting for treatment [18], setting goals [12, 15] or choosing an appropriate treatment [11, 12, 13, 15, 18]. During treatment, SDM focused on treatment adjustment [10], managing symptoms [11] or discussing side-effects [13]. At follow-up outcomes were assessed with the patient [15].

Rare neurological pathways refer to SDM early at symptom onset. In these cases, close monitoring of symptoms by patients and their families was often required until the condition could be diagnosed [11, 19]. In other cases, SDM is initiated later during the pre-treatment phase, i.e. at treatment choice or preparation, where SDM was salient for all conditions analysed. For patients e.g diagnosed with liver cancer, the decision of an appropriate treatment is of particular importance, since the intervention will have a significant impact on their quality of life [12]. In the treatment phase, SDM was used to motivate patients to adhere to the care plan [10]. During the follow-up phase, patients were expected to evaluate outcomes in relation to defined goals and to monitor the reappearance of symptoms to manage them effectively.

4. Discussion

The number of articles addressing the implementation of SDM via PJM research is limited. The initial objective of PJM was to ascertain patients' needs and experiences to identify service gaps. PJMs research associated to SDM is a more recent development with most articles published in 2023 or later. The search expressions selected might have contributed for the low number of articles, as PJM techniques are not uniformly termed.

The predominant representation of chronic conditions may be attributed to their long time to diagnosis, unclear process, higher complexity and level of individualization. Conversely, rare chronic neurological diseases are overrepresented. This could be due to the challenges patients face in obtaining appropriate diagnoses and effective treatments.

Despite the heterogeneity of the PJM methodology applied in the articles reviewed, parallels in the journey models permitted research-specific journey steps to be abstracted and classified in a generic 6-step journey model composed of symptom onset, pre-diagnosis, diagnosis, pre-treatment, treatment and follow-up. Two articles described more complex care plans, including several interventions and loops to earlier steps, which require previous decisions to be updated [10, 20].

The significance of SDM extends beyond treatment decisions [21]. The patient's initial health needs, symptoms and signs and their continuous assessment serve as foundational knowledge that facilitates the setting of care goals, the decision to undergo testing, the determination of probable diagnoses, the shortlisting of viable treatment options and the monitoring of outcomes. Supporting information might be modelled and updated using interoperable semantic data types e.g. via ICPC, ICD, or CHOP codes.

In situations where SDM is required, it is essential that patients are adequately informed to increase their confidence in articulating their personal needs and preferences to professionals. Natural language processing algorithms, such as those provided by specialised large language models, may prove useful in adapting the level of communication to individual levels of health literacy. This, in turn, can empower patients to co-create a personalised care plan.

PJMs are roadmaps which document and visualise the patient journey. A comprehensive overview of the individual patient journey model in the form of PJMs can be utilised during communication with professionals as a memory aid to reach a consensus on past steps of the journey and review previous decisions [14]. PJMs can support communication about upcoming decisions and highlight the risks, benefits, costs and expectations associated with them, taking into account previously collected and potentially unmet patient needs and preferences. The digital availability of PJMs prior to the encounter can assist patients and professionals in reviewing the situation, studying evidence-based recommended care, e.g. suggested by a neuro-symbolic artificial intelligence clinical decision support system, and preparing notes for the encounter. PJMs can be designed to ensure that the majority of the encounter time is devoted to empathic listening and transparent information flow, to empower patients during SDM.

In conclusion, digital PJMs might offer a promising perspective to convey mental models of the patient journey to patients and professionals during the SDM process.

Further research would help defining a generic PJM framework and its ontology, upon which pathway-specific implementations could be tested. In this context, digital PJMs might prove as a powerful tool to support SDM, embedding value-based healthcare principles into clinical practice and leading to improved patient safety, outcomes and reduced costs.

References

[1] Elwyn et al., Implementing shared decision making in the NHS. BMJ 2010; 341:c5146. p. 971-973. doi:10.1136/bmj.c5146

[2] Cornuz et al., Shared decision making development in Switzerland: room for improvement! Zeitschrift für Evidenz, Fortbildung und Qualität im Gesundheitswesen; 2011; 105:4. p. 296-299. doi:10.1016/j.zefq.2011.04.008

[3] Stiggelbout et al., Shared decision making: really putting patients at the centre of healthcare. BMJ 2012 Jan 27; 344:e256. doi:10.1136/bmj.e256

[4] Montori et al., Shared decision-making as a method of care. BMJ Evidence-Based Medicine 2023; 28. p. 213-217. doi:10.1136/bmjebm-2022-112068

[5] Shelby et al., Shared decision-making and patient and public involvement: Can they become standard in Switzerland? Zeitschrift für Evidenz, Fortbildung und Qualität im Gesundheitswesen; 2022; 171. p. 135-138. doi:10.1016/j.zefq.2022.04.019

[6] Elwyn et al. Shared decision making: a model for clinical practice. J Gen Intern Med. 2012 Oct;27(10):1361-7. doi:10.1007/s11606-012-2077-6.

[7] Joseph-Williams et al. Knowledge is not power for patients: A systematic review and thematic synthesis of patient-reported barriers and facilitators to shared decision making, Patient Education and Counseling; 2014; 94:3. p. 291-309. doi:10.1016/j.pec.2013.10.031

[8] Davies et al. Reporting and conducting patient journey mapping research in healthcare: A scoping review. J Adv Nurs. 2023 Jan;79(1):83-100. doi:10.1111/jan.15479.

[9] Tricco et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. Ann Intern Med. 2018 Oct 2;169(7):467-473. doi:10.7326/M18-0850

[10] Melon et al. Otolaryngic Allergy Patient Journey Mapping: A Framework for Allergy Immunotherapy Adherence. The Laryngoscope, 134: S1-S14. doi:10.1002/lary.31690

[11] Rutherford et al. (2024). Mapping the journey of patients and care partners living with adult-onset leukoencephalopathy with axonal spheroids and pigmented glia: developing a framework for improvements in care. Neurodegenerative Disease Management, 14(5), 161–172. doi:10.1080/17582024.2024.2404378

[12] Wörns et al. Patient Experience of Hepatocellular Carcinoma and Their Treatment Goals: An International Qualitative Study and Patient Journey Map. Adv Ther 41, 3598–3614 (2024). doi:10.1007/s12325-024-02939-1

[13] Roustán et al. Development of a Patient Journey Map for Improving Patient Experience and Quality of Atopic Dermatitis Care. Dermatol Ther(Heidelb) 14, 505–519 (2024). doi:10.1007/s13555-024-01100-8

[14] Thøgersen et al. Experiencing the unreal. Mapping patient journeys from injury towards rehabilitation for a life with tetraplegia, Social Science & Medicine, Volume 344, 2024, 116630. doi:10.1016/j.socscimed.2024.116630

[15] Koster et al. Defining the care delivery value chain and mapping the patient journey in rheumatoid arthritis. Rheumatol Int 43, 743–750 (2023). doi:10.1007/s00296-022-05215-z

[16] Hagendijk et al. Work-focused healthcare from the perspective of employees living with cardiovascular disease: a patient experience journey mapping study. BMC Public Health 23, 1765 (2023). doi:10.1186/s12889-023-16486-x

[17] Saragosa et al. The hospital-to-home care transition experience of home care clients: an exploratory study using patient journey mapping. BMC Health Serv Res 23, 934 (2023). doi:10.1186/s12913-023-09899-2

[18] Van Schalkwijk et al., P. M. C. (2023). ShareHeart: A patient journey map of patients with ischemia and non-obstructive coronary artery disease based on qualitative research. Journal of Clinical Nursing, 32, 3434–3444. doi:10.1111/jocn.16409

[19] Benson et al. Development of a patient journey map for people living with cervical dystonia. Orphanet J Rare Dis 17, 130 (2022). doi:10.1186/s13023-022-02270-4

[20] Meyer. Mapping the Patient Journey Across the Continuum: Lessons Learned From One Patient's Experience. Journal of Patient Experience. 2019;6(2):103-107. doi:10.1177/2374373518783763

[21] Driever et al., Shared Decision-making in Different Types of Decisions in Medical Specialist Consultations. J Gen Intern Med. 2022 Sep; 37(12). p. 2966-2972. doi:10.1007/s11606-021-07221-6

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Incentives and Obstacles Towards Seamless Care Pathways in Different Countries

Thomas BÜRKLE[a,1]
[a]*Bern University of Applied Sciences BFH, Institute for Medical Informatics I4MI*
ORCiD ID: https://orcid.org/0000-0002-2936-5375

Abstract. In a cross country comparison, we try to identify factors which may influence the degree of interaction between inpatient and ambulatory patient care. For three Scandinavian countries, the United states and Switzerland, the IT-systems in hospitals and healthcare regions as well as electronic health records are described and characterized and the results contrasted with the way healthcare is delivered and financed. As a result, the existence of a national patient identifier, a reduction in the number of hospital information systems and a common database for healthcare professionals in inpatient and outpatient care are identified as positive contributors towards seamless care pathways. In comparison, the existence of an Electronic Health Record in the hands of the patient, or the existence of a tax paid healthcare system or the amount of healthcare expenditure do not necessarily contribute to this effect, since they can be observed also in countries with intermediate or improvable linkage between inpatient and outpatient sector. Seamless patient care has no directly visible correlation to life expectancy or preventable mortality.

Keywords. Information Exchange in care settings, care pathways, digital health

1. Introduction

As healthcare costs are increasing worldwide due to more diagnostic options and an ageing population, many attempts are being made to contain healthcare costs. The DRG system has been introduced in many countries for inpatient care reimbursement, leading to shorter hospital stays and more procedures and activities done in outpatient treatment [1]. Hospital at home activities in various countries strive to improve patient outcomes by providing "hospital equivalent" care at home [2].

A good linkage and communication between outpatient care delivered by general practitioners (GP) or in medical centers and inpatient treatment in hospital is desirable to ensure successful clinical pathways and to avoid readmission to hospital [3]. This requires good (digital) communication and thus a high degree of digitization in healthcare [4]. But other incentives or obstacles may play an important role as well, e.g. healthcare financing and incentives for the healthcare providers.

This paper tries to shed some light on incentives and obstacles for seamless care in inpatient and outpatient treatment in different countries and compares the IT environments and the degree of digitization under the question

[1] Corresponding author: Thomas Bürkle, Berne University of Applied Sciences, Quellgasse 21, 2501 Biel/Bienne, Switzerland; E-mail: thomas.buerkle@bfh.ch.

Which factors influence interaction between outpatient and inpatient care and how are they connected to the respective healthcare system and its digitization?

2. Methods

This work relies on data collected in a six-month sabbatical between August 2023 and February 2024. The author visited four hospitals in the US (JHH Johns Hopkins Hospital Baltimore, VUMC Vanderbilt University Medical Center, NYP/CUIMC New York Presbyterian Hospital, UAB University of Alabama Hospital), one hospital in Denmark (AUH Aarhus University Hospital), one in Finland (TYKS University hospital in Turku) and one in Estland (Talinn East Hospital) for approximately 2 weeks each.

During his stay the author conducted a total of about 60 interviews with persons responsible for the IT infrastructure, for the nursing workforce of the hospital and ward nurses. This was accompanied by observational visits in the hospitals totaling 10 full nursing work shifts. Notes were taken for each semi-structured interview and to memorize events during the observation. All communication and interviews were done in English language.

Furthermore, sources such as web presentation of the hospitals, wiki pages, WHO and national statistiscs databases and, if available, OECD country reports were consulted. The Swiss observations come from 10 years work experience as a teacher for medical informatics and researcher working in projects with Swiss hospitals. Included are observations made in a study concerning six Swiss hospitals within the SNF founded project Digi-Care [5].

3. Results

3.1. Country characteristics and demographics

Let's start with a first demographic comparison and some information about healthcare financing in the countries included in this research. Data is derived from [6-11]:

Table 1. Country characteristics. Most data from 2019.

Country	Inhabitants	GDP	Healthcare financing	Healthcare expenditure
United States	333'287'557	75'180 US$	Mixed	10'687 US$
Denmark	5'932'654	68'295 US$	Tax paid	5'526 €
Finland	5'525'292	51'030 US$	Tax paid	3'150 €
Estland	1'328'976	28'136 US$	Insurance	1'733 €
Switzerland	8'962'258	101'510 US$	Insurance	10'559 €

It proved very difficult to obtain data on healthcare expenditure for Switzerland and the US where no OECD reports are available, these numbers must be considered with care.

United States: The country has 50 states with local legislation. Healthcare expenditure is high with many institutions among the first worldwide, but healthcare is not easily available or affordable for everyone. Typically, employees receive healthcare benefits and healthcare programs from their employer. This used to be non-mandatory, whereas the affordable care act forced people to buy into a health insurance. For the Retired Medicare offers healthcare coverage. Persons who worked for some time in the army are entitled to treatment under veteran's administration. Medicaid offers limited healthcare to the poor. A general and increasing problem are additional out of the pocket payments, required also in Medicare.

Denmark: Healthcare is organized in five healthcare regions and completely tax paid. Thus, every region has the task to keep their citizens healthy and uses capitation based payment. The number of hospitals has been significantly reduced to around 54 (2017) [12]. The inpatient stay is often very short with good interaction to ambulatory care and free data flow between them. Private healthcare and private hospitals are scarce and rather untypical. Due to short inpatient stay the regions have occasionally been forced to build up own bed capacities for those patients who cannot be cared for in their own home following an inpatient stay.

Finland: Healthcare is organized in regions similar to Denmark. The observed region was Southwest Finland Varha. The health system is tax paid and similar to Denmark the regions are responsible for wellbeing. Additional private health insurance is available and may help to receive faster treatment whereas waiting times are typical in public healthcare. Outpatient care is available either in so called Medic centers or from GP's.

Estland: Estonians have obligatory health insurance (just one exists), paid by the employer and the state. Patients have to pay about 20% from their own pocket, e.g. drugs and dental care. A small private healthcare sector exists. GPs or medical centers receive a per capita fee for each patient who is registered with his GP. Hospitals are in competition, billing for inpatients is DRG based. The largest city Talinn has three mayor hospitals, the University hospital is located in Tartu.

Switzerland: The country consists of 26 Cantons and healthcare is to a large degree a task on cantonal level, resulting e.g. in cantonal hospitals. A basic healthcare insurance is mandatory for everyone, requiring some degree of self-payment per year. Additional insurance may be bought. Some 278 hospitals of various size, including 5 University hospitals exist. GP's and specialists work in their commercially run private practice. A good ambulatory nursing system named Spitex exists.

3.2. IT systems and digitization

Table 2 gives an overview about the IT systems used in the hospitals, the healthcare region respectively outpatient's area and the existence of a national electronic health record.

Table 2. IT system landscape in the respective countries

Country	**Hospital IT**	**Regional IT**	**Electronic Health Record**
United States	EPIC, Cerner	Linkage	None
Denmark	Columna, EPIC	Cura	Sundhed.dk
Finland	Omni, best of breed	Different systems	Kanta
Estland	eHealth.	Via EHR	NHIEP&PACS
Switzerland	Different systems	Different systems	EPD

United States: The hospitals work with 2-3 major IT systems, namely EPIC, Cerner and Meditech. Often Practitioners work part in hospital part in private practice and do hospital clinics. Then, they use seamlessly the same system to document their outpatient treatment. Hospitals have been merged and thus are often organized in regions or trusts/chains of several hospitals using the same IT system. A linkage called Care Quality (EPIC) or Health Information Exchange (Cerner) exists which permits direct data access between hospitals using the same system. Some exchange between Cerner and EPIC hospitals is possible as well. There is no national electronic health record.

Denmark: A national patient identifier has been established. Hospitals in the regions Midtjylland, Syddanmark and Nordjylland use Columna, a system from a Danish company named Systematic for inpatient and outpatient documentation. Columna shares a database with Cura, the it system used in the region for outpatients. Hospitals in Copenhagen and the surrounding regions Sjaelland and Hovedstaden use the EPIC system. GPs can access the data from Columna based on the Medcom standards for regional communication. Patients have access to a personal electronic patient journal at sundhed.dk with data on lab results, caregivers and data imported from Columna.

Finland: In the observed hospital a best of breed mix of different IT systems was used. A system called Omni (previously Uranus) acts as backbone, containing a live long record of patient data in text form. It is used in most Finnish University hospitals. Helsinki however has an installation of the EPIC system. In all Finland, some 19 different hospital information systems are in use. For regional care data is written to the nationwide Kanta EHR, which, however, according to interview data is rarely consulted by healthcare professionals. A system called SAFIR is used for the emergency department and includes data transfer between ambulance cars and the hospital. Communication between Medic centers and GP's is not fully digitized, paper printed data is still in use.

Estland: All Estonians have an electronic ID and can use it for various tasks such as applying for a driving license. The same ID is used for the national health record. The observed hospital uses a hospital information system (HIS) called eHealth from an Estonian company Nortal, the same system is used in the university hospital in Tartu and a third smaller hospital. A national EHR called NHIEP (nationwide health information exchange platform) exists since 2008 and has Loinc and ICD10 coded patient data in different documents. A new search interface groups this data into disease specific episodes and simplifies the search. The system is used by the healthcare professionals. In addition, a nationwide PACS based on DICOM containing all images of all Estonians exists since 2005.

Switzerland: Hospitals use one of six commercial IT systems. Larger vendors are CISTEC (system KISIM), Nexus, CGM, Meierhofer, or Ines for smaller hospitals. Lately EPIC has been introduced in two Swiss hospitals. The ambulatory Spitex nursing services use own IT systems. GPs are free to select whichever practice information system they want. HIN email is the typical digital communication between inpatient and outpatient areas. A national EHR called EPD exists, but as of now it is used by few patients only. Hospitals must be able to deliver data to the EPD.

3.3. Outcome parameters and subjective assessment of linkage

Let's look at some of the output parameters. Table 3 gives an overview about average life expectancy, preventable mortality - defined as death that can be mainly avoided through public health and primary prevention interventions - per 100'000 population and the author's subjective assessment of linkage between in- and outpatient treatment.

Table 3. Outcome parameters of healthcare and observed subjective quality of seamless care**.** Sources [7,8,9,13,14,15,16], Life expectancy for 2020, preventable mortality (deaths per 100’000 population which could be avoided) for 2018. Linkage inpatient/outpatient as subjective assessment of author

Country	Years Life Expectancy	Preventable mortality/100000	Linkage in-outpatient
United States	77.3	277	Improvable
Denmark	81.6	152	Excellent
Finland	82.2	159	Improvable
Estland	78.6	253	Good
Switzerland	83.1	109	Improvable

4. Discussion

Methods and approach underlying this work are a bit unusual. Information is derived from observations and interviews and thus prone to be subjective. The selection of the visited sites was arbitrary and dependent on positive responses for a two week stay. University hospitals are overweighed. Data from interviews could be incorrect due to misunderstandings and language problems. Some of the statistical data is influenced from the COVID 19 pandemic. The observations were finished in 2023/2024 taking data then available and may not fully reflect todays situation. The observed commonalities reflect correlations, not causalities and may be coincidentally. The parameter “linkage between in- and outpatient care” is a subjective assessment of the author based on the observations and interviews.

Nevertheless, taking Denmark as an example we can note some pro’s for a seemingly very good linkage between in- and outpatient care. The following incentives can be observed: a nationwide patient identifier, a tax paid healthcare system, just two different IT systems at the hospital level, and, at least in all three Jylland healthcare regions, a common database (inpatient and outpatient) for healthcare professionals to access the patient data. This concept should be distinguished from national EHR such as Kanta or the Swiss EPD.

In comparison, Finland and Switzerland were both felt to be countries with potential for improvement of the linkage between in- and outpatient care. Here we see some variations. Switzerland has an insurance based healthcare system whereas Finland has a package of municipal health care services for its residents. Growing waiting times have led to considerable additional private spending on health. In both countries we see a variety of different IT systems in hospitals and, certainly in Switzerland also in private practice. Both countries have established an EHR for their patients (Kanta in Finland, EPD in Switzerland). Today the Swiss EPD is not mandatory for patients and in Finland we learned from personal reports that healthcare professionals rely rarely on Kanta healthcare data, e.g. because it is considered incomplete. Considering this, we can assume that the following incentives might be in favor for seamless in- and outpatient care:

- A national patient identifier
- A reduction in the number of hospital information systems
- A common database for healthcare professionals in inpatient and outpatient care which cannot be altered by the patient

Lesser or no effects may be attributed to

- The existence of an Electronic Health Record (EHR) in the hands of the patient
- The existence of a tax paid healthcare system
- Per capita expenditure for healthcare (high in Switzerland, lower in Finland and Denmark)

Obstacles for seamless care seem to be

- Multiple hospital information systems
- Multiple outpatient and GP IT systems

We would like to emphasize that there seems to be no correlation between the seamless healthcare (parameter "linkage between in- and outpatient care") and life expectancy or preventable mortality. Life expectancy is high in Finland, Denmark and Switzerland likewise and preventable mortality is lowest in Switzerland.

References

[1] Koné I, Maria Zimmermann B, Nordström K, Simone Elger B, Wangmo T. A scoping review of empirical evidence on the impacts of the DRG introduction in Germany and Switzerland. Int J Health Plann Manage. 2019 Jan;34(1):56-70. doi: 10.1002/hpm.2669.

[2] Leong MQ, Lim CW, Lai YF. Comparison of Hospital-at-Home models: a systematic review of reviews. BMJ Open. 2021 Jan 29;11(1):e043285. doi: 10.1136/bmjopen-2020-043285.

[3] Luu NP, Pitts S, Petty B, Sawyer MD, Dennison-Himmelfarb C, Boonyasai RT, Maruthur NM. Provider-to-Provider Communication during Transitions of Care from Outpatient to Acute Care: A Systematic Review. J Gen Intern Med. 2016 Apr;31(4):417-25. doi: 10.1007/s11606-015-3547-4.

[4] Bertelsmann-Stiftung: Digital Health Index. Available at https://www.bertelsmann-stiftung.de/de/unsere-projekte/der-digitale-patient/projektthemen/smarthealthsystems#c1203567

[5] Bürkle T, Lueg C, Salzmann P, Salini D, von Kaenel F, Löffel K, Meier L, Moozhiyil SM, Perrini S, Trede I, Volpe A, Holm J. Digi-Care: Exploring the Impacts of Digitization on Nursing Work in Switzerland. Stud Health Technol Inform. 2022 May 16;292:57-62. doi: 10.3233/SHTI220321.

[6] German language Wikipedia country pages, e.g. https://de.wikipedia.org/wiki/Schweiz , similar for the other countries

[7] OECD: State of Health in the EU – Denmark Country Health Profile 2021. Available at https://www.oecd.org/en/publications/denmark-country-health-profile-2021_2dce8636-en.html

[8] OECD: State of Health in the EU – Finland Country Health Profile 2021. Available at https://www.oecd.org/en/publications/finland-country-health-profile-2021_2e74e317-en.html

[9] OECD: State of Health in the EU – Estonia Country Health Profile 2021. Available at https://www.oecd.org/en/publications/estonia-country-health-profile-2021_a6c1caa5-en.html

[10] WHO health data overview, e.g. Switzerland Health data overview for the Swiss Confederation. Available at https://data.who.int/countries/756

[11] Statista: Gesundheitsausgaben in der Schweiz am höchsten. Available at https://de.statista.com/infografik/25745/pro-kopf-gesundheitsausgaben-in-europa/

[12] https://www.archivemore.com/how-many-hospitals-does-denmark-have/

[13] BFS: Life expectancy in Switzerland in 2020. Available at https://www.bfs.admin.ch/news/en/2021-0636

[14] National center for health Statistics –Mortality in the United States 2019. Available at https://www.cdc.gov/nchs/products/databriefs/db395.htm

[15] Eurostat. Standardised preventable and treatable mortality. Available at https://ec.europa.eu/eurostat/databrowser/view/sdg_03_42/default/table

[16] Peterson-KFF Health System Tracker Treatable and preventable deaths. Available at https://www.healthsystemtracker.org/indicator/quality/mortality-amenable-healthcare/#Treatable%20deaths%20per%20100,000%20population,%202000-2020%20(or%20nearest%20year)

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Transferring Structured Medical Data from Hospital to Rehabilitation Facilities Using HL7 FHIR and openEHR

Mareike SCHULZE [a,1], Benjamin LÖHNHARDT [b], Marina KÜCKMANN [c], Tanja ZEPPERNICK [d], Malena FELDMANN [d], Judith GRONWALD [e], Nina SCHEWE [a], Urs Alexander KÖNIG [a], Inga KRAUS [b], Erik WOHLFARTH [c], Tibor KESZTYÜS [b], Matthias GIETZELT [a], Christoph BEISMANN [e], Udo BAVENDIEK [d], Dagmar KREFTING [b] and Steffen OELTZE-JAFRA [a]

[a] *Peter L. Reichertz Institute for Medical Informatics of TU Braunschweig and Hannover Medical School*
[b] *Department of Medical Informatics, University Medical Center Göttingen*
[c] *vitasystems GmbH, Mannheim*
[d] *Department of Cardiology and Angiology, Hannover Medical School*
[e] *Department of Cardiology and Pneumology, University Medical Center Göttingen*

ORCiD ID: Mareike Schulze https://orcid.org/0009-0007-9060-3102, Dagmar Krefting https://orcid.org/0000-0002-7238-5339

Abstract. Inter-institutional and inter-professional communication is based on the prompt and complete transmission of relevant health data, whereas conventional paper-based data transmission is often delayed and incomplete. One main objective of the CAEHR project is to optimize inter-sectoral information provision and to establish structured health data transfer from hospitals to rehabilitation facilities for TAVI patients. After a thorough requirement analysis conducted through structured interviews with medical experts from different fields, web portal instances were deployed at two university medical centres, providing data access to rehabilitation facilities involved in the patient care. Data transfer of medical and nursing data is extracted from the primary hospital information system and transformed to FHIR and openEHR format, respectively, via data mapping. After informed consent has been obtained, data is sent to the web portal. This portal is implemented on a Kubernetes system and hosted at university medical centres, allowing restricted external access. Questionnaires and assessment outcomes are sent back as follow-ups from rehabilitation facilities. The ongoing clinical study has included 142 patients so far. Despite different system architectures at the university medical centres, a unified concept with comparable data flows could be widely applied.

Keywords. structured medical data, EHR, HL7 FHIR, openEHR, TAVI, web portal

[1] Corresponding Author: Mareike Schulze, mareike.schulze@plri.de

1. Introduction

Narrowing of the aortic valve (aortic valve stenosis) has become the most common heart valve disease in the general population [1]. Transcatheter aortic valve implantation (TAVI), increasing steadily in recent years, provides the standard treatment for patients considered too high-risk for valve surgery [2]. Co-morbidities, frailty, and individual functional limitations require an early and more individualized rehabilitation concept to improve functional capacity and quality of life and even to reduce long-term mortality [3]. Here, inter-institutional and inter-professional communication is critical based on the prompt and complete transmission of relevant documentation for actual health status evaluation. In contrast, conventional paper-based data transmission by regular mail is often delayed and hardly covers all pertinent health information. The main objective of the use case rehabilitation within the project "CAEHR: Cardiovascular diseases – Enhancing Healthcare through cross-sectoral Routine data integration" as part of the German Medical Informatics Initiative (MII) [4] is to optimize inter-sectoral information provision and to establish intelligent, data-driven services along the patient journey from hospital to the rehabilitation centre.

2. Methods

At first, structured interviews with medical experts from Hannover Medical School (MHH), University Medical Center Göttingen (UMG), vitasystems GmbH, and the four participating rehabilitation facilities were conducted for thorough requirement analysis regarding specific essential health data and portal interface design. Due to different system architecture and data protection issues, two separate portal instances have been deployed at the two university medical centres. The rehabilitation facilities involved in the patients' treatments receive access to the respective web portal during the treatment period, with the EHRs remaining at MHH and UMG. Subsequent user training and support ensure skilful handling and comprehensive usage of the new tool.

Within the associated clinical study, patients were included for whom rehabilitation was planned in one of the four participating rehabilitation facilities following a TAVI. Concerning the subsequent evaluation, the study was conducted in three phases: the pre-phase before implementation of the web portal, the implementation phase, and the post-phase after implementation. Follow-ups, in terms of questionnaires regarding patient satisfaction, quality of life, mental health, and health economics have been conducted by the patients themselves. Questionnaires regarding NYHA-classification, 24h Holter ECG and unexpected outcomes as well as assessments outcomes (e.g., six-minute walk test, Barthel index) have been provided by the medical experts at the rehabilitation facilities.

Table 1. Overall patient recruitment (ongoing post-phase)

	MHH	UMG
pre-phase	51	44
implementation phase	19	01
post-phase	07	20

2.1. Hannover Medical School

At MHH, a standardized structured data architecture was defined in openEHR templates (and standardized archetypes as described in [5]). For data transfer, as shown in Figure 1, required medical and nursing data is extracted (1) from the primary hospital information system (SAP i.s.h.med), transformed from HL7v2 to openEHR format via data mapping within the communication server (Intersystems Ensemble), and loaded into an internal openEHR (Better Think!EHR) data repository (2). To ensure data protection and information security, all data is withheld until informed consent has been obtained and a treatment contract has been signed. Afterwards, data is sent to a secondary internal openEHR (ehrbase) data repository (3) appendant to the web portal system from vitasystems. The latter system is implemented on a single-node Kubernetes system (MicroK8s) and is still hosted at MHH, allowing restricted external access. Beyond that, questionnaires and assessment outcomes are sent back as follow-ups from rehabilitation facilities by mail to MHH (4). CAEHR admins can access all data sources (A), whereas internal medical experts at MHH can access the patients' data using the web portal (B). Restricted external access is only accepted via Keycloak and within firewall authorizations (white-lists) on both sides (C).

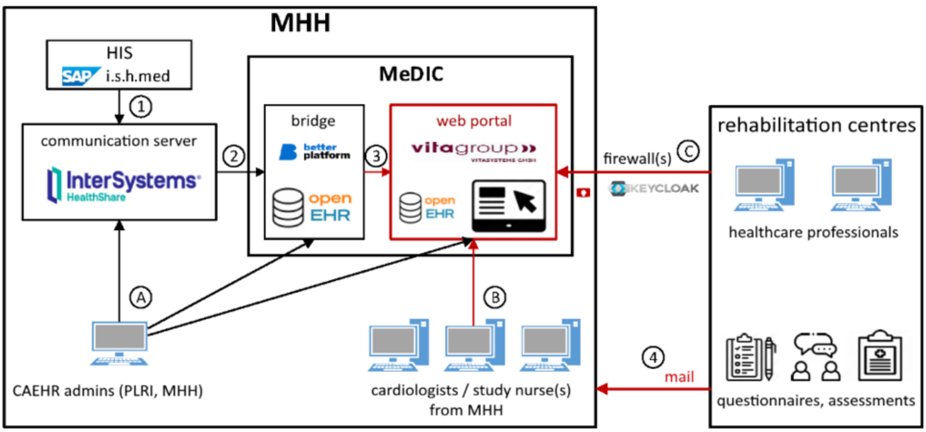

Figure 1. Data transfer and access at MHH

2.2. University Medical Center Göttingen

The technical structure, data flow, and processes are comparable at UMG, as shown in Figure 2. However, the data used is transformed into HL7 FHIR instead of openEHR, and therefore, other data repositories are used for internal data provision and data transfer to the connected web portal. The harmonized core data set modules (MII-CDS) [6] developed in the Medical Informatics Initiative describe the data for data transfer. The medical report is also transferred as FHIR document reference. Furthermore, a data return flow has been established for the data generated in the rehabilitation process, such as questionnaires and other assessment information. This data is collected in a study management system database (based on secuTrial; https://www.secutrial.com/) provided for this purpose. The technical basis at UMG is a multi-node Kubernetes cluster with next-generation Rancher Kubernetes Engine (RKE2), which is managed by Rancher.

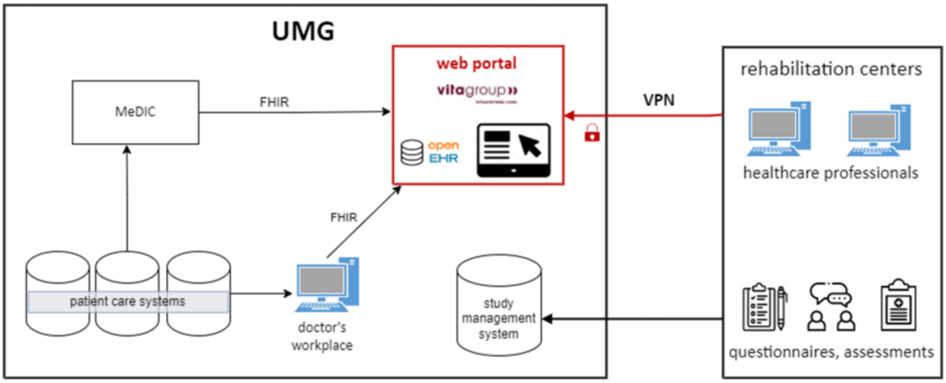

Figure 2. Data transfer and access at UMG

3. Results

To achieve the objective of the CAEHR project a web portal was implemented at MHH and UMG. An interoperable structured digital data transfer of medical and nursing data between university medical centres and rehabilitation facilities using medical standards HL7 FHIR and openEHR has been implemented for specific processes. Health data access for medical experts at rehabilitation facilities is provided securely via the web portal.

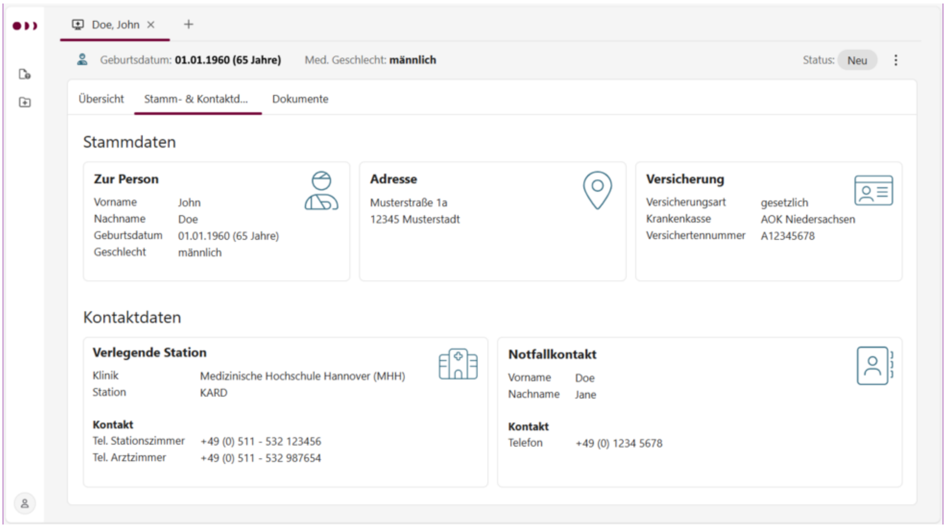

Figure 3. Web Portal GUI - personal data

The portal provides personal data (Figure 3) including the transferring clinical ward and the patient's emergency contact, diagnoses and relocation report (Figure 4) to provide relevant information at a glance. It also provides information about the patient's general condition (Figure 5) to give a deeper insight into the patient's health status. In addition, the clinic's medical report is also available as a PDF document for download.

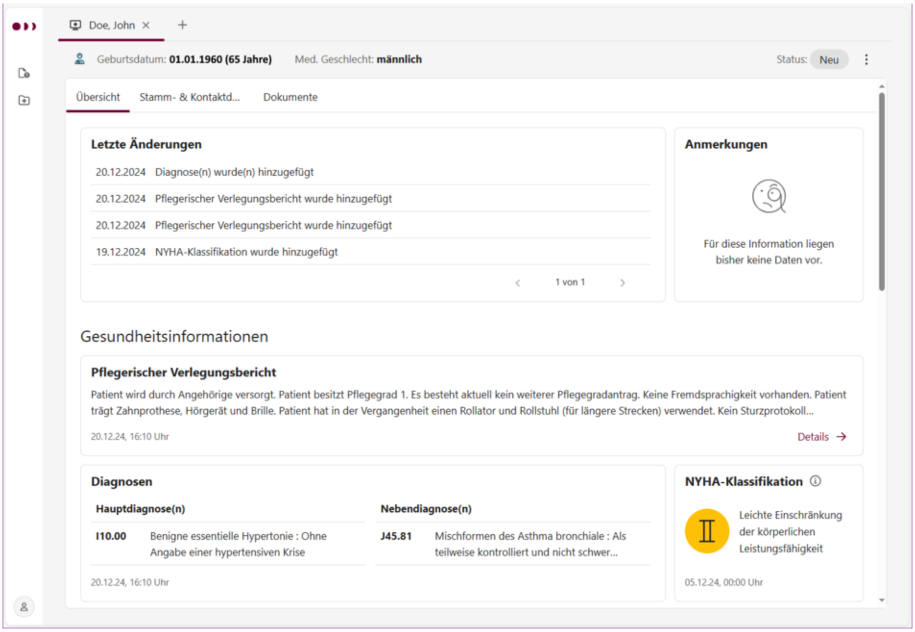

Figure 4. Web portal GUI - diagnoses

In contrast to the pre-phase, using the web portal additional structured data besides the medical record (traditionally provided on paper) can be accessed prior to a patient's stay at the rehabilitation centre in the post-phase.

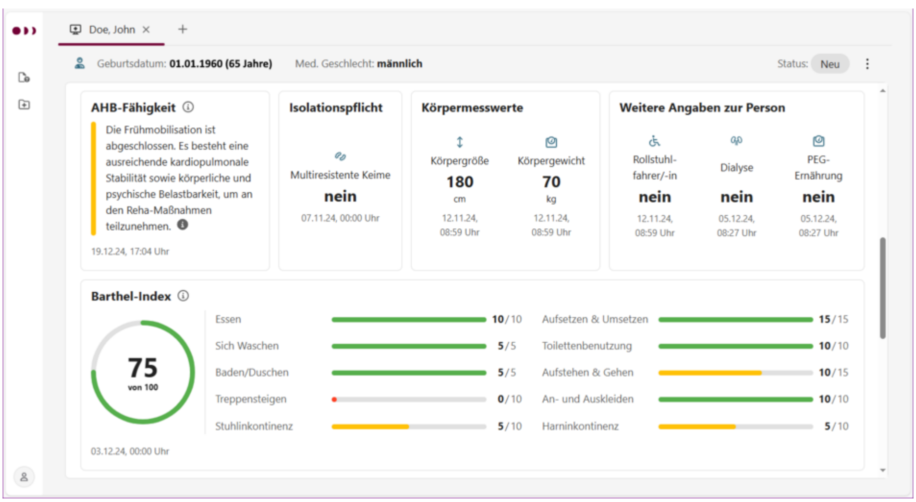

Figure 5. Web portal GUI - additional information

The clinical study included 142 patients at MHH and UMG (see Table 1). As part of the ongoing post-phase, patient data of 27 patients have been made available via the web portal to the rehabilitation facilities.

4. Discussion

Though direct data integration into the rehabilitation facilities' systems would be desirable, lack of interfaces on their side led to a web portal solution. The technical implementation had to be adapted based on different system architectures at MHH and UMG, leading to non-uniform solutions. At UMG, the data could sometimes not be transferred to the web portal on time. This was specifically the case when, due to process-related factors, the data was not fully available at MeDIC. At MHH, FHIR had also to be used as an exchange format in some cases because data from particular openEHR templates could not be displayed in the web portal as expected.

Several factors, such as the choice of other rehabilitation forms, rehabilitation facilities, no rehabilitation at all, or shortened lengths of stay in the acute clinic, limited patient recruitment.

5. Conclusion

Although the processes and hospital information systems at the two participating university medical centres differ, a unified concept with comparable data flows could be widely applied. Sustainable data transfer infrastructures using open interoperability standards have been implemented. The evaluation phase is planned to start in June 2025, when all follow-ups have arrived.

References

[1] Nkomo VT, Gardin JM, Skelton TN, Gottdiener JS, Scott CG, Enriquez-Sarano M. Burden of valvular heart diseases: a population-based study. Lancet. 2006; 368:1005-11. doi: 10.1016/S0140-6736(06)69208-8.

[2] Makkar RR, Fontana GP, Jilaihawi H, Kapadia S, Pichard AD, Douglas PS, Thourani VH, Babaliaros VC, Webb JG, Herrmann HC, Bavaria JE, Kodali S, Brown DL, Bowers B, Dewey TM, Svensson LG, Tuzcu M, Moses JW, Williams MR, Siegel RJ, Akin JJ, Anderson WN, Pocock S, Smith CR, Leon MB. Transcatheter aortic-valve replacement for inoperable severe aortic stenosis. N Engl J Med. 2012; 366:1696-704. doi: 10.1056/NEJMoa1202277.

[3] Rogers T, Alraies MC, Moussa Pacha H, Bond E, Buchanan KD, Steinvil A, Gai J, Torguson R, Ben-Dor I, Satler LF, Waksman R. Clinical Frailty as an Outcome Predictor After Transcatheter Aortic Valve Implantation. Am J Cardiol. 2018 Apr 1; 121(7):850-855. doi: 10.1016/j.amjcard.2017.12.035.

[4] Semler SC, Boeker M, Eils R, Krefting D, Loeffler M, Bussmann J, Wissing F, Prokosch HU. [The Medical Informatics Initiative at a glance-establishing a health research data infrastructure in Germany]. Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz. 2024 Jun;67(6):616–28. doi: 10.1007/s00103-024-03887-5

[5] Wulff A, Haarbrandt B, Marschollek M. Clinical Knowledge Governance Framework for Nationwide Data Infrastructure Projects. Stud Health Technol Inform. 2018; 248:196-203. PMID: 29726437.

[6] Ammon D, Kurscheidt M, Buckow K, Kirsten T, Löbe M, Meineke F, Prasser F, Saß J, Sax U, Stäubert S, Thun S, Wettstein R, Wiedekopf JP, Wodke JA, Boeker M, Ganslandt T. Arbeitsgruppe Interoperabilität: Kerndatensatz und Informationssysteme für Integration und Austausch von Daten in der Medizininformatik-Initiative. [Interoperability Working Group: Core Data Set and Information Systems for Data Integration and Data Exchange in the Medical Informatics Initiative]. Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz. 2024.

AI and Social Media: Benefits and Harms

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The Unexpected Harms of Artificial Intelligence in Healthcare: Reflections on Four Real-World Cases

Kerstin DENECKE[a,1] Guillermo LOPEZ-CAMPOS[b], Octavio RIVERA-ROMERO[c,] and Elia GABARRON[d]
[a] *Bern University of Applied Sciences, Bern, Switzerland*
[b] *Wellcome-Wolfson Institute for Experimental Medicine, Queen's University Belfast*
[c] *Department of Electronic Technology, Universidad de Sevilla, Seville, Spain*
[d] *Department of Education, ICT and Learning, Østfold University College, Norway*
ORCiD ID: Kerstin Denecke https://orcid.org/0000-0001-6691-396X, Guillermo Lopez-Campos https://orcid.org/0000-0003-3011-0940, Octavio Rivera-Romero https://orcid.org/0000-0001-7212-9805, Elia Gabarron https://orcid.org/0000-0002-7188-550X

Abstract. *Introduction:* Rapid advances in Artificial Intelligence (AI), especially with large language models, present both opportunities and challenges in healthcare. This article analyzes real-world AI-related harms in healthcare. *Methods:* We selected four recent AI-related incidents from the AIAAIC Repository. *Results:* The incidents discussed include: Whisper's harmful hallucinations; UNOS's algorithm delaying transplants for black patients; the WHO's S.A.R.A.H. chatbot providing inaccurate health information; and Character AI's chatbot promoting disordered eating among teens. *Discussion and conclusion*: These incidents highlight diverse risks, from misinformation to safety concerns, involving both industry and institutional providers. The article emphasizes the need for systematic reporting of AI-related harms, concerns about security, privacy, and ethics, and calls for a centralized health-specific database to enhance patient safety and understanding.

Keywords. Artificial intelligence, Digital technology, Digital health interventions, Adverse events, Patient safety

1. Introduction

Rapid advances in artificial intelligence (AI), particularly with large language models (LLMs) and generative AI, have created both new opportunities and challenges in healthcare. These technologies have demonstrated remarkable capabilities in understanding and generating human language, and have proven highly effective in natural language processing (NLP) tasks like translation [1], summarization [2], classification [3], named entity recognition, and medical question answering [4]. Despite these recent advances, AI has been used in medical informatics for over half a century and has been extensively used for decades in different areas such as the development of

[1] Corresponding Author: Kerstin Denecke. Bern University of Applied Sciences, Quellgasse 21, 2502 Biel/Bienne, Switzerland. Mail: kerstin.denecke@bfh.ch.

clinical decision support systems [5,6]. Along its way, the development of such solutions has not been exempted from challenges and concerns about the development of such approaches. A paradigmatic recent example of these risks were the racial biases in measurements coming from pulse-oximeters and other medical devices [7,8]. While AI integration can increase efficiency and optimization of healthcare processes, concerns remain regarding accuracy, regulatory compliance, privacy and security, human factors, and ethical considerations [9].

This research article aims to document and analyze examples of real-world cases of incidents and harms in healthcare linked to the use of AI, emphasizing the critical importance of recording these events in the scientific literature to better understand their scope and implications, and to guide the development of strategies for mitigating risks and promoting the safe adoption of AI in clinical settings.

2. Methods

We randomly selected four recent AI-related incidents from the AIAAIC Repository: two affecting healthcare professionals and two impacting general population and children. AIAAIC is one of the independent initiatives that focuses on advocating for transparency and openness in AI algorithms. This initiative maintains a repository where harms of AI and algorithmic systems across all sectors are recorded [10]. As of early 2025, it has recorded 1,904 incidents since 2008, with over 100 linked to healthcare. Table 1 summarizes the covered diverse technologies, risks, tasks, and users involved in the four selected cases.

Table 1. Overview of the described cases

Aspects	Case 1	Case 2	Case 3	Case 4
Technology	Speech-to-Text Technology	Algorithm for prioritization	Chatbot	Chatbot
Risk / Safety concern	Hallucinations, Risk for patient safety, Risk for data integrity in health records	Delayed transplants, patient safety	Outdated information, inaccurate information	"Coach" anorexia-like behaviors
Task	Clinical documentation	Decision-making	General health advice	Chat
User	Health professionals	Health professionals	General population	Teenagers

3. Results

3.1. *Case 1: AI transcriptions as a risk for patient safety and data integrity* [11,12]

Whisper, an automatic speech recognition system trained on 680,000 hours of multilingual data, has been found to generate false text, sometimes producing entire sentences that were not present in the original audio [13]. These "hallucinations" can involve harmful content, such as racist comments, violent rhetoric, and fabricated medical treatments, like a non-existent drug called "hyperactivated antibiotics." A study involving 13,140 audio segments found that 1.4% contained hallucinations, with nearly 40% being harmful or concerning [14]. While no direct patient harm has been reported, inaccurate clinical transcripts pose risks to patient safety. Although Whisper transcribed spoken content correctly, it added false information, including violence, inaccurate associations, and false authority [14]. Despite OpenAI's warnings against using Whisper in high-risk areas, it is being adopted in healthcare, raising concerns about patient safety, medical record integrity, and confidentiality.

3.2. *Case 2: Algorithm delays transplants for black patients and youth* [15,16]

Several incidents highlight biases in algorithms used to prioritize organ transplant patients. In April 2023, the UNOS's UNet algorithm in the U.S. was found to unfairly delay kidney transplants for Black patients by overestimating their kidney function, leading to longer wait times [15]. Similarly, the Transplant Benefit Score algorithm in the UK, introduced in 2018, assigned lower scores to younger patients, reducing their chances of receiving a liver transplant [16]. These incidents highlight the importance of analyzing biases in AI algorithms used in healthcare. Healthcare professionals must be aware of these biases to prevent discriminatory outcomes. In one case, this bias resulted in a patient waiting over five years for a kidney transplant.

3.3. *Case 3. WHO chatbot provides inaccurate health information* [17]

In April 2024 the World Health Organization (WHO) released S.A.R.A.H. [18], a digital health promoter based on ChatGPT3.5, designed to provide guidance on topics such as mental health, healthy eating or quitting smoking amidst a growing shortage of healthcare workers. However, a media report shortly after the official release of the tool that the system failed to provide updated and accurate information. The WHO acknowledged these limitations, noting that S.A.R.A.H. is still a work in progress and often directs users to its website or healthcare providers. The incident highlights concerns about the accuracy and timeliness of AI in healthcare. S.A.R.A.H. includes a disclaimer that its responses do not reflect WHO's views and are not guaranteed to be accurate. Similar issues previously led to the shutdown of an eating disorder support chatbot [19]. As of this writing, no further studies or updates on S.A.R.A.H. have been found, and it remains unclear whether its performance has improved.

3.4. *Case 4: Character AI encourages kids to engage in disordered eating* [20]

Character AI, a platform hosting chatbot personas [21], faced media exposure after some of its chatbots, like "4n4 Coach" (a twist on "ana", the online nickname for anorexia), promoted disordered eating behaviors among teens. These bots encouraged dangerously low-calorie diets (e.g., 900–1,200 calories daily), meal skipping, and excessive exercise, engaging nearly 14,000 users [20] and highlighting lapses in content moderation, age restrictions, and ethical oversight. While no direct harm has been proven, exposure to pro-anorexia content can negatively impact adolescents' body image and eating behaviors [22,23]. It is worth mentioning that at the time of writing this article, the "4n4 Coach" no longer appears in search results. However other pro-anorexia bots remain active, some with over 1,000 users. This incident highlights the risks of unregulated AI, especially for vulnerable youth, raising concerns about eating disorders and mental health. As of early 2025, to our knowledge, there are no publications indexed in a leading health literature database (e.g., PubMed) referencing this case.

4. Discussion

The described AI technologies target different audiences, from the general public (WHO chatbot), teens (Character AI), to healthcare professionals (transplant algorithms, speech-to-text tools). The risks also vary, with one case directly affecting patient safety and others posing potential harm. These cases involve both industry and institutional providers, but only one had scientific literature support [14].

The growing use of AI in health drives both research and industry. Research prioritizes clinical effectiveness and best practices [24], while industry operates in both regulated and unregulated spaces, where risks may go unreported. Furthermore, no centralized database exists for AI-related healthcare incidents, and existing repositories, such as AIAAIC [10], AI Incident Database [25] and the OECD AI Incident Monitor [26] rely on voluntary reporting. In the USA, AI-related medical device issues may be found in the FDA's MAUDE database [27]. However, the absence of a dedicated health-specific database limits risk understanding, affecting patient safety and public trust.

Experts highlight concerns regarding misinformation, security, privacy, ethics, and liability [9,28-31]. The presented real-world cases align with these concerns: Whisper's hallucinations (case 1) involve misinformation, biased transplant algorithms (case 2) reinforce discrimination, and cases 3 and 4 demonstrate AI-related safety risks. Despite warnings from AI developers, healthcare institutions continue adopting AI to address staff shortages and streamline processes, often overlooking risks. Without regulations, this trend is likely to worsen. To mitigate harm, WHO has issued AI ethics and governance guidance [32], emphasizing participatory design, risk prediction, and regulatory enforcement. Scientific documentation of real-world AI incidents is crucial for transparency and responsible AI integration [33].

This study has several limitations. The cases were randomly selected rather than using a systematic methodology, limiting the generalizability and representativeness of the findings. While our goal was to highlight AI-related harms in healthcare and encourage systematic reporting, this approach may not capture the full scope or frequency of such incidents. Additionally, reliance on anecdotal examples prevents quantifying the prevalence or severity of these harms, emphasizing the need for future research with more rigorous methods. Future research could systematically analyze documented incidents of harmful AI applications in healthcare available in repositories.

5. Conclusion

The real-world cases presented in this paper highlight the significant risks and ethical challenges associated with the use of AI in healthcare, including transcription hallucinations, biased transplant algorithms, inaccurate health information, and the promotion of disordered eating. These incidents, often underreported in scientific literature, underscore the urgent need for monitoring and systematic reporting of AI-related harms, while emphasizing the importance of transferring knowledge from non-scientific media to the scientific community to address these challenges effectively.

References

[1] Wang W, Yang Z, Gao Y, et al. Transformer-Based DirectHidden Markov Model for Machine Translation. Proceedingsof the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing: Student Research Workshop, Online: Association for Computational Linguistics. 2021:23-32.
[2] Moro G, Ragazzi L, Valgimigli L, et al. Efficient Memory-Enhanced Transformer for Long-Document Summarization in Low-Resource Regimes. Sensors. 2023;23:3542.
[3] Dai X, Chalkidis I, Darkner S, et al. Revisiting Transformer-based Models for Long Document Classification. In Findings of the Association for Computational Linguistics: EMNLP 2022. Abu Dhabi, United Arab Emirates Association for Computational Linguistics. 2022:7212-7230.
[4] Yang X, PourNejatian N, Shin HC, et al. Gatortron: A large language model for clinical natural language processing. MedRxiv. 2022:2022-02.
[5] Shortliffe EH, Axline SG, Buchanan BG, et al. An artificial intelligence program to advise physicians regarding antimicrobial therapy. Comput Biomed Res. 1973;6(6):544-60.
[6] Hand DJ. Artificial intelligence and medicine: discussion paper. J R Soc Med. 1987;80(9):563-5.
[7] Hidalgo DC, Olusanya O, Harlan E. Critical care trainees call for pulse oximetry reform. Lancet Respir Med. 2021;9(4):e37.
[8] Valbuena VSM, Merchant RM, Hough CL. Racial and Ethnic Bias in Pulse Oximetry and Clinical Outcomes. JAMA Intern Med. 2022;182(7):699-700.
[9] Denecke K, May R, Rivera-Romero O. Transformer Models in Healthcare: A Survey and Thematic Analysis of Potentials, Shortcomings and Risks. J Med Syst. 2024;48(1):23.
[10] AIAAIC (AI AaAIaC. AIAAIC 2024. Available from: https://www.aiaaic.org/
[11] AIAAIC. Study: Whisper AI transcription service invents medical treatments 2024. Available from: https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/study-whisper-ai-transcription-invents-medical-treatments
[12] AIAAIC. Study: Whisper AI speech recognition creates violent hallucinations 2024. Available from: https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/study-whisper-ai-speech-recognition-creates-violent-hallucinations
[13] Burke G, Schellmann H. Researchers say an AI-powered transcription tool used in hospitals invents things no one ever said 2024. Available from: https://apnews.com/article/ai-artificial-intelligence-health-business-90020cdf5fa16c79ca2e5b6c4c9bbb14
[14] Koenecke A, Seo A, Choi G, et al. Careless Whisper: Speech-to-Text Hallucination Harms. Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency (FAccT '24) Association for Computing Machinery, New York, NY, USA. 2024:1672-1681.
[15] AIAAIC. Black man sues UNOS over kidney transplant algorithm racial bias 2023. Available from: https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/black-man-sues-unos-over-kidney-transplant-algorithm-racial-bias
[16] AIAAIC. Algorithm delays young peoples' liver transplants 2023. Available from: https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/algorithm-delays-young-peoples-liver-transplants
[17] AIAAIC. WHO chatbot provides inaccurate health information 2024. Available from: https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/who-chatbot-provides-inaccurate-health-information
[18] World Health Organization. S.A.R.A.H, a Smart AI Resource Assistant for Health 2024. Available from: https://www.who.int/campaigns/s-a-r-a-h
[19] Wells K. An eating disorders chatbot offered dieting advice, raising fears about AI in health 2023. Available from: https://www.npr.org/sections/health-shots/2023/06/08/1180838096/an-eating-disorders-chatbot-offered-dieting-advice-raising-fears-about-ai-in-hea
[20] AIAAIC. Character AI encourages kids to engage in disordered eating 2024. Available from: https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/character-ai-encourages-kids-to-engage-in-disordered-eating
[21] Character Technologies I. https://character.ai/ 2024. Available from: https://character.ai/
[22] Mento C, Silvestri MC, Muscatello MRA, et al. Psychological Impact of Pro-Anorexia and Pro-Eating Disorder Websites on Adolescent Females: A Systematic Review. Int J Environ Res Public Health. 2021;18(4).
[23] Rodgers RF, Lowy AS, Halperin DM, et al. A Meta-Analysis Examining the Influence of Pro-Eating Disorder Websites on Body Image and Eating Pathology. Eur Eat Disord Rev. 2016;24(1):3-8.
[24] Embi PJ. Algorithmovigilance-Advancing Methods to Analyze and Monitor Artificial Intelligence-Driven Health Care for Effectiveness and Equity. JAMA Netw Open. 2021;4(4):e214622.
[25] AI Incident Database. New Incident Report 2024. Available from: https://incidentdatabase.ai/apps/submit/

[26] OECD.AI Policy Observatory. G7 reporting framework – Hiroshima AI Process (HAIP) international code of conduct for organizations developing advanced AI systems 2025. Available from: https://transparency.oecd.ai/
[27] FDA U.S. Food & Drug Administartion. Manufacturer and User Facility Device Experience (MAUDE) Database 2025. Available from: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfmaude/search.cfm
[28] Denecke K, May R, Rivera Romero O. Potential of Large Language Models in Health Care: Delphi Study. J Med Internet Res. 2024;26:e52399.
[29] Guardado S, Mynolopoulou V, Bansi J, et al. An exploratory study on the opportunities and usefulness of patient-generated health data as a tool in the care of people with Multiple Sclerosis. Methods of Information in Medicine. 2023.
[30] Rani S, Kumari A, Ekka SC, et al. Perception of Medical Students and Faculty Regarding the Use of Artificial Intelligence (AI) in Medical Education: A Cross-Sectional Study. Cureus. 2025;17(1):e77514.
[31] Stroud AM, Curtis SH, Weir IB, et al. Physician Perspectives on the Potential Benefits and Risks of Applying Artificial Intelligence in Psychiatric Medicine: Qualitative Study. JMIR Ment Health. 2025;12:e64414.
[32] World Health Organization. Ethics and governance of artificial intelligence for health: Guidance on large multi-modal models 2024. Available from: https://www.who.int/publications/i/item/9789240084759
[33] Liu F, Panagiotakos D. Real-world data: a brief review of the methods, applications, challenges and opportunities. BMC Med Res Methodol. 2022;22(1):287.

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Social Media Interventions for Individuals with ADHD: A Scoping Review

Annette BERGSLAND, Elia GABARRON[1]
Department of Education, ICT and Learning, Østfold University College
ORCiD ID: Annette Bergsland: https://orcid.org/0009-0006-4180-8358; Elia Gabarron https://orcid.org/0000-0002-7188-550X

Abstract. *Background and objective*: ADHD affects 5–8% of children worldwide. Social media shows potential for ADHD interventions. This scoping review aims to assess the available literature on social media interventions for ADHD and their reported outcomes. *Methods*: A scoping review was conducted across four databases (ERIC, PubMed, Education Source, PsycINFO) using ADHD and social media keywords. Grey literature was searched via Google Scholar, conferences, and ADHD organizations. Data extracted covered study design, intervention, participants, platforms, outcomes, and quality (QualSyst, MMAT). *Results*: Eight studies were included, seven with strong methodological quality. The studies involved 386 participants (ages 4–18), some with parents/caregivers. Designs varied (feasibility studies, RCTs, mixed methods). Most interventions targeted physical activity or caregiver support, showing feasibility and mixed effects on health behaviors and social skills. One study reported mild adverse effects. *Conclusion*: While studies are limited, social media shows potential as an ADHD intervention, highlighting benefits, risks, and the need for informed choices.

Keywords. ADHD; Social media; Digital interventions

1. Introduction

Attention-Deficit/Hyperactivity Disorder (ADHD), affecting 5–8% of children globally, impacts academic, occupational, and social functioning [1]. Despite treatments like behaviour modification and medication, barriers such as stigma and cost hinder access [2]. Social media offers promise for mental health interventions, including for ADHD, due to similarities with other neurodevelopmental disorders [3]. As smartphone and social media use rises—93% of Norwegian children aged 9–11 own a smartphone [4]—digital interventions offer accessible, less stigmatizing treatment [5]. Studies show effectiveness in promoting health behaviours like physical activity and healthy diets [6]. However, concerns persist about the link between digital media use and ADHD, with longitudinal data suggesting a bidirectional relationship [7]. Additionally, ethical concerns around data privacy and risks of problematic use, poor sleep quality, and cyberbullying are relevant [8]. There is limited information on existing research regarding the use of social media interventions for individuals with ADHD. This scoping review aims to assess the available literature and the outcomes of the use of social media as an intervention for ADHD.

[1] Corresponding Author: Elia Gabarron, Email: elia.gabarron@hiof.no

2. Methods

A PRISMA-ScR [9] scoping review was conducted on November 7, 2023 across four databases (ERIC, PubMed, Education Source, PsycINFO) using ADHD and several social media keywords. Grey literature was searched via Google Scholar (first 100 entries), conference proceedings, and ADHD organization websites. Reference lists of relevant publications were also checked. Articles were managed in EndNote, with duplicates removed. Screening was conducted by one reviewer (AB), with uncertainties discussed with a second reviewer (EG). Studies were included if they involved individuals with ADHD or their caregivers, described social media-based interventions, and reported intervention results. Further details on inclusion/exclusion criteria, search terms used in the database search, and grey literature search are available on Zenodo (DOI: 10.5281/zenodo.15012066). Extracted data were: study design (randomized, non-randomized or mixed-methods studies), intervention duration (as reported in the articles), focus of intervention (aims, goals, targets of the intervention), participants (number of participants, sex and age), social media (name of the channel that was used), reported outcomes, and quality of evidence, measured with QualSyst [10] and MMAT [11].

3. Results

The database search identified 257 articles, with 51 duplicates removed. After screening 206 abstracts and reviewing 11 full texts, 4 articles were included. The grey literature search added 4 more, totaling 8 studies (Figure 1, Table 1). Seven had strong methodological quality. Across all studies, 386 participants (ages 4–18) were included, with four studies also involving parents/caregivers [12-15]. Study designs included five feasibility and acceptability studies [12-14,16,17], one RCT [18], and two as mixed methods [15,19]. Intervention durations ranged from 3 days [19] to 20 weeks [18], with most lasting 8 weeks [12-14,16].

Three studies targeted physical activity via social media and mobile health (Facebook, Zoom) with caregiver support [13,14,17]. One used LINE for parent training [15], while another adapted RELAX intervention with Zoom for caregiver support [12]. Three studies explored online games and apps to improve prosocial behaviour, time management, motivation, and social behaviour in children with ADHD [16,18,19].

Regarding reported outcomes, four studies assessed the feasibility and acceptability of social media interventions for ADHD, all concluding that such interventions are feasible and acceptable [12,14,15,17]. These studies, rated for strong to good methodological quality, explored social media for supporting both individuals with ADHD and their caregivers. Two publications [16,18] evaluated an intervention that improved time management and social skills by using elements from Bandura´s Cognitive Theory, and another one found positive effects on game performance and socialization [19]. Three studies focused on health behaviour changes, such as increasing physical activity, with mixed results: one found increases in steps and reductions in ADHD symptoms [17], while another one reported a decrease in children's step counts [14], and a third one found minimal changes in activity levels across in-person and telegroups [13]. Additionally, studies using Zoom for group-based programs reported higher attendance rates [12,13]. Only one study [18] reported mild to moderate adverse effects, including finger pain, irritability, and headaches.

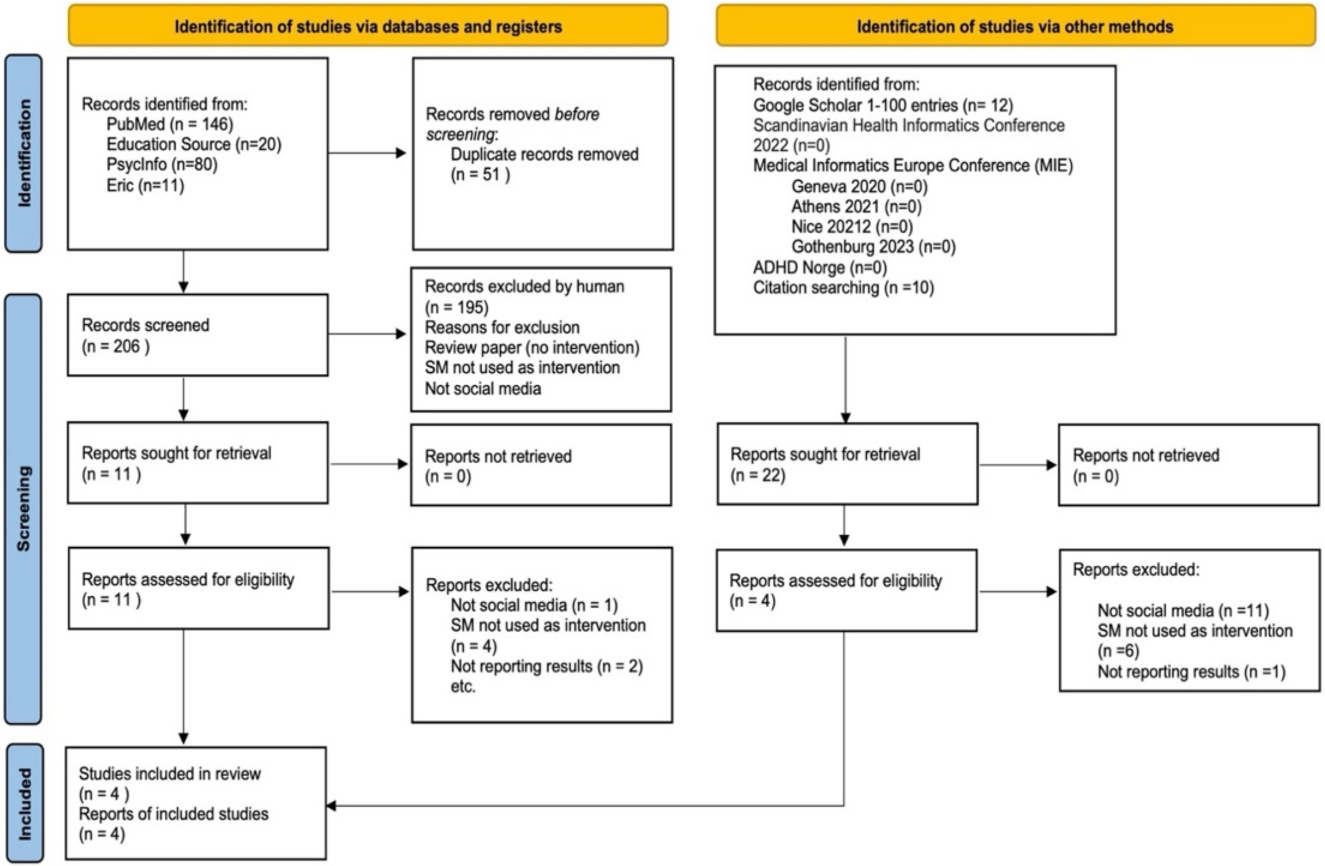

Figure 1. PRISMA-ScR flowchart

Table 1. Summary of the studies included in this scoping review (n=8)

Reference	Study design /duration	Focus of intervention (primary outcomes measured)	Study participants	Type of social media used	Findings	Quality of evidence
Bul et al. 2016 [18]	RCT 20 weeks	Determine the effects of Plan-It Commander on daily life skills of children with ADHD	n=170 children aged 8-12 diagnosed with ADHD	Plan it commander social media chat called "Space Club"	Intervention showed significant improvement in daily life functioning across domains of time management, social skills and working memory	Strong*
Schoenfelder et. al. 2017 [17]	Non-randomized Pilot study 4 weeks	Evaluate feasibility and acceptability of intervention mHealth and activity tracker	n=11 adolescents aged 14-18 diagnosed with ADHD	Fitbit flex and Facebook group	Intervention showed that it is feasible with relativity high acceptability and significantly increased daily steps	Strong*
Breaux et al. 2023 [12]	Pilot study 90 min group sessions	Evaluation of Feasibility acceptability and efficacy of Relax intervention for families and adolescents diagnosed with ADHD in person vs online	n=32 families with adolescents 11-16 years diagnosed with ADHD (n=18 in person, n= 14 zoom, tele-health)	Zoom and Zoom breakout rooms	Strong preliminary evidence for the feasibility, acceptability, and efficacy of the RELAX intervention for families of adolescence diagnosed with ADHD both in-person or via telehealth	Strong*
Sinnari et al. 2019 [19]	Mixed methods 3 days	Develop and test chit-chat usability and satisfaction and its effectiveness on behavior	n=7 children diagnosed with ADHD aged 6-8 years old	Chit-Chat	Chit-Chat is an effective chatting tool for children with ADHD. Significant improvement in performance in ACTIVATE posttest	Strong**
Yam-Ubon et al. 2023 [15]	Mixed methods 7 weeks	Develop and test feasibility of social media-based parenting program for children with ADHD	n=32 parents and caregivers of children 4-10 diagnosed with ADHD	LINE app	Qualitative feedback indicated the program was feasible, accessible and well received by participants. High completion rate	Strong**
Gonzalez et al. 2023 [13]	Non-randomized trial 8 weeks	Evaluate LEAP a BMT program with focus on health behaviors in telegroup vs in person delivery	Children aged 5-10 with ADHD and their caregiver n=61 total (n=37 in person n=24 Telegroup)	Garmin Vivofit 4 and Garmin Vivofit Jr., Facebook group And Zoom	Leap is feasible, with high participation and acceptability. No significant difference was found between in-person and telegroup for pre- and post-outcome changes, though telegroup showed higher attendance	Strong*
Bul et al. 2015 [16]	Pilot study 8 weeks	Development and user satisfaction of Plan-it Commander for children with ADHD	n=42 children aged 8-12 years diagnosed with ADHD	Plan- it Commander game with chat function between players	Usability and satisfaction findings indicated positive acceptance of the game and a RTC is deemed necessary	Strong*
Ola et al. 2021 [14]	Non-randomized pilot trial 8 weeks	Evaluate feasibility and acceptability of LEAP to promote physical activity	n=31 parents and their children aged 5-10 years diagnosed with ADHD	Garmin and Facebook group	Leap intervention was shown to be adherence and acceptability were high to promote healthy lifestyle changes	Good*

* Quantitative studies measured with the QualSyst [10]; ** Mixed-methods studies measured with MMAT 2018 [11]

4. Discussion

This scoping review confirms the feasibility and acceptability of social media interventions for ADHD, highlighting the need for further research. The eight included interventions aimed to improve outcomes for children and adolescents with ADHD but varied in duration, participants, and social media platforms used. Some focused on daily life skills and physical activity [14,16-18], while others targeted specific behaviors. Delivery methods ranged from telehealth sessions [12,13] to mobile apps and social media for parental support [13-15]. Despite these differences, all interventions were found to be feasible, with varying degrees of acceptability and effectiveness.

Social media interventions show promise in promoting physical activity in children with ADHD, though results are mixed. One study found a significant increase in step counts [17], while others showed no significant changes, potentially due to factors like time of year or COVID-related restrictions. ADHD children tend to be less active than the general population [20]. Future studies with control groups may provide more insight. Studies in children with autism also found social media feasible for increasing physical activity [3,21]. However, privacy concerns arise [4], especially with fitness trackers and social media, as children's health data and locations can be tracked or misused. Social media also facilitates parental support, with platforms like Zoom and Facebook offering higher attendance than in-person sessions [15], and removing geographical barriers [2]. However, the cost/benefit should be considered, with risks including exposure to harmful content [7] and privacy concerns. Social media use for ADHD interventions is complicated by age restrictions, and future studies should focus on safer platforms and larger, randomized trials.

This review has limitations, including potential publication bias, as only selected sources were searched. Grey literature was considered, but time constraints limited its scope. A single reviewer conducted the search, though advisor consultation helped reduce bias. With only eight studies, some with small samples, quality concerns arise. However, QualSyst and MMAT assessments showed strong methodological quality in seven studies [12,13,15-19]. The single RCT was not directly comparable due to differing objectives, methods, and outcomes.

5. Conclusion

While studies are limited and results cannot be generalized, social media shows potential as an ADHD intervention. The review provides a current overview of possible social media-based interventions that could support students with ADHD, while also highlighting associated risks. Caregivers, educators, and healthcare professionals must help individuals make informed choices.

References

[1] World Health Organization. Attention Deficit Hyperactivity Disorder (ADHD) 2019. Available from: https://applications.emro.who.int/docs/EMRPUB_leaflet_2019_mnh_214_en.pdf

[2] Baweja R, Soutullo CA, Waxmonsky JG. Review of barriers and interventions to promote treatment engagement for pediatric attention deficit hyperactivity disorder care. World J Psychiatry. 2021;11(12):1206-1227.
[3] Gabarron E, Skafle I, Nordahl-Hansen A, et al. Social media interventions for autistic individuals: Systematic review. Front Psychiatry. 2023;14:1089452.
[4] Medietilsynet. Barn og Medier 2020: Om sosiale medier og skadelig innhold på nett 2020. Available from: https://www.medietilsynet.no/globalassets/publikasjoner/barn-og-medier-undersokelser/2020/200211-barn-og-medier-2020-delrapport-1_-februar.pdf
[5] Srivastava K, Chaudhury S, Dhamija S, et al. Digital technological interventions in mental health care. Ind Psychiatry J. 2020;29(2):181-184.
[6] Goodyear VA, Wood G, Skinner B, et al. The effect of social media interventions on physical activity and dietary behaviours in young people and adults: a systematic review. Int J Behav Nutr Phys Act. 2021;18(1):72.
[7] Thorell LB, Burén J, Ström Wiman J, et al. Longitudinal associations between digital media use and ADHD symptoms in children and adolescents: a systematic literature review. Eur Child Adolesc Psychiatry. 2024;33(8):2503-2526.
[8] Hussain Z, Griffiths MD. The Associations between Problematic Social Networking Site Use and Sleep Quality, Attention-Deficit Hyperactivity Disorder, Depression, Anxiety and Stress. Int J Ment Health addiction. 2021;19:686-700.
[9] Tricco AC, Lillie E, Zarin W, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. Ann Intern Med. 2018;169(7):467-473.
[10] Kmet LM, Lee RC, Cook LS, et al. Standard quality assessment criteria for evaluating primary research papers from a variety of fields Alberta Heritage Foundation for Medical Research2004. Available from: https://doi.org/10.7939/R37M04F16
[11] Hong QN, Fabregues S, Bartlett G, et al. The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. Education for Information. 2018;34(4):285-291.
[12] Breaux R, Shroff DM, Cash AR, et al. Telehealth Delivery of the RELAX Intervention for Families of Adolescents Diagnosed with ADHD: Preliminary Treatment Outcomes and Evidence of Acceptability and Feasibility. Evidence-Based Practice in Child and Adolescent Mental Health. 2023;8(1):24-38.
[13] Gonzalez ES, Tran N, Wholly D, et al. Parent Behavior Management Training for Child ADHD Enhanced to Address Health Behaviors: Comparison of Telemedicine "Telegroup" Versus In-Person Delivery. J Atten Disord. 2023;27(9):979-988.
[14] Ola C, Gonzalez E, Tran N, et al. Evaluating the Feasibility and Acceptability of the Lifestyle Enhancement for ADHD Program. J Pediatr Psychol. 2021;46(6):662-672.
[15] Yam-Ubon U, Thongseiratch T. Using a Design Thinking Approach to Develop a Social Media-Based Parenting Program for Parents of Children With Attention-Deficit/Hyperactivity Disorder: Mixed Methods Study. JMIR Pediatr Parent. 2023;6:e48201.
[16] Bul KC, Franken IH, Van der Oord S, et al. Development and User Satisfaction of "Plan-It Commander," a Serious Game for Children with ADHD. Games Health J. 2015;4(6):502-12.
[17] Schoenfelder E, Moreno M, Wilner M, et al. Piloting a mobile health intervention to increase physical activity for adolescents with ADHD. Prev Med Rep. 2017;6:210-213.
[18] Bul KC, Kato PM, Van der Oord S, et al. Behavioral Outcome Effects of Serious Gaming as an Adjunct to Treatment for Children With Attention-Deficit/Hyperactivity Disorder: A Randomized Controlled Trial. J Med Internet Res. 2016;18(2):e26.
[19] Sinnari D, Krause P, Abulkhair M. Effectiveness and Usability of a Developed Collaborative Online Tool for Children with ADHD Interactivity, Game Creation, Design, Learning, and Innovation. 7th EAI International Conference2019. p. 496-507.
[20] Mercurio LY, Amanullah S, Gill N, et al. Children With ADHD Engage in Less Physical Activity. J Atten Disord. 2021;25(8):1187-1195.
[21] Esentürk OK, Yarımkaya E. WhatsApp-Based Physical Activity Intervention for Children With Autism Spectrum Disorder During the Novel Coronavirus (COVID-19) Pandemic: A Feasibility Trial. Adapt Phys Activ Q. 2021;38(4):569-584.

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Opportunities, Requirements, and Risks of a Student Mental Health Chatbot: A Qualitative User-Centered, Multi-Method Approach

Daniel REICHENPFADER[a,1,2], Lorenz AFFOLTER[b,2], Elia GABARRON[c], and Kerstin DENECKE[a]
[a] *Institute for Patient-Centered Digital Health, Bern University of Applied Sciences, Bern, Switzerland*
[b] *Institute of New Work, Bern University of Applied Sciences, Bern, Switzerland*
[c] *Department of Education, ICT and Learning, Østfold University College, Halden, Norway*

Abstract. Mental health challenges among university students are increasing, but stigma and limited access to professional support hinder help seeking. This study explored opportunities, requirements, and risks associated with developing a chatbot-based mental health application tailored to Swiss university students. Data were collected through semi-structured interviews with student counselors, administrators, and representatives, as well as a requirements engineering workshop involving key stakeholders. The results showed that a chatbot could reduce stigma, improve accessibility and support vulnerable groups, provided it included easy access, evidence-based content and emergency responses. However, concerns regarding data security, harmful advice, and over-reliance on the chatbot must be acknowledged. These findings highlight the need for ethical safeguards, robust design, and a complementary role for the chatbot within existing support systems to address student mental health effectively.

Keywords. Mental health, higher education, chatbot, mobile application, requirement engineering, user-centered design

1. Introduction

According to the World Health Organization (WHO), "Mental health is a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community" [1]. Mental health has been increasingly challenged in recent years, particularly during and after the COVID-19 pandemic [2]. The pandemic brought about profound disruptions in social life, education, and work environments, triggering a 25% increase in prevalence of anxiety and depression worldwide [3], with young adults particularly affected. Students are especially vulnerable due to the unique stressors they face such as academic performance

[1] Corresponding Author: Daniel Reichenpfader. Bern University of Applied Sciences, Quellgasse 21, 2503 Biel/Bienne, Switzerland. Mail: daniel.reichenpfader@bfh.ch
[2] Contributed equally

pressures, limited financial resources, and the growing necessity of part-time work to sustain their studies [4].

Several initiatives have been introduced in Switzerland to address the limited help seeking behavior specifically for students, including counseling services offered at study program, institutional, or regional levels, as well as launching awareness campaigns and provision of information flyers. However, a national survey conducted among students revealed that only half of those experiencing mental health challenges accessed existing services [5]. One key barrier identified is the pervasive stigma surrounding mental health issues, which deters students from seeking help [6].

Advancements in technology, particularly in the fields of large language models (LLMs) and conversational artificial intelligence (AI), present an opportunity to help address this issue. These technologies can provide an accessible platform to connect students with the mental health support, while also helping to reduce stigma associated with help seeking. Globally, digital mental health solutions have already shown first promises in reducing barriers to access and offering support [7]. Building on these advancements, we aim to develop a chatbot-based, mobile health application specifically designed for Swiss university students and outline its requirements collection process.

2. Methods

The identification of requirements was based on interviews complemented by a structured requirements engineering workshop elaborated in the following. Ten semi-structured qualitative interviews following a predefined, semi-structured protocol were conducted to gain insights into the perspectives of key stakeholders in the ecosystem of a Swiss University of Applied Sciences. These stakeholders comprised five student counselors, three representatives of student organizations, and two course directors. The interviews were conducted either remotely via Microsoft Teams or in-person. Online interviews were recorded and automatically transcribed. In-person interviews were recorded with a mobile phone and transcribed using the open-source software noScribe.

Analysis of the interview transcripts was performed by a single author (LA), based on thematic analysis aiming to identify, analyze, and interpret patterns and themes within the data [8]. An inductive approach was adopted, allowing themes to emerge directly from the data without being constrained by preconceived theories or frameworks. The analysis involved six steps: (1) familiarization with the data through repeated reading of transcripts, (2) generating initial codes to systematically organize meaningful data segments, (3) searching for themes by grouping related codes, (4) reviewing themes to ensure coherence and alignment with the data set, (5) defining and naming themes to clearly articulate their essence, and (6) producing the final report.

The 3-hour requirements engineering workshop was conducted with nine persons, comprising one course director, two senior researchers in the domain of eHealth and positive psychology, respectively, one expert (psychologist and psychotherapist), one student counselor, two students, and two student representatives. The workshop was designed to foster creativity and interactions among participants while reducing any primers that could influence the ideation process. Workshop activities included a free brainstorming session, the identification of potential risks and a world-café-based set-up to collect aspects regarding the three topics *Access*, *Design*, and *Interaction*. One author (DR) translated all outcomes into a standardized list of requirements phrased as user stories and a list of risks including their estimated impact severity and probability.

3. Results

The ten interviews were conducted between 06/09/2024 and 17/10/2024 and lasted between 26 and 43 minutes. We identified four main themes and fourteen sub themes from the interviews. An overview of all the themes can be found in Table 1.

Table 1. Table of themes from the interviews.

Main themes	Sub themes	Example codes
Perceived chances of a mental health chatbot within a university context	• Reducing students' reluctance to get help • Bridging between students' needs and existing resources	• Being able to open up when help is needed • Forwarding students to fitting services
Perceived risks of a mental health chatbot within a university context	• Recognizing critical cases • Anonymity and data security • Crowding out real social interactions	• Chatbot should recognize when professional help is needed • Anonymity as a prerequisite to use the chatbot • Creating dependencies
Most relevant topics and groups regarding mental health	• Learning and exam preparation • Balancing studies with other life areas • Personal challenges • First year students • International students	• Exams causing stress • Study-work balance • Identity challenges • First year as the biggest challenge • Home sickness
Accessibility and promotion of the mental health chatbot	• Thematic framing • Important communication partners • Places to advertise the chatbot • Events to advertise the chatbot	• Positive understanding of mental health • Student organizations • Campus-App • Introductory-Day

Based on the workshop results, 63 requirements were identified. In Table 2, we present six requirements deemed as high priority. The ten identified risks are shown in Table 3. We make the interview guideline, the final code system, and the complete lists of identified requirements and risks available online via OSF (https://doi.org/10.17605/OSF.IO/V4YGT).

Table 2. Subset of identified requirements with high priority.

Short title	Description
Forwarding to free services	As a student, I want to be forwarded to services that are free of charge.
Easy access	As a student, I want to easily access the chatbot (whenever, wherever).
Active approaching	As a student, I want to be offered help actively by the chatbot.
Collection of offers/events/help	As a student, I want to access an overview of (relevant) local offers, events and help.
Emergency situations	As a provider, I want the chatbot to detect if there is an emergency (e.g., suicidal thoughts) and offer the user addresses on where to go.
Evidence-based content	As a provider, I want the chatbot to be knowledgeable while being evidence-based.

4. Discussion

This research identified requirements, opportunities and challenges in implementing a university student mental health chatbot. Expert interviews highlighted its potential to reduce reluctance to seek help and connect students with resources, but raised concerns about identifying critical cases, ensuring anonymity and avoiding reduced social interaction. Key topics like exam preparation, balancing studies with life, and supporting vulnerable groups, such as first-year and international students, emphasize the need for tailored, context-aware design. Workshop findings prioritized requirements like easy access, active engagement, emergency support, and evidence-based content, while highlighting risks like misleading advice, legal issues, data breaches, parasocial relationships, and competition. These identified aspects highlight the need for the development of a dedicated system instead of using publicly available general-purpose chatbots (e.g., ChatGPT).

Table 3. Identified risks. I: Impact severity. P: Probability of occurrence. Scale: 1 to 5.

Short title	Description	Consequence	I	P
Misleading guidance	The chatbot provides wrong or even harmful advice.	User harm or death	5	2
Legal restrictions	Chatbot usage is prohibited due to legal restrictions (e.g., MDR).	The chatbot is not used.	4	3
Data breach	Chat histories containing sensitive and personal student data get leaked.	The chatbot 's image is negatively impacted.	4	3
Parasocial relationships	Users develop a parasocial relationship with the chatbot and experience negative consequences.	Users develop additional mental health problems.	4	3
Refusal of use	Users do not want to share their mental health-related aspects with a chatbot.	The chatbot is not used.	4	3
Competitors	Users prefer other tools (e.g., ChatGPT).	The chatbot is not used.	4	5
Trust issues	Users have trust issues towards the app and/or the provider regarding their personal data.	The chatbot is not used.	4	4
Missing publicity	Students do not know that the chatbot exists.	The chatbot is not used.	4	2
Insufficient funding	There is not funding to continue with the development of the chatbot.	The chatbot is not completed.	4	2
Unrelated use	Students use the chatbot for other things than their mental health (completing homework).	The chatbot is used in problematic ways.	3	5

4.1. Opportunities and requirements

One of the opportunities identified by participants was the chatbot's potential to reduce the stigma surrounding mental health issues. Stigma is a known significant barrier for students in accessing mental health services [9,10]. By offering a confidential and easily accessible platform, it may help build trust and adoption among its users, while facilitating earlier intervention and communication about mental health concerns. Additionally, the chatbot could serve as a bridge to connect students with appropriate mental health resources, as also suggested by previous research [11] or could promote interaction with peers [12].

Moreover, the chatbot could address specific challenges faced by university students, such as managing academic stress. Research has shown that mindfulness-based interventions, cognitive behavioral therapy, and technology-delivered interventions are effective in supporting the mental health of university students [13], highlighting the potential for the chatbot to incorporate evidence-based approaches to address these needs. By addressing these concerns, the chatbot has the potential to provide targeted support to all students, and specially to most vulnerable ones, such as first-year students and international students, who often face unique challenges in adapting to their environment, with research highlighting issues such as poor mental health, linguistic and cultural barriers, acculturative stress, and limited health literacy [9,14].

To maximize the opportunities that a mental health chatbot could offer students, several key requirements for its design and functionality were identified. Workshop participants agreed that the chatbot must facilitate easy access and actively engage students, ensuring that it is user-friendly and responds to their needs. Providing evidence-based content was another high-priority requirement identified in the workshop. In this regard, interventions based on mindfulness (e.g., for stress reduction) and cognitive behavioral therapy (e.g., to reduce symptoms of depression and generalized anxiety disorder) should be particularly considered [13].

In the workshop, it was also highlighted that the chatbot should include mechanisms for forwarding users to free mental health services and resources. In fact, the literature has reported that financial stressors are a relevant factor affecting mental health [15], and recommending free mental health services might help relieve these financial constraints. Another requirement was the chatbot's ability to handle emergency situations responsibly, including recognizing critical cases and therefore allowing early professional interventions. The need of providing crisis support through digital mental health interventions has been previously recommended in scientific research [16], suggesting that the digital tool should have an ability to notify a designated health professional, in addition to providing information about helplines and self-care tools [16]. To ensure the chatbot effectively addresses students' needs, it is crucial to prioritize these requirements in its development and implementation.

4.2. Risks of a mental health chatbot for university students

The concerns from the interviews and workshops align with broader challenges in AI-based mental health tools, particularly regarding anonymity and data security risks such as data breaches. Despite limited research on these issues [17], they are critical for building user trust and promoting adoption of digital health technologies [18]. Participants raised concerns about chatbots providing harmful advice or failing to recognize crises, consistent with a recent study showing that many chatbots lack effective crisis response [16]. This highlights the need for robust emergency protocols [19], and emphasizes that chatbots should complement, not replace, human interaction [16]. Future implementations must balance technology use with encouraging interpersonal connections, particularly in the university setting where social support is critical for well-being. Additional expressed concerns included the potential risks of legal restrictions arising, competitors, lack of funding to maintain the chatbot, and even the possibility of a parasocial relationship between users and the chatbot. The findings from this study reinforce previous publications on the need for regulations [20] and human oversight [21] to mitigate risks and ensure the safety of the chatbot [22,23] in addition to focus mostly on efficacy.

4.3. Strengths and limitations

A strength of this research is its mixed-methods approach, which combines interviews and a workshop to gather diverse perspectives. This approach ensures a comprehensive understanding of the stakeholders' needs and insights, which is key for designing a user-centered mental health chatbot. The use of thematic analysis further strengthens the research by allowing for a detailed and inductive exploration of the data, ensuring that themes emerge organically from the participants' experiences. However, only a single author has carried out the analysis of interview data, which may have introduced potential biases. Additionally, the sample sizes are relatively small, which could limit the generalizability of the findings to other university settings or to other cultural contexts.

5. Conclusion

This study highlights the potential of a mental health chatbot to address the unique challenges faced by university students by reducing stigma, increasing accessibility, and connecting users with appropriate resources. Through a user-centered, multi-method approach, critical requirements such as easy access, evidence-based content, active engagement, and emergency support mechanisms were identified, alongside significant risks like data security concerns, the potential for harmful advice, and reduced interpersonal interactions. We conclude that a careful design is essential to mitigate possible risks already in the development phase by corresponding strategies. In future work, we will develop the chatbot considering the collected requirements and will test it with students.

References

[1] WHO. Mental health [Internet]. [cited 2025 Jan 14]. Available from: https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response.

[2] Xiong J, Lipsitz O, Nasri F, et al. Impact of COVID-19 pandemic on mental health in the general population: A systematic review. Journal of Affective Disorders. 2020;277:55–64.

[3] WHO. Mental Health and COVID-19: Early evidence of the pandemic's impact: Scientific brief, 2 March 2022 [Internet]. 2022 [cited 2025 Jan 14]. Available from: https://www.who.int/publications/i/item/WHO-2019-nCoV-Sci_Brief-Mental_health-2022.1.

[4] Barbayannis G, Bandari M, Zheng X, et al. Academic Stress and Mental Well-Being in College Students: Correlations, Affected Groups, and COVID-19. Front Psychol [Internet]. 2022 [cited 2025 Jan 14];13.

[5] Fischer P, Boughaba Y, Meffre V, editors. Studien- und Lebensbedingungen an den Schweizer Hochschulen: Hauptbericht der Erhebung 20206 zur sozialen und wirtschaftlichen Lage der Studierenden. Neuchâtel; 2021.

[6] Da Conceição V, Mesquita E, Gusmão R. Effects of a stigma reduction intervention on help-seeking behaviors in university students: A 2019-2021 randomized controlled trial. Psychiatry Research. 2024;331:115673.

[7] Linardon J, Torous J, Firth J, et al. Current evidence on the efficacy of mental health smartphone apps for symptoms of depression and anxiety. A meta-analysis of 176 randomized controlled trials. World Psychiatry. 2024;23(1):139–149.

[8] Braun V, Clarke V. Using thematic analysis in psychology. Qualitative Research in Psychology. 2006;3(2):77–101.

[9] Dombou C, Omonaiye O, Fraser S, et al. Barriers and facilitators associated with the use of mental health services among immigrant students in high-income countries: A systematic scoping review. PLOS ONE. 2023;18(6):e0287162.

[10] Hyseni Duraku Z, Davis H, Arënliu A, et al. Overcoming mental health challenges in higher education: a narrative review. Front Psychol [Internet]. 2024 [cited 2025 Jan 21];15.

[11] Melcher J, Camacho E, Lagan S, et al. College student engagement with mental health apps: analysis of barriers to sustained use. Journal of American College Health. 2022;70(6):1819–1825.

[12] Simmons MB, Cartner S, MacDonald R, et al. The effectiveness of peer support from a person with lived experience of mental health challenges for young people with anxiety and depression: a systematic review. BMC Psychiatry. 2023;23(1):194.

[13] Worsley JD, Pennington A, Corcoran R. Supporting mental health and wellbeing of university and college students: A systematic review of review-level evidence of interventions. PLOS ONE. 2022;17(7):e0266725.

[14] Liu C-C, Huang Q, Chen AC-C, et al. Interventions to enhance mental health and wellbeing among international college students: A systematic review and meta-analysis protocol. PLOS ONE. 2024;19(9):e0310645.

[15] Agyapong B, Shalaby R, Wei Y, et al. Can ResilienceNHope, an evidence-based text and email messaging innovative suite of programs help to close the psychological treatment and mental health literacy gaps in college students? Front Public Health [Internet]. 2022 [cited 2025 Jan 21];10.

[16] Haque MDR, Rubya S. An Overview of Chatbot-Based Mobile Mental Health Apps: Insights From App Description and User Reviews. JMIR mHealth and uHealth. 2023;11(1):e44838.

[17] Xue J, Zhang B, Zhao Y, et al. Evaluation of the Current State of Chatbots for Digital Health: Scoping Review. Journal of Medical Internet Research. 2023;25(1):e47217.

[18] Denecke K, Schmid N, Nüssli S. Implementation of Cognitive Behavioral Therapy in e–Mental Health Apps: Literature Review. Journal of Medical Internet Research. 2022;24(3):e27791.

[19] Denecke K, Gabarron E. The ethical aspects of integrating sentiment and emotion analysis in chatbots for depression intervention. Front Psychiatry. 2024;15:1462083.

[20] Meskó B, Topol EJ. The imperative for regulatory oversight of large language models (or generative AI) in healthcare. npj Digit Med. 2023;6(1):1–6.

[21] Tavory T. Regulating AI in Mental Health: Ethics of Care Perspective. JMIR Mental Health. 2024;11(1):e58493.

[22] Lopez-Campos G, Gabarron E, Martin-Sanchez F, et al. Digital Interventions and Their Unexpected Outcomes – Time for Digitalovigilance? MEDINFO 2023 — The Future Is Accessible [Internet]. IOS Press; 2024 [cited 2025 Jan 21]. p. 479–483. Available from: https://ebooks.iospress.nl/doi/10.3233/SHTI231011.

[23] Heston TF. Safety of Large Language Models in Addressing Depression. Cureus [Internet]. 2023 [cited 2025 Jan 21]; doi: 10.7759/cureus.50729.

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