cii Student Papers 2023

Karlsruhe Institute of Technology

CRITICAL INFORMATION INFRASTRUCTURES RESEARCH GROUP

cii Student Papers - 2023

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Editorial

Critical information infrastructures (cii) are sociotechnical systems comprising essential software components and information systems with a pivotal impact on individuals, organizations, governments, economies, and society. For more than five years now, our research group here at the Karlsruhe Institute of Technology (KIT) has been investigating a variety of practice- and research-driven challenges while looking at the design, development, and evaluation of reliable and secure software and information systems. The main driver for our research is theorizing on and designing the applications and methods required for the creation and innovation of sociotechnical systems with promising value propositions. Hereby, we are multifaceted in the use context, including the Internet and healthcare industries, as well as on the industry-specific application of secure and trustworthy artificial intelligence (AI) models. As we focus on human behavior affecting critical information infrastructures and vice versa, our research enables us to rigorously generate strong theoretical insights while simultaneously producing research outputs of relevance to practical audiences.

Every year, our research group supervises more than 150 bachelor and master students during their studies at the KIT. Teaching is an essential part of research, as it allows us to incorporate these topics directly into the education of students. In doing so, we are highly motivated to ensure that we can provide excellent teaching to students, whereby we apply inquiry-based learning methods and actively introduce our research topics to them in various seminars and lectures. In our opinion, good research and working with a team go hand in hand. Students mostly work in groups and deal with problems and issues related to sociotechnical challenges in the realm of (critical) information systems during our courses. To ensure high relevance, the topics generally correspond to what we are currently researching. In addition, we allow students to propose their own research topics or even conduct their studies in collaboration with small, medium, or large companies.

Following cutting-edge information systems research, topics change from semester to semester, including disruptive health information systems (Thiebes et al., 2023), secure design of cloud, fog, and edge services (Blume et al., 2023; Brecker, Lins, Trenz, et al., 2023), conceptual ambiguity concerning gamification and serious games in health care (Warsinsky, Schmidt-Kraepelin, Rank, et al., 2021), the evaluation of AI explanations for industry experts (Toussaint et al., 2024), designing and implementing requirements for distributed ledgers (Beyene et al., 2022; Kannengießer et al., 2020), adoption and trust concerns regarding the use of AI in autonomous vehicles (Renner et al., 2021), and theory development for transparency of information privacy practices (Dehling & Sunyaev, 2023). Our research team supports students throughout the research process, helping them identify and organize problems, apply appropriate research methods consistently, develop and communicate approaches to solutions, and write research papers.

Involving students in daily work and bringing research to students provides many benefits, not only to the students but also to our research group, to the research community, and to practice in general. Students will be involved in current practice problems that research is trying to solve. Moreover, they can better understand the theoretical principles learned in the previous lectures and apply them when working on their seminar theses. By offering such science courses, students can gain first-hand experience and a deeper understanding of writing upcoming bachelor's and master's theses.

In fact, most students continue their research after attending a seminar or lecture, either in the form of a dissertation, as part of their work as a student assistant in our research groups, or even volunteer work in their free time. Students also regularly interact with organizations, which can lead to initial collaborations and even pave the way for upcoming jobs. We think that the student works are of high value. Nonetheless, they often disappear into drawers despite the disruptive and valuable insights students have come up with.

As a research group, we always appreciate the work of great students, incorporate their insights into our own research projects, and often publish exceptional results in conference proceedings or journals (e.g., Bodynek et al., 2023; Hu et al., 2023; Klein et al., 2022; Schmidt-Kraepelin, 2024).

Thus, we came up with the idea to publish the best works in this book, and we are very happy to present this collection for the third time in a row now (previous collections: Sunyaev et al., 2021, 2022). In this work, we bring together the best student works from the previous summer term 2022 and winter term 2022/2023.

Contributions in this anthology come from four different courses that provide students with a broad range of topics related to (critical) information systems:

Emerging Trends in Internet Technologies:

The seminar *Emerging Trends in Internet Technologies* aims at providing students with insights into current topics in the field of information systems while mainly focusing on fundamental and innovative Internet technologies. Students are offered a selection of topics around the lectures and present research of our group, including distributed ledger technology (Kannengießer et al., 2020), cloud, fog, and edge computing (Brecker, Lins, Trenz, et al., 2023), AI (Brecker, Lins, & Sunyaev, 2023), security (Adam, 2023; Greulich et al., forthcoming), and privacy (Renner et al., 2022; Yari et al., 2021). For example, our research group gave a profound conceptualization of the phenomena of *Artificial Intelligence as a Service* due to the lack of conceptual clarity in research and practice (Lins et al., 2021).

Emerging Trends in Digital Health:

Similarly, the seminar *Emerging Trends in Digital Health* aims to provide insights into current topics in the field of information systems with a focus on innovative digital healthcare systems. Kicking off with a short introduction and corresponding topics, students can choose to work on many different topics around the lectures and research topics of the research group, including genomics (Thiebes, Toussaint, et al., 2020; P. A. Toussaint et al., 2022), distributed ledger technology (Beyene et al., 2022), patient consent (Beyene et al., 2019), AI (Pandl, Feiland, et al., 2021; Thiebes, Lins, et al., 2020), and gamification in healthcare (Schmidt-Kraepelin et al., 2023). An example of our interdisciplinary work in this field is a recent scoping review on the use of distributed ledger technology in the field of genomics, where we investigate how blockchain and other ledger systems are currently or could be used to store and share genomic data between multiple entities such as patients, doctors, hospitals, researchers, and many more (Beyene et al., 2022).

Digital Health:

The course *Digital Health* introduces master students to the subject of digitization in healthcare. Students learn about the theoretical foundations and practical implications of various topics surrounding digitization in healthcare, including health information systems, telematics, big healthcare data, and patient-centered healthcare (e.g., Pandl, Thiebes, et al., 2021; Rädsch et al., 2021; Thiebes, Schlesner, et al., 2020; Warsinsky, Schmidt-Kraepelin, Thiebes, et al., 2021). After an introduction to the challenge of digitization in healthcare, the following sessions focus on an in-depth exploration of selected cases that represent current challenges in research and practice. Students work in groups of three to four on specific topics and must write a course paper. One current topic our research group investigates in this field is how and why consumers perceive certain direct-to-consumer genetic testing business models as fair or unfair, respectively (Philipp A. Toussaint et al., 2022).

Critical Information Infrastructures:

The course *Critical Information Infrastructures* introduces students to the world of complex sociotechnical systems that permeate societies on a global scale. Being offered every winter term, master students learn to handle the complexities involved in the design, development, operation, and evaluation of critical information infrastructures. At the beginning of the course, critical information infrastructures are introduced on a general level. The following sessions focus on an in-depth exploration of selected cases that represent current challenges in research and practice. Students work in groups of four on specific topics and must write a course paper. The research group has also published a book chapter providing a discussion on the characteristics and challenges of critical information infrastructures (Dehling et al., 2019).

Selected Issues on Critical Information Infrastructures: Using Chatbots for Education

The COVID-19 pandemic had a significant impact on teaching at KIT, as a radical shift from face-to-face to online teaching had to be accomplished at short notice. While online teaching has meanwhile become more and more successful, the pandemic has highlighted an important need: innovative, digital teaching concepts are required that can be used in times of remote but also face-to-face teaching. We at the cii research group have therefore set ourselves the goal of rethinking our teaching concepts and techniques to adapt to changing needs and offer our students an insightful and engaging learning experience. Hence, we decided to offer a groundbreaking course beginning in the winter term of 2021. During the course, students collaboratively developed innovative, digital, and scientifically based teaching concepts while being supported by researchers from our research group. In the winter semester of 2022/2023, we particularly considered how chatbots can be used in teaching to support students in their learning. How can a chatbot help in a meaningful way? Which interaction possibilities do students need? How can a Chatbot answer questions from students adequately? ... Many questions are open and were explored collaboratively during the seminar. Students based their chatbot concepts on existing research or scholarly theories to ensure an effective and pedagogically valuable teaching experience. While students really enjoyed participating in this unique course and were excited to better understand how teaching feels at the KIT, we also valued learning what students desire from (post)-pandemic teaching experience.

Out of these courses, we selected the student works that represent the best and most interesting studies. The student works in this book cover a wide range of research problems, including a summary of possible explainable AI applications in biomedicine, the utilization of avatars in various applications, an overview of the effects of digital transformation and advances in computer vision on healthcare, and the capabilities of chatbots within the administrative settings of universities.

- Stetter conducted a systematic mapping study on explainable AI applications in biomedicine. She provides an overview of the existing applications in literature between 2021 and 2022 and thus lays the groundwork for further research in the area.
- Muff, Sommer, and Weber examined the utilization and features of avatars in gamified health applications. They identified 17 apps incorporating avatars and analyzed their categories, interactions, and avatar design.
- Hoffmann, Neutz, and Otten investigated digital health concepts via an umbrella literature review. They identified six crucial concept domains concerning digital transformation in healthcare and established connections between various concepts in literature.
- Ohmstedt, Landwehr, and Ness explored the ways healthcare professionals adapt new computer vision (CV) technologies through expert interviews. They found that CV technology holds the potential to improve diagnostics but does not fully automate the process yet.
- Dang, Huck, Micol, and Sesar conducted a study assessing the potential of chatbots in the administrative environment of universities through an online survey. They found that while chatbots are not intended to replace student services, they can effectively complement existing services, particularly for tasks that require minimal personal consultation.

In concluding this brief overview, we are grateful that students have once again taken the time to revise and improve their work to ensure the high quality of this Miscellany. In addition to the students who wrote the articles, this book would not have been possible without the dedicated researchers in our research group who mentored the students throughout the course. We would like to take this opportunity to express our sincere appreciation for their active support, motivation, and commitment to all student works in the cii research group. We are committed to our mission of excellence in teaching and intend to publish the best papers in a compendium each year to bring students closer to scientific work.

Sincerely,

Ali Sunyaev, Maximilian Renner, Philipp A. Toussaint, Scott Thiebes, Sebastian Lins

Miscellany Team 2023

Supervising Research Associates

CRITICAL INFORMATION INFRASTRUCTURES RESEARCHGROUP

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A Systematic Mapping Study on Explainable Artificial Intelligence for Biomedical Data

Emerging Trends in Digital Health, Summer Term 2022

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Abstract

Background: *The advent of artificial intelligence in healthcare is seen as a great opportunity for new approaches to applications in medicine. In the future, this digitalization should enable programs to use algorithms to evaluate correlations far more accurately and quickly than with conventional methods. Since the complexity of most programs denies insight into the internal processes and causes distrust among experts and the general public, there is a need to use a number of techniques that bring explainability to artificial intelligences. For this, the term Explainable Artificial Intelligence (XAI) was established. Currently, the distribution of insights from XAI applications for biomedical omics data shows a wide dispersion in various scientific fields such as biology and computer science, leading to a lack of overview of the current state of the research field.*

Objective: *This research paper provides an overview of the existing XAI applications in literature between 2021 and 2022.*

Methods: *The methodology of the research paper is based on conducting a systematic mapping study. For this, three databases (Scopus, PubMed, and Web of Science) were traversed using a search string and provided a list of potential literature from 2021 to 2022. Relevant literature was then identified through abstract screening and full text analyses. Using a classification scheme, 20 relevant sources were finally classified by text analysis and pie charts and systematic maps were created based on this classified literature.*

Results: *The results are presented in form of five pie charts and two systematic maps. The models applied were model-specific and model-independent in equal proportions. Likewise, the distribution of the XAI models with respect to the parameters explainability and interpretability was 50% each. Furthermore, a clear focus of the use cases in the omics domain of genomics was visible. In this study, 7 medical use cases emerged in the analyzed literature, such as cancer detection or cancer type classification. In the interplay between AI methods and explainability approaches, a versatile combination of the two concepts was found. Here, explainability focused on the following three methods: feature relevance, transparent model, and visual explanation combined with widely used AI methods. When considering the combination of omics data and AI methods, versatile combinations were also found. In 25% of the cases, the literature dealt with DNA-sequencing combined with a variety of AI methods*

Conclusion: *This paper lays the groundwork for further exploration in the aforementioned area. It is recommended to conduct further research due to the limited amount of literature analyzed in this work.*

Keywords: *explainable artificial intelligence, omics data, systematic mapping study, explainability methods, artificial intelligence methods, genomics*

Einleitung

Problemstellung

226.337 Personen starben im Jahre 2015 in Deutschland an Krebserkrankungen, was einem Viertel (25,27%) aller Sterbefälle in Deutschland entspricht (Statistisches Bundesamt [Destatis], 2017). Laut dem Statistischen Bundesamt gelten diese bösartigen Neubildungen zu „der bedeutendsten Todesursache in den mittleren Lebensjahren“ (Destatis, 2017). Als große Chance für neue Ansätze in der Krebsforschung und Anwendungen in der Medizin gilt die Digitalisierung im Gesundheitswesen, die unter Anderem den Einzug von künstlichen Intelligenzen beispielsweise in die Krebsforschung bereits etabliert hat (Bundesministerium für Bildung und Forschung, o. D.) . Dadurch soll in Zukunft Programmen ermöglicht werden, mit Algorithmen Zusammenhänge weitaus genauer und schneller auswerten zu können als mit herkömmlichen Methoden.

Der Fortschritt von Artificial Intelligence (AI) (deutsch: Künstliche Intelligenz) hat bereits zu einem signifikanten Anstieg von medizinischen AI-Anwendungen geführt, beispielsweise in der Diagnose von Krankheiten (Zhang et al., 2022). Allerdings sind AI-Technologien einigen Herausforderungen gegenübergestellt, allem voran die Komplexität der meisten Systeme, die es schwierig macht, Einsicht in die internen Vorgänge zu erhalten (Adadi & Berrada, 2018). Diese Eigenschaft führt zu großem Misstrauen bei medizinischen Experten in der Anwendung, da sie Ihnen nicht ermöglicht zu beurteilen, wie verlässlich der Datenoutput der AI ist. Es besteht also eine Notwendigkeit zu verstehen, wie solche Systeme ihren Datenoutput generieren, besonders wenn es einen direkten Affekt auf Menschenleben hat (Goodman & Flaxman, 2017).

Um diesem Problem entgegenzuwirken, hat sich der Begriff eXplainable Artificial Intelligence (XAI) (Barredo Arrieta et al., 2020) durchgesetzt. XAI ist ein Teilgebiet der AI, das darauf abzielt, eine Reihe an Techniken zu entwickeln, die mehr erklärbare Modelle unter Beibehaltung hoher Leistungsperformance liefert (Adadi & Berrada, 2018). XAI hat in letzter Zeit immer mehr Aufmerksamkeit erregt. Die wachsende Dynamik in diesem Bereich wird in verschiedenen wissenschaftlichen Veranstaltungen reflektiert, was eine vielversprechende Forschung für den Einsatz in kritische Systeme darstellt.

Für die Akzeptanz von medizinischen AI-Anwendungen und für deren Integration in die Praxis ist XAI also von entscheidender Bedeutung (Zhang et al., 2022). Gemessen an der geringen Anzahl an Reviews über Anwendungen von XAI für biomedizinische (Omics) Daten scheint jedoch ein Überblick des Forschungsgebietes zu fehlen, was die Identifikation von Forschungslücken und neuer Ansätze erschwert. Ausschlaggebend dafür ist wohl die weite Streuung der Erkenntnisse in den verschiedensten Bereichen der Wissenschaft (Biologie, Informatik etc.).

Zielsetzung

Ziel der Seminararbeit ist es, einen Überblick über die bereits existierenden XAI-Anwendungen der Literatur aus den Jahren 2021 und 2022 zu geben. Dadurch können unter anderem analysierte Modelle in die Praxis übernommen und Vorschläge für zukünftige Forschung durch die Identifikation von Forschungslücken und neuen Ansätzen abgeleitet werden.

Aufbau der Arbeit

Um sich mit der Zielsetzung auseinander zu setzen, wurde in dieser Seminararbeit eine systematische Mapping Studie nach Petersen et al. (2008) durchgeführt. Zunächst wird der theoretische Hintergrund und Begrifflichkeiten geklärt, um darauf aufbauend die Methode der durchgeführten systematischen Mapping Studie zu beschreiben. Anschließend werden die Ergebnisse der Studie werden beschrieben und diskutiert. Hierbei wird das Research Paper mit Vorschlägen bezüglich zukünftiger Forschung abschließen.

Theoretischer Hintergund

Artificial Intelligence

AI ist ein unscharfes Konzept mit einer Vielzahl an möglichen Definitionen, abhängig davon, in welchem Kontext man sich befindet oder welche Anwendungen man betrachtet (Visvikis et al., 2019). Allgemein definieren kann man den Begriff als eine Intelligenz, die im Gegensatz zu der natürlichen Intelligenz von Menschen oder Tieren, von Maschinen generiert wird. Betrachtet man den Begriff beispielsweise im medizinischen Kontext, gilt AI als die Fähigkeit eines Systems, externe Daten beispielsweise mit Algorithmen oder durch Neuronalen Netze richtig interpretieren zu können und aus diesen Daten zu lernen. Mit den gewonnenen Erkenntnissen kann das System daraufhin bestimmte Ziele und Aufgaben mittels flexibler Anpassung erreichen.

Explainable Artificial Intelligence

Heutzutage hat AI großflächig Einsatz in kritischen Systemen gefunden, welche direkte Einflüsse auf menschliches Leben haben (z.B. im Gesundheitswesen, autonomes Fahren, Militär etc.) (Das & Rad, 2020). Aufgrund der hohen Komplexität von AI-Konzepten kann das Verhalten und die generierten Ergebnisse meist nicht erklärt und interpretiert werden, was zu einem Mangel an Vertrauen in die Ergebnisse führt. XAI ist ein Teilgebiet der AI, das ein Set an Techniken, Algorithmen und Anwendungen liefert, die Interpretierbarkeit und (für Menschen) verständliche Erklärungen von AI-Entscheidungen bietet. Hierbei lassen sich die erklärbaren Methoden in zwei Unterklassen einordnen: globale Methoden, welche die Ergebnisse für den gesamten Daten-Input erklären und lokale Methoden, die individuellen Input erklären (Souza et al., 2022).

In der Literatur wird oft eine austauschbare Verwendung der Begriffe Erklärbarkeit (engl: explainability und Interpretierbarkeit (engl.: interpretability) genutzt (Barredo Arrieta et al., 2020). In diesem Paper wird jedoch ein grundlegender Unterschied der Begriffe angenommen. Während die Interpretierbarkeit eines Modells von seinem Design selbst kommt und Transparenz bietet, wird die Erklärbarkeit eines Modells durch externe Techniken geboten (Barredo Arrieta et al., 2020).

XAI Methoden

Um die Zusammenhänge von XAI-Methoden verstehen zu können, ist in Abbildung 1 die schematische Einordnung aufgezeigt. Abbildung 1 zeigt die Unterteilung der XAI-Methoden in post-hoc Erklärbarkeitsmethoden (Post hoc Methods) und transparente Methoden (Intrinsic Methods). Typische transparente Modelle sind beispielsweise die Linear/ Logistic Regression, Decision Trees oder Bayesian Models, während erklärbare Modelle beispielsweise durch visuelle Erklärungen zusätzliche Erklärbarkeit der AI-Modell liefern.

Omics Daten

Der Ausdruck Omics bezieht sich auf eine Reihe von Forschungsgebieten in der Biologie, die alle auf den Suffix -omics enden (RD-Connect coordination team, o. D.). „Omics-Technologien messen in einer einzigen Probe alle (oder zumindest eine umfassende Zahl) molekularen Features der jeweiligen Kategorie“ (Oberbauer, 2012). Die Analyse von Omics Daten bietet dementsprechend neuartige, umfassende Ansätze vollständiger genetischer oder molekularer Profile von Menschen, was zu einem rasanten Wachstum des Omics Bereichs führt und neue Perspektiven für die Praxis und Forschung erlaubt (RD-Connect coordination team, o. D.) Befindet man sich beispielsweise im Forschungsgebiet der Genomics, untersucht man das Genom in seiner Gesamtheit, während man sich bei der Analyse von mRNA im Bereich Transcriptomics befindet (Akademie der Naturwissenschaften Schweiz [SCNAT], 2018). Die Untersuchung von Proteinen ordnet man dem Bereich Proteomics zu, während sich Metabolomics um die Stoffwechselprodukte kümmert. Von Microbiomics wird bei der Analyse der im Körper befindlichen Mikroorganismen gesprochen.

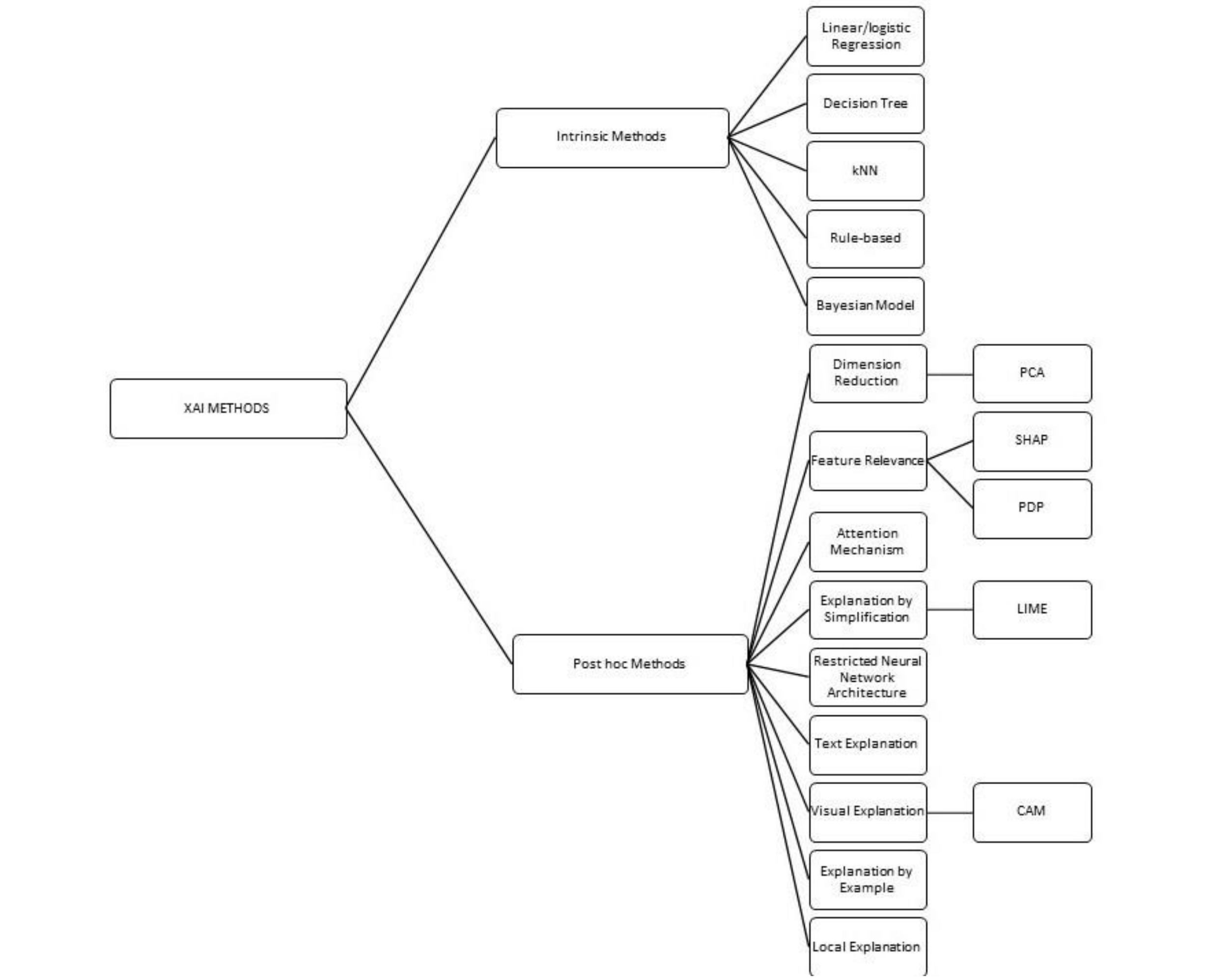

Abbildung 1: Taxonomie von XAI-Methoden Adaptiert von (Zhang et al., 2022)

Methoden

Zur Auseinandersetzung mit der Problemstellung und Verfolgung der Zielsetzung wird in dieser Seminararbeit eine systematische Mapping Studie nach Peterson et al. (2008) durchgeführt.

Das Konzept der systematischen Mapping Studie von Peterson et al. (2008) basiert auf der Identifizierung und Kategorisierung existierender Literatur und dem Analysieren dieser Literatur mit Hilfe von systematischen Maps. Abbildung 2 illustriert den Ablauf der anzustrebenden Teilziele, die schlussendlich zum Bau dieser systematischen Maps führen. Diese Maps stellen eine visuelle Zusammenfassung der kategorisierten Literatur dar und bieten hierbei einen grobkörnigen Überblick über die Erschlossenheit eines Forschungsgebietes, der mit wenig Aufwand verbunden ist im Vergleich zu klassischen Literaturrecherchen. Daraus ableiten lassen sich ebenso Forschungslücken wie auch neue Ansätze, die bisher wenig oder unerforscht sind (Petersen et al., 2008).

Hauptziel

Als Hauptziel der Studie gilt die Beantwortung der Forschungsfrage, welche gleichzeitig die Rahmenbedingungen der Literaturrecherche setzt und hier wie folgt definiert ist: Welche XAI-Methoden werden aktuell laut der Literatur der Jahre 2021 und 2022 für Omics Daten verwendet? Angelehnt an diese

Studie ist die vorangegangene Forschung von Toussaint et al. (2023), welche eine systematische Mapping Studie über den Einsatz von XAI zur Verarbeitung von Omics Daten bis Mai 2023 zum Gegenstand hatten.

Abbildung 2: Systematischer Mapping Prozess Adaptiert von (Petersen et al., 2008)

Teilziele

Sammeln Potenzieller Literatur

Datenbanken: Zur Ermittlung potenzieller Literatur wurde mit Hilfe eines Such-Strings verschiedene Datenbanken durchsucht. Hierbei beschränkte sich die Suche auf drei wissenschaftliche Datenbanken: Scopus, PubMed und Web of Science. Während Scopus und Web of Science Datenbanken mit bibliographischen Angaben zu wissenschaftlicher Literatur sind ((Clarivate, 2022), (Elsevier, o. D.)), ergänzt PubMed das Literaturangebot durch Referenzen im gesamten biomedizinischen Bereich (National Library of Medicine, o. D.).

Such-String: Die Datenbanken wurden mithilfe eines Such-Strings durchlaufen, wobei man sich auf den Titel, Abstract und die Schlüsselwörter der Literatur der Jahre 2021 und 2022 fokussierte. Der Aufbau des Strings ist durch drei Teilbereiche gekennzeichnet, die mit einer AND-Verknüpfung miteinander verbunden sind. Grundlegend wurde mit Hilfe des Such-Strings nach Literatur gesucht, die sich von erklärbaren und/oder interpretierbare Anwendungen von AI verknüpft mit dem Themengebiet von Omics Daten, beziehungsweise der Biomedizin, handeln. Der Such-String lautet:

```
(explainab* OR interpretab*) AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND (*omic* OR biomedical OR "life science" OR genom* OR genetic* OR metagenom* OR neurogenom* OR pangenom* OR epigenom* OR lipidom* OR proteom* OR glycom* OR foodom* OR transcriptom* OR metabolom* OR nutrigenetic* OR nutrigenomic* OR pharmacogenomic* OR pharmacomicrobiomic* OR toxicogenomic*)
```

Ergebnisse: Insgesamt ergab die Suche 2084 Ergebnisse. Zum Speichern und Verwalten dieser Ergebnisse wurden jeweils die wichtigsten Informationen in eine Microsoft Excel-Tabelle übernommen. Das Resultat dieses ersten Teilergebnisses stellte eine Liste von potenzieller Literatur für die Beantwortung der Forschungsfrage dar.

Identifikation Relevanter Literatur

Abstract Screening: Nachdem zunächst Duplikate markiert und diese für die weitere Bearbeitung ausgeschlossen wurden (Anzahl= 846), beschränkte sich die Auswertung mittels Abstract Screening auf die ersten 500 Quellen der Liste. Das Vorgehen des Screenings beinhaltete das Lesen der Abstracts und das Einordnen der Literatur nach Relevanz in die Kategorien `ja` (= relevant), `nein` (= unrelevant) und `maybe` (= Abstract unzureichend). Relevant waren 127 Quellen.

Volltextanalyse: Aufbauend auf das Abstract Screening war eine weitere Betrachtung der Literatur von 39 Quellen notwendig, die ungenügend Informationen im Abstract lieferten (Kategorie `maybe`). Durch die Analyse dieser 39 Quellen konnte durch das Lesen der Volltexte weitere 13 Quellen als relevant eingestuft werden.

Ergebnisse: Das Ergebnis der Analysen lieferte eine Liste von relevanter Literatur im Umfang von 140 Quellen.

Bau von Systematischen Maps

Klassifizierungsschema: Um systematischen Maps aus der relevanten Literatur erstellen zu können, wurden hierfür 20 relevante Quellen zufällig ausgewählt und in ein Klassifizierungsschema anhand einer Textanalyse eingeordnet. Das Schema wurde von Toussaint et al. (2023) adaptiert und angewendet. Folgende Fragestellungen wurden durch das Klassifizierungsschema betrachtet:

1. In wieweit konzentriert sich die Literatur auf Explainability/ XAI? (Focus on Explainability)
2. Stellt die Literatur einen neuen XAI-Modellansatz vor oder wird ein bestehendes Modell verwendet? (Model Approach)
3. Verwendet die Literatur ein interpretierbares Modell oder verwendet sie (post-hoc) Erklärbarkeitsmethoden zusätzlich zur grundlegenden AI-Methode? (XAI Modell)
4. Was ist die zugrunde liegende AI-Methode? (AI Method)
5. Was ist die Aufgabe des Maschinellen Lernens (ML)? (ML Task)
6. Welche spezifische Erklärungsmethode wird verwendet? (Explainability Method)
7. Ist die beschriebene Methode modellspezifisch oder modellunabhängig? (XAI Generalizability)
8. Was ist der medizinische Anwendungsfall? / Was ist das Ziel diese Literatur im Hinblick auf die medizinische Analyse? (Medical Use Case)
9. Welches ist das medizinische Fachgebiet, das dem medizinischen Anwendungsfall am nächsten kommt? (Medical Field)
10. Welches ist der allgemeine Omics Bereich des medizinischen Anwendungsfalls? (Omics Field)
11. Welche spezifischen Omics Daten werden verwendet? / Was verwendet diese Literatur als Input für ihr Modell? (Omics Data)
12. Was ist der Ansatz dieser Arbeit? (Research Approach)
13. Wie sieht die Methode des Papiers aus? (Research Method)

Systematische Maps: Im letzten Schritt der Studie wurden anhand der klassifizierten Literatur systematische Maps sowie Kreisdiagramme erstellt, welche im folgenden Kapitel beschrieben werden.

Ergebnisse

Kreisdiagramme

Die Ergebnisse der Studie lassen sich neben den systematischen Maps auf vielzählige Arten und Weisen beschreiben. Um zunächst einzelne Facetten des Klassifizierungsschemas aufzuzeigen, wurden Kreisdiagramme erstellt und im folgenden Abschnitt beschrieben.

Model Approach: Abbildung 3 zeigt, dass überwiegend neue Modelle angewendet wurden (80%) und lediglich in 20% der Fälle existierende Modelle eine weitere Betrachtung fanden. Ein Beispiel eines neuen Modells ist DLearnMS (Iravani & Conrad, 2022), ein neuartiger Ansatz für die Erkennung von Biomarkern.

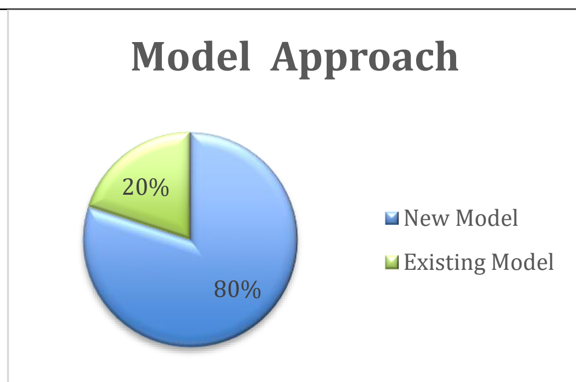

Abbildung 3: Modellansatz

XAI Generalizability: Betrachtet man die Generalisierbarkeit der XAI in Abbildung 4, ist leicht zu erkennen, dass die angewendeten Methoden in der untersuchten Literatur zu 50% modellunabhängig waren und zu 50% modellspezifisch. Angelopoulos et al. (2022) (Seite 6) untersuchte beispielsweise eine XAI, welche durch die Modellunabhängigkeit dieser Methode auf verschiedene Krankheiten angewendet werden kann.

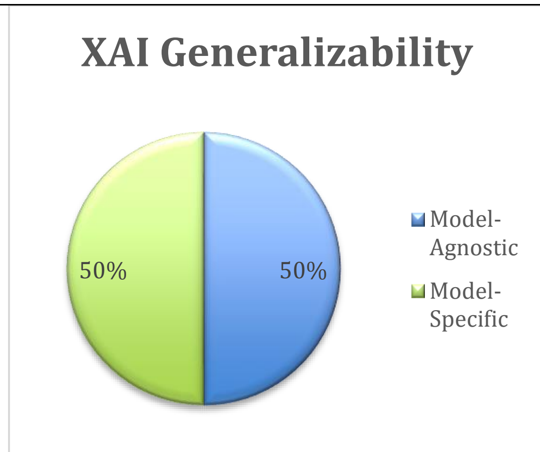

Abbildung 4: XAI Generalisierbarkeit

XAI Model: Untersucht man die Aufteilung der XAI-Modelle in Explainability und Interpretability, stellt man fest, dass in dieser Studie die Verteilung bei genau 50% für beide Parameter lag (Abbildung 5). Ein Beispiel für ein interpretierbares Modell liefert beispielgebend Wang et al. (2021), während das Konzept von Gupta et al. (2021) im Gegenzug ein erklärbares Modell aufzeigt.

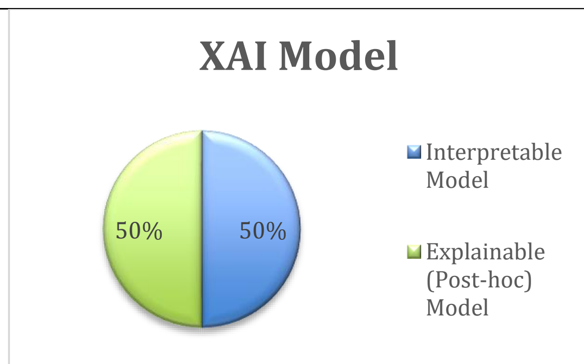

Abbildung 5: XAI Modell

Omics Field: Des Weiteren ist eine deutliche Ausprägung der gefundenen medizinischen Anwendungsfälle im allgemeinen Omics Bereich Genomik sichtbar, was in Abbildung 6 mit 60% deutlich ersichtlich ist. Weitere, in dieser Studie vertretene Omics Felder sind die Bereiche Proteomics (15%), Transcriptomics (10%) sowie Multiomics, Cellomics und Microbiomics mit jeweils 5%. Alle weiteren Omics Felder wurden in dieser Studie nicht in der Literatur identifiziert.

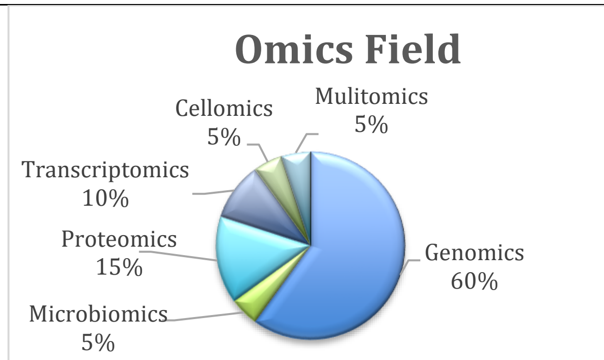

Abbildung 6: Omics Felder

Medical Use Case**:** Anlehnend an die analysierten Omics Bereiche in Abbildung 6 sind in Abbildung 7 die medizinischen Anwendungsfälle der relevanten Literatur visualisiert. In verschiedenen Ausprägungen hat die Literatur sich mit dem Thema Krebs auseinandergesetzt, angefangen von Krebserkennung (10%) und Krebsartklassifizierung (10%) bis hin zur Berechnung der Überlebenschancen (15%) und Arzneimittelwirkungen (15%) (mitunter bei Krebs). Mit 15% Anteil stellt das DNA-Mapping einen weiteren großen Bereich der Anwendungsfälle in der Medizin dar und beschäftigt sich mit dem linearen Anordnen der Gene im Genom eines Organismus. Die restlichen in Abbildung 7 ersichtlichen Anwendungsfälle sind Proteinstrukturvorhersagen (5%), Vermeidung von Mutationen durch Nebeneffekte (5%), Tumorzellenerkennung (5%), Sequenzerfassung von mRNA-Einzelzellen (10%), Analysen von Darmbakterien (5%) und Biomarker-Identifikation (5%). Alle weiteren möglichen Anwendungsfälle des Klassifizierungsschemas kamen in den 20 analysierten Quellen nicht vor.

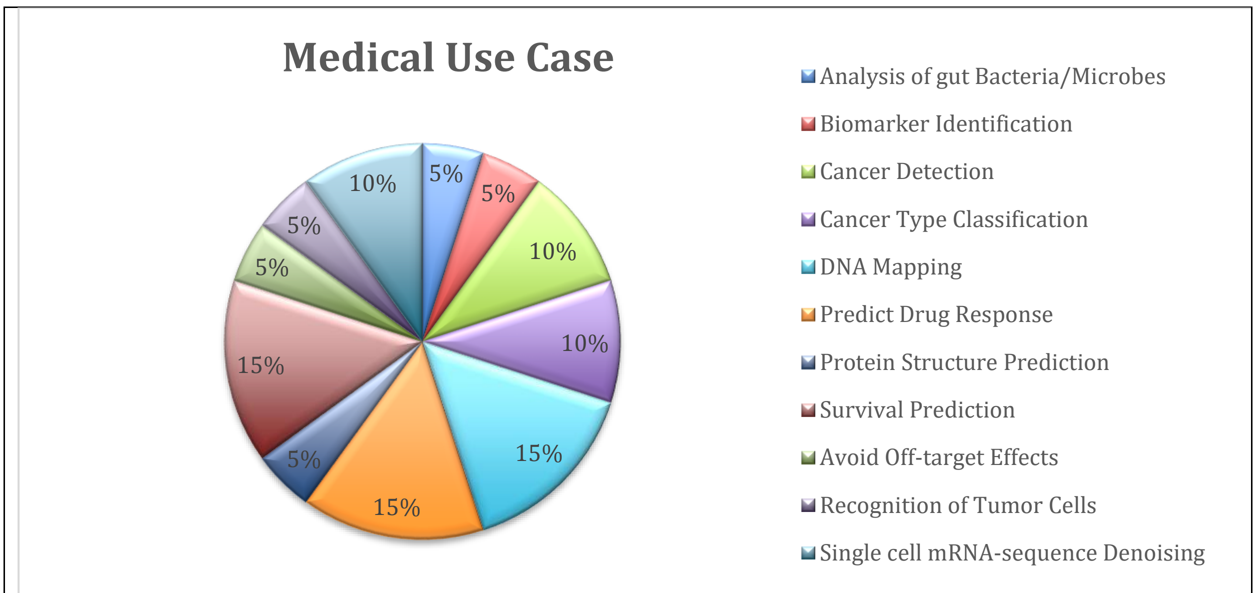

Abbildung 7: Medizinische Anwendungsfälle

Systematische Maps

Um die Forschungsfrage schlussendlich beantworten zu können, wurden anhand der gewonnenen Ergebnisse zwei systematische Maps gebaut, die im folgenden Abschnitt näher betrachtet werden.

Explainability Method vs. AI Method

Beginnend mit der Auswertung von Abbildung 8 wird das Zusammenspiel der AI-Methoden und der Erklärbarkeit der Methoden beschrieben. Wichtig ist, dass bei den Erklärbarkeitsansätzen nur drei der acht Ausprägungen des Schemas in der analysierten Literatur aufgetaucht sind und bei den AI-Methoden ebenfalls einige nicht vorkamen. Ebenfalls auffällig ist, dass keine große Ansammlung im Schaubild an einem Punkt existiert und maximal 10% der einzelnen Kombinationen erreicht wurde.

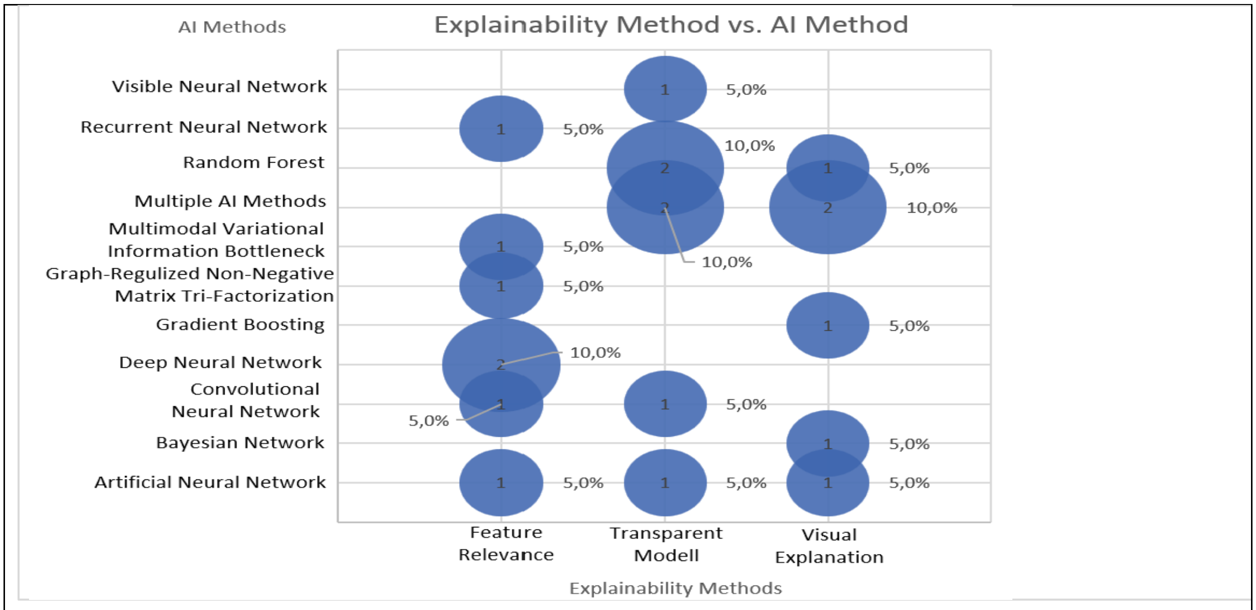

Abbildung 8: Kombinationen von Explainability Methods und AI Methods

Artificial Neural Network (ANN): Die AI-Methode ANN ist ein oft genutztes Konzept in der Literatur und wurde in dieser Studie jeweils einmal in der Kombination mit Feature Relevance für Krebsdiagnosen (Bourgeais et al., 2022), als Transparent Model in der Analyse von RNA-Sequencing (Seninge et al., 2021) und mit Visual Explanation für die Analyse von RNA-Sequencing (Walbech et al., 2021) genutzt. Insgesamt betrug das Vorkommen dieser AI-Methode also 15%.

Bayesian Network: Eher selten (5%) kam das Bayesian Network-Konzept zu tragen und wurde einmal mit der Visual Explanation kombiniert. Hierbei konnte mithilfe dieser erklärbaren Methode ein Bayes'sches Netzwerk genutzt werden, um die Krebssorte von Patienten präzise zu bestimmen (Bourgeais et al., 2022).

Convolutional Neural Network (CNN): In der Kategorie des CNN wurden zu jeweils 5% die Ergebnisse durch die Ergänzung mittels Feature Relevance oder durch die Transparenz des Modells selber erklärt, was einerseits eine Anwendung zur Klassifizierung von Krebsarten ermöglichte (Li et al., 2022), andererseits einer neuartigen Erkennung von Biomarkern (Iravani & Conrad, 2022) diente.

Deep Neural Network (DNN): Als einziges Vorkommen einer Kombination mit einem DNN wurde die Erklärbarkeitsmethode der Feature Relevance beschrieben und entspricht mit 2 Anwendungsfällen 10% des Vorkommens aller Kombinationen. Hierbei zum Beispiel beschrieb Feng et al. (2021) in deren Literatur eine Möglichkeit der Krebserkennung und die Vorhersage der Überlebenschancen durch ein DNN namens DeepSigSurvNet.

Gradient Boosting, Graph-Regularized Non-Negative Matrix Tri-Factorization (GNMTF) und Multimodal Variational Information Bottleneck (MVIB): Alle drei AI-Methoden wurden jeweils einmal in dieser Studie thematisiert (jeweils 5%). Kombiniert wurde sie im ersten Fall mit Visual Explanation (Gupta et al., 2021) und Feature Relevance in den beiden anderen Fällen ((Grazioli et al., 2022), (Zambrana et al., 2021)).

Multiple A Methods: Die größte Häufung (20%) einer Ausprägung findet sich in der Anwendung von mehreren AI-Methoden innerhalb eines Forschungsprojekts und wurde in zwei Fällen als transparentes Modell gestaltet und in weiteren zwei Fällen mittels Visuell Explanation erklärt, was beispielsweise in der

Literatur von Gundogdu et al. (2022) genutzt wurde, um Tumorzellen erkennen zu können und visuell zu erklären.

Random Forest: 15% der analysierten Literatur basierte auf Random Forest-Modellen. Hierbei wurde diese zweimal durch die Transparenz des Modells selber und einmal visuell erklärbar gestaltet. Dabei wurde bei der visuellen Erklärung auf eine Methode namens SHAP values (Souza et al., 2022) zurückgegriffen.

Recurrent Neural Network (RNN) und Visible Neural Networks (VNN): Die letzten beiden AI-Methoden, beides Ausprägungen neuronaler Netzwerke und beschrieben von Lin und Lichtarge (2021) und (Xiao et al., 2021), griffen zur Erklärung der Modelle auf die Methode der Feature Relevance und des Transparent Models zurück (jeweils 5%).

Omics Data vs. AI Method

In Abbildung 9 wird zuletzt der Zusammenhang der AI-Methoden mit den verwendeten Omics Daten dargestellt.

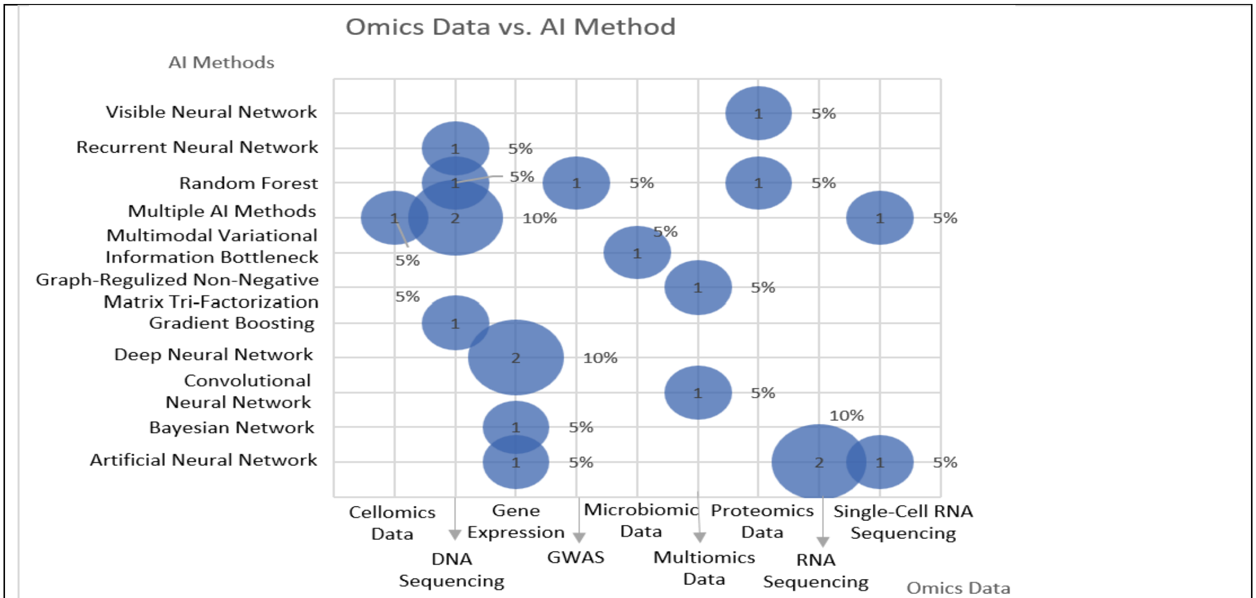

Abbildung 9: Kombinationen von AI Methoden und Omics Daten

Cellomics Data: Cellomics Data wurde lediglich einmal (5%) als Input verwendet und im medizinischen Bereich der Radiologie zur Erkennung von Tumorzellen eingesetzt (Chen et al., 2022). Hierbei wurden die Daten mit mehreren AI-Methoden vereint um die Daten zu analysieren.

DNA-Sequencing: Insgesamt war der Dateninput in 25% der Fällen DNA-Sequenzen, kombiniert mit einer Vielzahl an Kombination der AI-Methoden. Beispielsweise wurde mithilfe eines Gradient Boosting Verfahrens namens LightGBM die Vorhersage der Konformation der DNA untersucht (Gupta et al., 2021), in den anderen Fällen wurden DNA-Sequenzen jeweils zu 5% mit der Random Forest Methode verarbeitet (Fallerini et al., 2022) sowie mit einem RNN (Xiao et al., 2021). Zweimal kamen mehrere AI Methoden zum Einsatz.

Gene Expression: Ein weiterer, vermehrt genutzter Input waren Gene Expressions in insgesamt 20% der Fälle. Die Kombination mit einem ANN wurde einmal identifiziert (5%) (Bourgeais et al., 2022) und ein weiteres mit einem Bayesian Network (5%). Die größte Häufung (10%) tauchte in Kombination mit DNN auf ((Feng et al., 2021), (Wang et al., 2021)).

GWAS: GWAS (Vorkommen = 5%) ist eine genomweite Assoziationsstudie, welche von Fallerini et al. (2022) genutzt wurde um den Schweregrad von COVID-19 Erkrankungen vorherzusagen, indem als Dateninput Exome eingelesen und diese mittels einer Random Forest-Methode analysiert wurden (Fallerini et al., 2022).

Microbiomic Data: Lediglich 5% behandelte die Verwendung von Microbiomic Data, welche mithilfe von MVIB ausgewertet wurden.

Multiomics Data: CNN und GNMTF sind zwei AI-Methoden, die jeweils einmal gefunden wurden und als Daten Input Multiomics verwendeten.

Proteomic Data: Der Fall der Verwendung von Proteomic Data wurde zweimal identifiziert, jeweils einmal kombiniert mit Random Forest und VNN.

RNA-Sequencing und Single-Cell RN- Sequencing: Beide Kategorien zusammen hatten ein Aufkommen von 20%. RNA-Sequenzen wurden zweimal mithilfe von ANN zur Vorhersage von Proteinstrukturen (Souza et al., 2022) sowie zur Vorhersage der Reaktionen auf Medikamenteneinsatz (Lin & Lichtarge, 2021).

Diskussion

Wesentliche Erkentnisse und Forschungslücken

Basierend auf den Ergebnissen dieser Literaturrecherche wird XAI vor allem im Bereich Onkologie (Lehre von Geschwulstkrankheiten, vorangehend Krebs) geforscht. Dies wurde sowohl durch das Abstract Screening deutlich als auch bei der Auswertung der 20 relevanten Quellen. Hierbei wird vorzugsweise die Vorhersage der Krankheit an sich sowie das Einordnen von Patientengruppen in Subgruppen erforscht, was auf lange Sicht eine personalisierte Krebsmedizin mit zugeschnittener Therapie und passgenauen Medikamenten ermöglicht (Bundesministerium für Bildung und Forschung, o. D.).

Ein weiterer Themenschwerpunkt ist die Vorhersage der Reaktion von erkrankten Patienten auf Medikamente, was vor allem hohe Relevanz durch das COVID-19 Virus erfuhr. Da gerade zu Beginn der Pandemie ein Mangel an biomedizinischen Trainingsdaten zum Anlernen der XAIs herrschte, konnten künstliche Intelligenzen im Bereich der Omics Daten noch nicht wirklich helfen (Naudé, 2020).

Die Studie zeigt ebenfalls den vermehrten Einsatz von neuen XAI-Methoden für Omics Daten. In nur wenigen Fällen werden bestehende Methoden unverändert nochmals behandelt. Daraus lässt sich schließen, dass das Forschungsgebiet XAI für Omics Daten relativ neu ist und noch viele unerforschte Bereiche hat, was durch die weite Streuung der Ergebnisse in den systematischen Maps gestützt wird. Hinzu kommt die Aufnahme von drei AI-Methoden in das Klassifizierungsschema, was auf spezielle und wenig angewendete Methoden hinweist.

Im Bereich der Explainability Methoden ist ein deutlicher Fokus auf drei Methoden erkennbar: Feature Relevance, Transparent Model und Visual Explanation. Hierbei scheint die Methode Feature Relevance oft im Einsatz zu sein, die mit verschiedensten AI-Methoden in der Literatur bereits kombiniert wurde.

Als letzte wesentliche Erkenntnis ist festzuhalten, dass in 50% der Fälle die vorgestellte Methode auf andere Methoden angewendet werden kann. Dies beinhaltet viel Potenzial für weitere Forschung ohne enormen Aufwand, zeigt aber auf der anderen Seite auch, dass in jedem zweiten Fall eine spezielle Lösungsmethode erforscht wurde und/ oder gefordert wird.

Forschungslücken:

1. AI Method - Support Vector Machine: Support Vector Machines (SVM) ist eine der effizientesten ML-Algorithmen (Karamizadeh et al., 2014). Der Algorithmus wird meisten für Mustererkennung verwendet und wäre daher ein guter Forschungsansatz für biomedizinische Daten, da in der Medizin viele Anwendungsbereiche per Musterkennung erfolgen. Da eine SVM nicht transparent ist, müsste sie hierfür mit einer post-hoc Explainability Methode kombiniert werden (beispielsweise Visual Explanation).
2. Explainable Method - Simplification: Die Erklärbarkeitsmethode Simplifikation wurde in dieser Seminararbeit in keiner Literatur identifiziert. Die Erklärung durch eine Simplifikation kann beispielsweise durch eine Methode namens LIME vollzogen werden (Zhang et al., 2022). LIME bietet lokale Erklärungen anstatt globalen (Dieber & Kirrane, 2020). Dies bedeutet, dass die Methode zwar keine generelle Erklärung des Verhaltens der Modelle liefert, jedoch erklärt wird, wie und warum eine spezifische Beobachtung kategorisiert wird. Diese Eigenschaft würde speziell in der Analyse von Omics Daten vorteilhaft sein. Außerdem kann das Modell auf verschiedenste Arten von Dateninput angewendet werden und wäre somit vielseitig einsetzbar.

3. Multiomics Daten: Ein weiterer, logisch erschließbarer Forschungsansatz ist die vermehrte Verwendung von Multiomics Data (Datensatz besteht aus mehreren Omics Feldern wie Proteomics, Genomics, Transcriptomics, etc.) in Kombination mit mehreren AI-Methoden. Die Verwendung von mehreren AI-Methoden zur Analyse von Multiomics Data innerhalb eines Systems ist einerseits sinnvoll, da dies am meisten in der Literatur identifiziert wurde und dementsprechend ein bekanntes Feld ist. Andererseits kann durch den Dateninput aus verschiedenster Omics Felder die AI-Methoden gewählt werden, die bestmöglich die jeweiligen Daten verarbeiten kann. Die Ausweitung der Forschung auf Multiomics Data würde weitere Erkenntnisse in vielen Bereichen der Biomedizin liefern, da hier nicht nur ein Datentyp betrachtet wird.
4. Anwendungsgebiet COVID-19: Die Auswirkungen der Pandemie sind aktuell zwar überwiegend kontrollierbar, dennoch leiden viele Menschen unter gesundheitlichen Langzeitfolgen durch eine Erkrankung an COVID-19 (Bundeszentrale für gesundheitliche Aufklärung, 2022). Der Ausbau der Forschung von XAI in diesem Bereich könnte zum einen tausenden von Menschen im Umgang von Spätfolgen helfen, zum anderen würde es einen Ansatz bieten, erneute Zusammenbrüche sozialer Strukturen durch Lockdowns zu vermeiden. Dies wird unterstützt durch die Tatsache, dass einige Quellen beim Analysieren in den Themenbereich des COVID-19 Virus fielen (im Abstract Screening).

Auswirkungen auf Forschung und Praxis

Die Seminararbeit liefert wertvolle Einblicke in Anwendungen von XAI-Methoden für Omics Daten und bietet der Forschung einen Überblick des aktuellen Forschungsstandes. Somit können bereits gewonnene Erkenntnisse aus der Forschung (erforschte Modelle) auf weitere medizinische Bereiche ausgeweitet und weiterentwickelt werden. Dadurch besteht die Möglichkeit, schnelle und effiziente Forschung zu betreiben. Außerdem lassen sich aus dieser Studie auch Ansätze für zukünftige Forschung ableiten, die basierend auf nichtexistierender Literatur entstanden sind. Betrachtet man die Auswirkungen auf die Praxis, so besteht die Möglichkeit, XAI-Konzepte in die Praxis umzusetzen. Durch den Einzug dieser intelligenten Systeme in die Praxis könnten einerseits medizinische Fortschritte erreicht werden, andererseits würden Anwendungsfälle der erforschten Modelle in der Praxis Stärken und Schwächen der Modelle aufzeigen. Diese Erkenntnisse würden wiederum der Forschung zu Gute kommen und dieser neuen Richtungen weisen.

Grenzen und Zukünftige Forschung

Die systematische Mapping Studie dieser Seminararbeit wurde mit einigen Beschränkungen durchgeführt, was ohne Zweifel zu einer Beeinflussung der Ergebnisse geführt hat. Die größte Einschränkung gilt hierbei der beschränkten Anzahl an analysierter Literatur beim Abstract Screening auf 500 Quellen, angefangen im zweiten Teilziel beim Identifizieren relevanter Literatur, bis hin zur Beschränkung auf 20 Quellen bei der Anwendung des Klassifizierungsschemas. Auch, wenn die Auswertung der Ergebnisse dieser Studie die Forschungsfrage beantwortet, repräsentiert die Antwort dennoch nicht die gesamte existierende Literatur und kann dadurch durch verzerrte Ergebnisse liefern.

Ergänzend kommt die nicht gänzlich objektive Einschätzung der Literatur und Anwendung des Klassifizierungsschemas. Hinzu kommt auch die bereits erwähnte Uneindeutigkeit der Begriffe Explainability und Interpretability, die in der Literatur oft nicht unterschieden werden und das Klassifizieren dieser Literatur teilweise schwierig gestaltete.

Forschende können diese Arbeit durch die weitere Analyse der restlichen 738 Quellen, die bisher nicht analysiert wurden, unterstützen und darauf aufbauen. Somit würden schlussendlich mehr klassifizierte Literatur den Prozess der systematischen Mapping Studie nach Petersen et al. (2008) durchlaufen und den Maps zu höherer Präzision verhelfen. Hierbei könnten neue Erkenntnisse erlangt werden und Themenschwerpunkte deutlicher sichtbar werden. Zusätzlich könnten dadurch weitere spezifische Anwendungen gefunden werden, die seltener auftreten, aber dennoch Potenzial aufweisen.

Fazit

Diese Seminararbeit beschäftigt sich mit der Fragestellung, welche XAI-Anwendungen für biomedizinische Daten aus existierender Literatur der Jahre 2021 und 2022 bereits bekannt ist. Die Auseinandersetzung erfolgte mit Hilfe einer systematischen Mapping Studie nach Petersen et al. (2008), indem zunächst eine

Liste potenzieller Literatur erstellt und darauf aufbauen eine Liste der relevanten Literatur identifiziert wurde. Durch die Klassifizierung dieser relevanten Literatur konnten schlussendlich systematische Maps gebaut und ausgewertet werden. Die Studie zeigt eine vermehrte Forschung in der Onkologie, was durch Klassifizierung, Mustererkennung und Vorhersagen von Krankheiten und Verläufen gekennzeichnet ist. Also Dateninput werden überwiegend DNA-Sequenzen eingesetzt. Die meist genutzten AI-Methoden sind der Einsatz von mehreren AI-Methoden innerhalb eines Konzeptes, die dementsprechend mithilfe von verschiedensten Erklärbarkeitsmethoden zusätzliche Erklärbarkeit erlangen. Der Fokus der Explainability Methods liegt eindeutig auf Feature Relevance und Visual Explanation für intransparente Modelle, gleichzeitig wurden aber auch einige AI-Methoden genutzt, deren Design direkt interpretierbar gestaltet war.

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Investigating the Use of Avatars in mHealth Apps

Digital Health, Winter Term 22/23

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Abstract

Background: *Mobile health apps have become increasingly important, particularly due to the Covid-19 pandemic and the growing digitalization of various aspects of our lives. To encourage app usage, developers often use gamification techniques, with avatars being one potential game design element. However, the effectiveness of avatars has not been extensively studied. Research on avatars in marketing contexts has yielded mixed results, but there is a lack of investigation into their use in mHealth apps. Therefore, further research is needed to identify how avatars are used in mHealth apps and what design features are employed.*

Objective: *This seminar paper aims to address the research question of "How are avatars currently used in gamified health apps?" (RQ1) and "What are the specific features of avatars found in the identified apps?" (RQ2).*

Methods: *In order to answer the research question of this paper, a quantitative evaluation of mHealth apps was conducted, resulting in the identification of N=17 apps employing avatars. Within the identified apps, avatars are systematically examined in order to develop a typology based on the acquired insights.*

Results: *The app analysis revealed that avatars were predominantly found in the categories of 'sports & fitness' and 'mental health & wellbeing' apps, indicating a potential need for additional user motivation in these categories. The interaction with avatars in mHealth apps mainly involved touch gestures, contrasting with previous findings in the marketing context where speech and text interactions were more common. Additionally, there was a trend towards three-dimensional and dynamic avatars, likely influenced by advancements in device capabilities and animation techniques.*

Conclusion: *This study has established a groundwork for future research on avatars in gamified health apps. By refining the definition of avatars and developing a typology, this work provides a solid foundation for further exploration in the field of mHealth apps Initial patterns and trends in avatar usage have been identified, but additional research is necessary to validate these trends and understand their potential advantages.*

Keywords: mHealth, Mobile Health Apps, Avatars, Health Apps, Avatar Typology, App Review, Categorizing Avatars, Avatar Properties

Introduction

Factors, including demographic changes, pandemics, and the increasing prevalence of diseases such as obesity and mental health issues contribute to a growing demand for health services (Finkelstein et al., 2012; Ogden et al., 2014; Santomauro et al., 2021). This, in turn, fuels the demand for digital health services, particularly mHealth apps. These apps cater to various aspects of health and wellness, leveraging the convenience and ubiquity of smartphones (Smith, 2017). Consequently, the app stores are witnessing a proliferation of mHealth apps (Kao & Liebovitz, 2017). In fact, estimates suggest that the health app segment is poised for significant annual revenue growth of 12.4% in the coming years (Statista, 2023). Overall, the convergence of these influences underscores the increasing importance of the healthcare sector and the pivotal role that digital health services like mHealth apps play in addressing the evolving needs of individuals seeking accessible and personalized healthcare solutions. When developing health apps, one of the key considerations is how to effectively meet the needs of users and encourage them to use the app regularly (Vaghefi & Tulu, 2019). Recently, gamification has become a popular and promising tool to enhance users' engagement with mHealth apps (Alsawaier, 2018; Johnson et al., 2016). Generally gamification refers to "the use of game design elements in non-game contexts" (Deterding et al., 2011). Alongside features like rankings and badges, avatars are a prevalent gamification element (Hunter & Werbach, 2012; Tóth & Tóvölgyi, 2016). Avatars hold a special appeal because they allow users to identify with a virtual character and establish a unique connection. This, in turn, increases users' motivation to use the health app consistently and continuously (Birk et al., 2016; Sailer et al., 2017).

However, a significant challenge arises when it comes to the detailed research on avatars. While there are mixed results regarding the effectiveness of avatars in various contexts, such as marketing, there is a lack of research specifically focused on avatars in mHealth apps (Miao et al., 2022). While initial taxonomies and characterizations exist regarding the use of avatars as a gamification element in marketing, no studies have specifically delved into the context-specific features of avatars in health apps (Miao et al., 2022). Therefore, it is important to note that findings regarding the design of avatars from the field of marketing cannot simply be transferred to the context of mHealth apps, since the application context matters for the effect of a single game design element (Klock et al., 2020). This is due to the fact that contexts differ, such as the goals of the engagement or even the medium, for example, whether it is an avatar featured in an app or on a website (Schrader, 2019). Research found, for example, that users had different preferences for avatars depending on whether they were avatars designed for blogging, dating, or gaming (Vasalou & Joinson, 2009). Thus, a challenge arises in determining the context-specific characteristics and design features of an avatar that lead to a desirable user experience and subsequently motivate users to engage with the app (Klock et al., 2020; Miao et al., 2022). Currently, this aspect remains unclear in the realm of mHealth apps, necessitating further research and exploration. Understanding the impact of avatar design on user motivation and experience is crucial for developers seeking to create compelling health apps. By uncovering avatar attributes and design elements, developers can effectively enhance user engagement, encourage long-term app usage, and ultimately promote positive health outcomes. The prevailing knowledge gap in the field of mHealth apps leads to the research questions for this study: "How are avatars currently used in gamified health apps?" (RQ1) and "What are the specific features exhibited by avatars in the identified apps?" (RQ2). To shed light on these research questions and provide insights into the current usage and characteristics of avatars in mHealth apps, this paper will embark on a three-fold approach. Firstly, the paper will establish a clear definition of avatars in the context of mHealth apps. This initial step is crucial to ensure a standardized understanding of what constitutes an avatar within this particular domain. Secondly, the paper will compile a comprehensive list of health apps that incorporate avatars, based on the established definition. Moving forward, the subsequent section will involve a systematic classification of the collected avatar data obtained through an exploratory app review. This classification process will enable a more in-depth analysis of how avatars are employed in mHealth apps, allowing for the identification of patterns and trends. By undertaking these three steps, valuable insights can be derived regarding the current utilization and characteristics of avatars in the realm of mHealth apps.

Background

Gamification and mHealth

In order to have a common and concise understanding of fundamental concepts, relevant definitions for the subsequent app review are first identified in the existing literature.

The term mobile health app (mHealth) was first mentioned in literature twenty years ago, however, there is still no standardized definition of mHealth. The emerging field of technology and healthcare is in a constant process of development, thus making an adequate definition challenging (Cameron et al., 2017). For this paper, mHealth is defined as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices" (Who & others, 2011), whereby the primary focus is placed on apps for mobile phones.

Gamification is a practice that has been of great interest to researchers and developers over the past few years. The term originated in 2008 and was still called 'gameification' at the time, however, the 'e' was later dropped, giving rise to the word gamification, which is the common designation today (Fitz-Walter, 2018). Due to the success of the local search-and-discovery mobile app Foursquare (Foursquare Labs, 2022), which uses gamification mechanisms, the term gained popularity in 2009. Nowadays, gamification is used in various areas such as health, education, marketing, and sales (Schöbel & Söllner, 2016). While there are many different but analogous definitions of gamification in the literature, the most widely accepted one is the one that refers to gamification as "the use of game design elements in non-game contexts" (Deterding et al., 2011). More precisely, gamification is defined as "game-based mechanics, aesthetics, and game thinking to engage people, motivate action, promote learning, and solve problems" (Kapp, 2012). The motivation for adopting gamification varies depending on the domain in which it is being employed. In general, however, it can be said that the adoption of gamification is used to support user engagement and promote positive patterns of service use (Hamari et al., 2014). The question of how this can be achieved makes it worthwhile to take a look at games, i.e., the domain in which gamification and its mechanisms are rooted. Games enable different types of experiences; they can, for example, put an individual into a kind of flow state, creating a sense of autonomy or mastery (Ryan et al., 2006). It is precisely these experiences that often lead to games being perceived as intrinsically motivating. This refers to the fact that potential users interact with the game merely for the sake of using it. Intrinsic motivation thus comes from within a person, meaning that a person finds an activity useful, interesting, or challenging without the involvement of external factors such as rewards (Legault, 2020). Gamification tries to exploit these positive effects and mechanisms of games and apply them in a non-game context.

This approach can be described in terms of a three-stage process consisting of affordances, psychological outcomes, and motivational outcomes (Koivisto & Hamari, 2019). Affordances refer to mechanics and elements used in games as well as in gamification that contribute to the fulfillment of users' psychological requirements. Psychological outcomes are psychological experiences, such as the feeling of autonomy or enjoyment, which are promoted by such elements and mechanics (Koivisto & Hamari, 2019). These in turn have an influence on motivational outcomes, i.e., the behaviors that are promoted by a gamified system, such as a more continuous and long-term exercise activity through the use of a pedometer app (Deterding et al., 2011; Koivisto & Hamari, 2019). According to this framework, different game elements and mechanics also lead to different psychological and thus motivational outcomes.

While many elements try to take advantage of intrinsic motivation, gamified systems also use mechanics that are based more on extrinsic motivation. Both types of motivation have advantages and disadvantages, making a situation-specific evaluation necessary before implementation (Hamari et al., 2014; Legault, 2020). In the gamification context, there are a variety of elements and mechanics, ranging from achievements that a user must achieve, as well as leaderboards to avatars (Hunter & Werbach, 2012). Due to the scope of this paper, the following will be limited to avatars as a component of gamification.

Avatar Definition

Avatars are becoming increasingly popular and are being used in various areas such as social media, education, but also in mHealth apps (Nowak & Fox, 2018). This is facilitated by the progress of computer technology, which, for example, enables more complex three-dimensional avatars with multidimensional behaviors. Furthermore, the wider dissemination of technology, e.g., in the context of health and education, also contributes to the increasing popularity of avatars (Miao et al., 2022). Before discussing the benefits and impact of avatars, an analysis of the existing definitions will be attempted, as there is currently no unified definition of avatars (Miao et al., 2022). Complicating matters further is the lack of any tangible definition in many papers dealing with the effects and impacts of avatars (Gunser et al., 2020). However, a concise definition of avatars is indispensable for evaluating the impact of avatars, particularly also for the subsequent app review. For the following review, therefore, the definition will be drawn from the four components of an avatar proposed by Miao et al. (2022), partially modifying them to facilitate adaptation to the field of mHealth apps (Miao et al., 2022). Overall, an avatar should have an anthropomorphic appearance, meaning, a human-like image. Research has shown that individuals ascribe social attributes, at least in part, to anthropomorphic appearances, making the avatar seem more credible and competent to the user and thus increasing their willingness to engage with it (Miao et al., 2022; Westerman et al., 2015).

With respect to this aspect, we define avatars as a fictional representation that does not require an anthropomorphic appearance, but to which anthropomorphic properties can be attributed. This extends the proposed definition, whereby, for example, the representation of an animal that wants to lose weight would be defined as an avatar. The second aspect, interactivity refers to the ability of an avatar to participate in two-way interactions, though the type of interaction can vary (e.g., verbal via voice, nonverbal via text messages, mimic, or gestures) (Miao et al., 2022). Interactivity implies that the avatar must be able to participate in a two-way interaction with the user. That is, both the user must be able to communicate with the avatar and the avatar must be able to communicate with the user (Miao et al., 2022). Once again, the proposed definition is extended for the context of the present paper to prevent excessive restriction for avatar identification in mHealth apps. In doing so, the requirement of bilateral interaction is dropped, so that representations that can only communicate unilaterally are similarly identified as avatars. Thus, for example, the representation of a doctor who welcomes the user and gives an onboarding to the app would also be an avatar by our definition (Liew et al., 2017). The third aspect, controlling entity, refers to whether the avatar, i.e., its communication and behavior, is controlled by a computer (e.g., with the help of AI) or involves a human operator (Miao et al., 2022; Nowak & Fox, 2018). According to Miao et al. (2022), due to budgetary constraints, most avatars are controlled by AI. However, the origin of the control, i.e., computer or human, is usually not apparent to the user (Kim & Sundar, 2012). Due to this lack of insight by the user, the origin of control does not have much influence on the effects of the avatar (Miao et al., 2022). For this reason, both AI and human-controlled representations are defined as avatars by Miao et al. (2022). Therefore, we also adopt this definition, as it is often not clear to researchers who exactly controls the avatar in an app.

To sum it up, an avatar, according to our adapted definition based on Miao et al. (2022),

(1) needs to have at least anthropomorphic properties or an anthropomorphic appearance;

(2) needs to allow at least one-way communication or interaction;

(3) needs to be controlled either by a computer (e.g., AI) or a human being

(4) needs to be a digital entity

Based on their definition, Miao et al. (2022) further provide a taxonomy intended to isolate individual elements of an avatar that make it more or less effective for a particular goal. A distinction is made between form realism, i.e., the extent to which the appearance of an avatar is human-like, and behavioral realism, i.e., the extent to which an avatar behaves like a human (Konijn et al., 2008; Miao et al., 2022). Due to our adapted definition and the extension of the aspect of anthropomorphic appearance to anthropomorphic behavior, the proposed taxonomy cannot be directly applied to the avatars identified in mHealth apps. In addition, the taxonomy by Miao et al. (2022) was developed based on avatars in a marketing context, although the desired effects in marketing may differ, at least in part, from those in the mHealth domain (Miao et al., 2022). In the following, we propose our taxonomy based on the characteristics of avatars identified in the mHealth realm.

Method

In order to answer the research question of this paper, a quantitative evaluation of mHealth apps was conducted. Apps were first searched for in the Google Play Store using the search term 'health' (G. P. Store, 2022). All apps found under these search parameters were then listed in a table and reviewed one by one. Via referrals/recommendations from individual apps, 34 health apps were added that were not listed under the entered search term but still were deemed to be mHealth apps. Additionally, a comparison with the Apple App Store is made to investigate whether there are different health apps listed in the App Store that are not yet on the list. These additional apps have been added to the Google Play Store apps in Figure 1 as "Apps identified by searching Google Play Store". Therefore, the total number of apps is N=276 as shown in Figure 1. Furthermore, 59 Apple App Store exclusive apps were added to the list (A. A. Store, 2022).

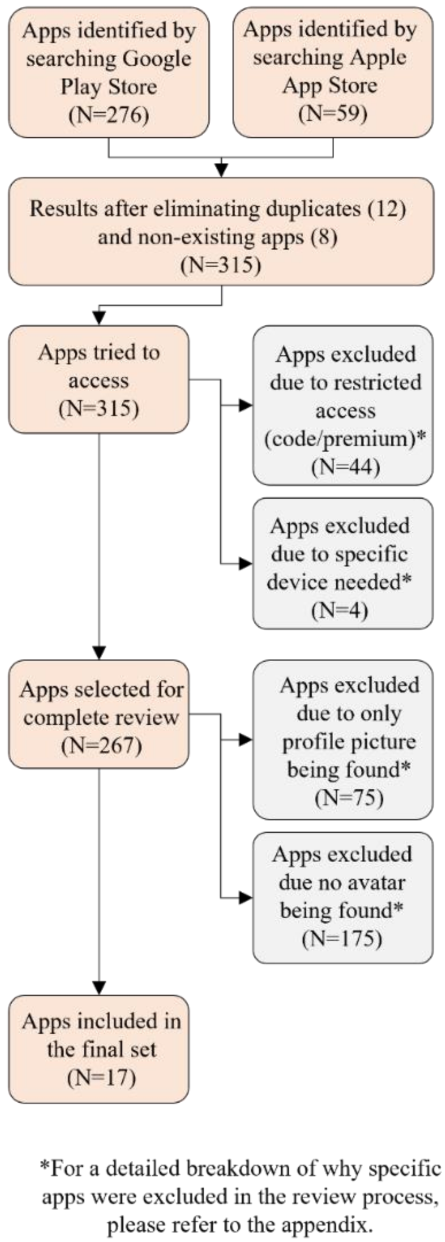

Figure 1: Flow Chart of the App Review Process and Exclusion Criteria

The screening process described above resulted in N=17 apps being selected for the final avatar classification (see Figure 1). Since both the Google App Store and, in part, the Apple App Store were used for the search for mHealth apps, redundant results were obtained (N=12). Therefore, these were excluded from the dataset for the further screening process. In addition, not all identified apps could be reviewed at the same time, which resulted in some apps (N=8) no longer being available in the app stores at the time of review. After the review, the apps that could not be accessed were divided into two categories:

1) the app could not be viewed due to missing access rights;

2) the app could not be viewed due to device restrictions (physical component);

With regard to the access right component, apps that did not allow a free account were excluded, i.e., where payment information had to be submitted even for test access. Moreover, apps were omitted that only provided a free trial version with a limited functional scope. In these cases, it was not possible to reliably determine whether the app included an avatar, as the avatar may only be available in the paid version.

In addition, apps were excluded from the review that required an identification or access code to be entered before an account could be created in order to use the app. This category also includes apps that are aimed at a specific user base, such as members of certain health insurance companies, as a full review of the app could not be guaranteed in this case either. The App Store search for mHealth apps yielded several apps that targeted specific geographic regions, particularly the Asian region (Bangladesh, Pakistan, India). Generally, such mHealth apps were included in the review, but there were some cases where country-specific phone numbers were required to access the app. In line with category 1 of the lack of access authorization, these apps were excluded from the further review process. This further includes apps that require a specific citizenship in order to be accessed, such as the Maltese citizenship. Category 2 comprises apps that were excluded in the screening process, as specific device specifications needed to be met in order to be granted access. This resulted in the identification of N=3 apps that can only be used in conjunction with a smart bracelet and one app that generally requires smart devices in order to be used. In the latter case, it was not possible to identify the exact type of smart device required.

The remaining N=267 apps could be fully reviewed as there were no restrictions regarding access rights. In this step, the majority of the apps were eliminated since no avatar could be found according to our definition. Several apps did not include any avatar-like component at all and were excluded accordingly (N=175). However, there was a large sample of apps that did include a profile picture. This was either transferred automatically by logging into the app via third-party providers such as Google, Facebook, etc., or could be individually configured by the user in the respective app. Based on the definition of an avatar that has been developed within our company, a profile picture alone does not qualify as an avatar. This can be justified by the fact that point 2 of the definition, the communication and interaction component, is not satisfied in the case of a static profile picture. Accordingly, apps that were excluded from the final dataset due to a static profile picture that does not represent an avatar were added as a separate category (N=75). After the app screening, 17 apps containing an avatar were able to meet our defined requirements (see Table 1). Based on the identified avatars, a typology is created based on the typology of Miao et al. (2022). The avatars are classified according to the different properties and shown in a schematic table. This schematic representation is done under the classification of a matrix to the preceding definition. For this purpose, the four divisions are shown as the four avatar categories and the associated factors. Therefore, the required areas are anthropomorphic properties, communication, or interaction, controlled by and digital entity. These areas are further subdivided into design elements, as well as the associated definitions. The avatars found are matched to the corresponding elements.

Within the N=17 mHealth apps that included an avatar according to the definition developed previously, there is one notable exception, an app that uses an avatar and was found under the search term ‘health’, but in our assessment is more of a game than a mHealth app (M. Limited, 2023). The fictional, personified player character runs in a world and has to make health-related decisions (M. Limited, 2023). In this respect, the representation would correspond to the definition of an avatar developed above, yet the app was excluded as it does not fit the definition of an mHealth app. In this respect, the representation would correspond to the definition of an avatar developed above, yet the app was excluded due to the game content. In parallel to the review process, the distinct apps found in the app stores were categorized. This includes all apps, i.e., those that were excluded during the process, except for apps identified as duplicates. The categories were derived and synthesized based on different factors. The Google Play Store itself assigns labels or tags to the respective apps, such as ‘meditation’, ‘sleep analysis’, etc. According to Google, these tags can be set individually by the app developers before submitting the app. The tags subsequently influence under which search terms an app is listed in the search results (G. I. Limited, 2023). However, it is unclear how exactly this algorithm works and how conscientiously and genuinely app developers define these labels for their apps. Additionally, this type of label does not exist in the Apple App Store; developers can only define labels in terms of the data collected by the app (Inc., 2023). Therefore, it was not considered realistic to derive app categories solely from the labels assigned to the apps, besides this possibility simply did not exist in the Apple App Store. Accordingly, although the label descriptions were used for thematic categorization for the apps for which these labels were available, the app descriptive texts were employed in addition.

Avatar ID	App Name	Reference
(1)	Samsung Health	(Samsung Electronics Co., 2023)
(2)	Ada - Check deine Gesundheit	(A. Health, 2023)
(3)	MyPossibleSelf: Mental Health	(Ltd, 2023)
(4)	Player´s Health	(P. Health, 2023)
(5)	Flo Perioden- & Zyklustracker	(F. H. U. LIMITED, 2023)
(6)	Spagat Lernen in 30 Tagen	(A. LIMITED, 2023b)
(7)	Oral-B	(Productions, 2023)
(8)	Fitness App Workout & Abnehmen	(LLC, 2023)
(9)	Six Pack in 30 Days	(A. LIMITED, 2023a)
(10)	Breeze: mental health	(Apps, 2023)
(11)	Sensely	(S. Corporation, 2023)
(12)	CycleGo	(SL, 2023)
(13)	Zwift	(Zwift, 2023)
(14)	VOS: Psychische Gesundheit	(s.r.o., 2023)
(15)	Finch: Self Care Widget Pet	(F. C. P. B. Corporation, 2023)
(16)	Reflectly	(ApS, 2023)
(17)	Amaru: The Self-Care Pet	(Seraph Games, 2023)

Table 1: Apps with Identified Avatars

Every app, whether in the Play Store or in the Apple App Store, is required to provide a more or less detailed description of what exactly the app in question offers. Especially the descriptions of apps from well-known developers like Samsung or Huawei provided a relatively good impression of what the respective app is actually focused on. However, there were large qualitative differences in the descriptions, particularly in the case of rather unknown apps with fewer downloads. Consequently, even in combination with the labels, no sufficient thematic categorization of the mHealth apps could be achieved. The app itself was used as a third source of information, i.e., the apps that could be accessed were manually classified thematically, considering the labels and descriptions of the app developers. This resulted in a total of 14 categories (see Table 2), with N=21 assigned to the "not definable" category.

This category particularly includes apps that were no longer found during the course of the review, or which did not permit (full) access, and no adequate description or labels were available. In addition, the category "other" was introduced, under which apps were grouped for which no focus, and thus a clear categorization was not feasible. It should be noted that the "total" number is lower than the sum of the apps in the individual categories, as some apps fit into several categories thematically and are therefore listed under more than one category. A specific breakdown of which apps have been assigned to which categories, as well as a description of each category, complete overview of all reviewed apps, categorizations and exclusion criteria are available upon request by the authors.

App Categories	Apps Reviewed	Avatars Identified
sports & fitness	32	5
health data tracking	63	1
nutrition	28	0
health insurance	8	0
fitness data tracking	24	0
mental health & wellbeing	28	6
women's health	11	1
sleep	7	0
education	28	0
doctor services	20	2
institutional apps	22	0
specific health problem	10	1
other	32	2
not definable	21	0
total	323	18

Table 2: App Categorization

Results

Subsequently, the 17 avatars identified in the mHealth apps were categorized, drawing on the typology of Miao et al. (2022) (see Figure 2). In doing so, they were analyzed in more depth by applying the four characteristics from the definition of an avatar. In particular, the first three elements, i.e., anthropomorphic properties/appearance; communication/interaction; and controlled by an entity; are discussed. The fourth characteristic, which specifies that an avatar must be a digital entity, could not be typologized further. Concerning anthropomorphic properties, a differentiation was made between spatial dimension, i.e., 2 dimensional or 3 dimensional, motion, i.e., static, or dynamic, and human-like attributes (age, name, gender, feelings/needs, human body parts). It should be noted that the typology does by no means claim to be complete but was merely developed based on the apps featuring avatars identified in the review. Especially regarding human-like characteristics or attributes, the proposed list can be extended as required. Of the 17 avatars, N=5 were found in iOS apps, while N=12 were discovered in Android apps. However, this differentiation is of little informational value, as the majority of the apps were available in both the Android Play Store and the Apple App Store. The identified avatars are divided almost equally in terms of spatial dimension into 2-dimensional (N=7) and 3-dimensional (N=10) appearance.

A distribution that is mirrored in terms of the movement aspect, where it is noticeable that a large part of the 2D avatars are static, while the 3D avatars increasingly perform in dynamic movements. The 'Samsung Health' app, for example, allows users to scan their own faces, based on which a 2D augmented reality (AR) emoji is subsequently created resembling the user's appearance (Samsung Electronics Co., 2023). The emoji can be displayed in the user's personal profile. The appearance of the avatar emoji is static, i.e., it does not change in the process of using the app but depends solely on the initial scanning process. The emoji additionally incorporates a whole range of human attributes such as age, gender, or name, all properties that can be individually defined by the user. The 'Sensely' app, which offers consultations regarding specific symptoms or chronic diseases, incorporates a three-dimensional avatar (S. Corporation, 2023). Unlike the 'Samsung Health' app, it is not an image of the user himself, but a lifelike three-dimensional model of a fictional doctor. The fictional doctor behaves in a lifelike manner, i.e., the movements are dynamic, and, pronounced facial expressions and lip movements can be detected. This avatar additionally features a name, gender, and human body parts, although, in contrast to the 'Samsung Health' app, all of these parameters are predefined and cannot be set by the user.

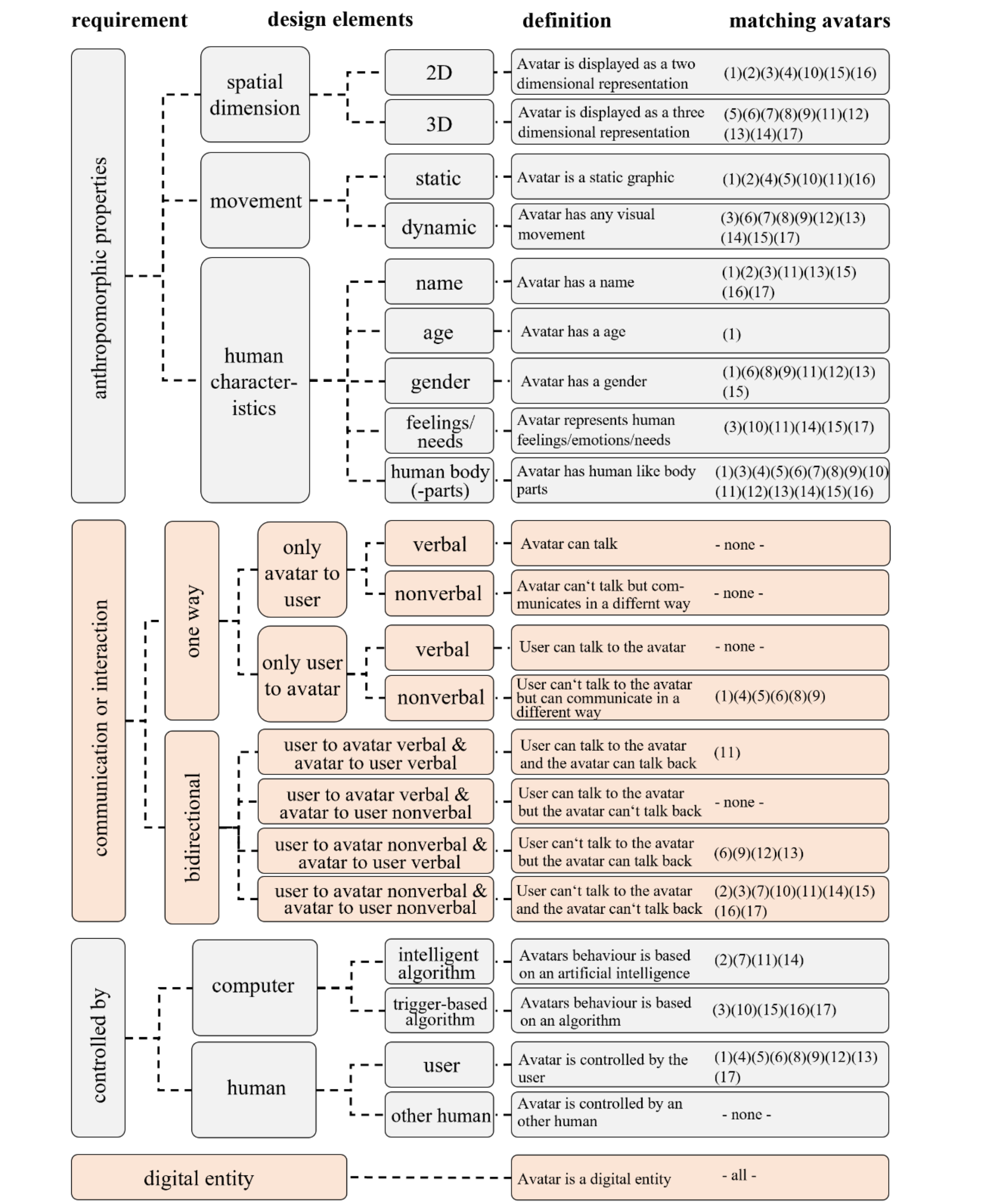

Figure 2: Typology of Avatar Design

Regarding the communication and interaction requirements, a basic distinction was made between one-way communication and bidirectional communication resp. interaction. In the case of one-way communication, a differentiation was made between the direction of communication, i.e., either the user communicates with the avatar or vice versa, whereby the communication can take place either verbally or nonverbally, e.g., via text messages. With respect to one-way communication, only avatars where the user was able to communicate non-verbally with the avatar were identified. In the case of the app 'Spagat Lernen in 30 Tagen', for instance, which offers a 3D animation of a character performing exercises, interaction is facilitated by clicking on the animated character (A. LIMITED, 2023b). For example, the sequence can be paused, or the level of difficulty can be adjusted, which is reflected in a changed sequence of motions of the animation. The vast majority of identified avatars enable nonverbal bidirectional communication, respectively interaction. The mental health and well-being app 'Reflectly', for example, makes it possible to specify states of mind via predefined responses (ApS, 2023). According to the selection, a ball-like facial presentation changes and reflects the user's state of mind, for instance. The user interacts with the avatar via predefined mood presets, while the face-shaped avatar reacts to the user via facial expressions, in particular eye movements and mouth movements. Similar elements are implemented by the app 'Breeze', but in the form of a face-like cloud that can again be influenced by mood presets and reflects the user's feelings and emotions through its expression. The cycling and running app 'CycleGo' enables the user to create a highly realistic, three-dimensional representation of themselves as professional cyclist or runner (SL, 2023). When using the app, the user can only interact with the avatar via onscreen gestures, but the avatar can in turn interact with the user via voice output. Similarly, the triathlon app 'Zwift' implements functionalities, where the individual avatar can be configured down to the smallest details such as bike frame size or color (Zwift, 2023). The avatar is then able to communicate verbally with the user, while the latter can react or take actions via onscreen gestures.

With the third definition element, a classification of avatars is attempted based on the factor controlling them. This can be either a human being or a computer. A distinction was made whether the controlling human is the user himself or another human, such as a communication partner who controls the avatar. However, this typecase was not identified. All identified avatars that are controlled by humans are controlled by the user himself. This is also the case with the app 'CycleGo', where the user influences the avatar through his own athletic performance on, for example, an exercise bike (SL, 2023).

If the avatar is controlled by a computer, a distinction can be made between control by a 'trigger-based' algorithm or an 'intelligent' algorithm. Under a trigger-based algorithm, avatars were assigned whose behavior or changes follow predefined patterns and are triggered by, e.g., temporal triggers. An assignment to an intelligent algorithm was carried out when the avatar had no predefined behavior but adapted to the user itself or occurring situations individually. Some apps already mention this functionality in their app description. For others, a closer review and observation of the avatar's behavior is necessary to determine whether the avatar behaves according to predefined patterns or whether it can react to situations itself. An intelligent algorithm-controlled avatar can be found, for example, in the app 'Oral-B', which is supposed to support the user in brushing his teeth and integrates the results of past brushing processes into the suggestions for current and ongoing brushing processes (Productions, 2023). A classic trigger-based algorithm-controlled avatar, on the other hand, can be found in many mental health apps, such as the app 'Breeze: mental health' (Apps, 2023). In this case, a certain input by the user or a certain period of time ensures that the avatar always changes in the same way for every user.

Discussion

Based on the identified avatars and the resulting classifications, as well as the categorization of the apps, some initial patterns in the use of avatars in digital health apps could be identified.

It is immediately noticeable that most avatars were identified in apps of the categories 'sports & fitness' (5 out of 17 avatars) and 'mental health & wellbeing' (6 out of 17 avatars). This suggests that it might be important in these app categories to additionally motivate the user to use them regularly, while it is less important in 'health insurance' apps (0 out of 17 avatars), for example, since the user uses such apps more as a service provider and does not need to be encouraged to use the app as often as possible. However, it seems that the use of avatars in mHealth apps is still relatively nascent. Additionally, it became apparent that, presumably due to the medium of the smartphone, the nonverbal interaction of the user with the avatar often took place with the help of touch gestures on the device display. This finding contrasts with the findings of Miao et al. (2022) regarding avatars in the marketing context, where avatars are often located on websites and accordingly, instead of touch gestures, mainly speech and text are used as interaction options. This aspect is particularly relevant in relation to a general definition of avatars. To establish such a definition, the different media in which avatars can potentially appear should be considered, since some manifestations of the characteristics seem to be media specific. Another trend could be identified, which is presumably due to more performant devices and animation techniques. The majority of avatars were displayed three-dimensionally and behaved dynamically instead of statically.

Limitations

The first thing to note is that there is still no clear and generally accepted definition of avatars. Although there are some good and well-founded approaches to define avatars in the marketing context, e.g., by Miao et al. (2022), it is questionable to what extent this definition can be applied to other contexts such as mHealth apps. Accordingly, the definition developed in this paper is also only one possibility and should be considered as a suggestion on how avatars could be defined in the mHealth context. What seems clear, however, is that a cross-context definition of an avatar is challenging, as specific implementations vary, sometimes significantly, depending on the context. Furthermore, this review is far from providing a complete overview of the use of avatars in the mHealth context. The plethora of apps in the various app stores are vast and it is unclear on what basis specific apps are displayed under the search term 'health'. However, it became clear that download numbers alone do not play a role, since apps were found on a large scale that whose download numbers ran into the low thousands. Accordingly, this review and typology based on it provide only a glimpse of what characteristics and components avatars in mHealth apps are composed of. Additionally, the categorization as well as the assignment of the apps to the respective categories is only a subjective approach. Nevertheless, an attempt was made to categorize the apps as objectively as possible, e.g., based on labels, tags, or app descriptions. However, the assignments and results can vary accordingly, depending on the criteria applied. Additionally, it is worth noting that no inferences can be made about the effectiveness of the respective avatars based on this app review. The classification only serves the purpose of distinguishing avatars based on various components; which of these components are more or less effective requires additional research.

Future Research

Future research could revisit the definition of an avatar and, considering the avatar dimensions of other contexts, develop a well-founded, universal definition of an avatar that can be applied to the mHealth context. With the continued proliferation of avatars in the mHealth context, the proposed typology should be expanded to include additional factors to represent a rigid construct. Evidently, a more extensive selection of apps, limited to apps with high download numbers, would significantly improve the understanding of avatars in health apps. In addition, as mentioned earlier, it would be interesting to investigate the efficiency of different avatar properties, e.g., whether the user prefers bidirectional communication over one-way communication.

Conclusion

Overall, it can be stated that this work has laid a foundation for further research on avatars in the context of gamified health apps. By specifying and adapting the definition of avatars by Miao et al. (2022) a good basis for further work in the field of health apps has been laid. Furthermore, based on the elaborated typology, initial patterns and trends for avatars usage can be identified. With the classification of the typology into different requirements, the avatars are categorized according to their specific characteristics. However, further research in this area is needed to verify clear trends and their benefits.

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Understanding the Digital Transformation in the Healthcare Sector:
A Concept-Centric Umbrella Review

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Abstract

Background: *The healthcare sector is facing increasingly complex challenges, including rising costs, concerns about the quality of care, limited patient access to healthcare, and an aging population. Digital transformation emerged as a potential solution to address these challenges. Therefore, comprehending the impact of digital transformation on healthcare, particularly medical work, the ensuing requirements for medical staff, and organizations, is crucial for successful and efficient implementation.*

Objective: *The primary objective of this research is to present a comprehensive overview of digital health concepts, construct a coherent framework to categorize and structure them, and synthesize existing research outcomes. We particularly focused on aspects related to medical work, including the impact of digital technologies on working environments, processes, and the evolving requirements for staff and organizations.*

Methods: *For the purpose of our work, we first conducted an umbrella literature review by searching six databases before we organized the findings in a concept matrix according to Webster and Watson and visualizd the possible interdependencies of the concepts found also with a concept board that displays the interdependencies*

Results: *The initial database search yielded 1990 results. After applying eligibility criteria, 25 reviews were included in the final review. The concept matrix structure enabled the identification and organization of 13 concepts into six concept domains.*

Conclusion: *Through the method of an umbrella review, we successfully developed and validated a concept matrix. This matrix helped to identify six crucial concept domains concerning digital transformation in healthcare, with a specific emphasis on medical work, and allowed us to establish connections between various concepts in the literature. Nonetheless, further studies are required to gain a deeper understanding of digital transformation in healthcare and its potential benefits.*

Keywords: Digital transformation, Digitalization, Digitization, Healthcare, Medical work, Umbrella review, Concept matrix, Framework

Introduction

Increasing challenges in the healthcare (HC) sector, not only regarding costs but also the quality of care, patient access to care and an aging society, are making significant changes imperative (Agarwal et al., 2010). Hence, it is not surprising that digital transformation (DT), which provides innovations and has revolutionized various industry sectors, is often expected to provide solutions to the mentioned challenges (Kraus et al., 2021). It is defined as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" (Vial, 2019, p. 121). In recent years, increasing numbers of publications have highlighted the importance of DT, especially in HC, which comprises "all services that medical professionals deliver to preserve people's physical and mental well-being" (Kraus et al., 2021, p. 557). Several digital tools and technologies, such as electronic health records (EHR) or telemedicine, have transformed today's HC (Ricciardi, 2019) and medical work, which can be defined as the application of scientific knowledge and technical skills by medical staff to promote health, prevent disease and alleviate suffering in the human population (Greiner, 1900). However, the overall implementation of DT in HC is lagging behind, leaving a lot of improvement potentials unexploited (Kraus et al., 2021).

For an effective and efficient implementation, it is crucial to understand how DT affects HC, particularly medical work, and imposes new requirements on medical staff and organizations. For that, existing researched concepts of this area as well as their linkages must be understood. In the past, research has tended to focus more on the implementation of specific digital health solutions (Mathews et al., 2019; Ross et al., 2018) and key drivers (Agarwal et al., 2010; Kruszyńska-Fischbach et al., 2022) associated with them rather than providing an overall conceptualization. Two first attempts of the latter approach have been proposed by Kraus et al. (2021) and Carboni et al. (2022). However, due to the extensive research in this area, the question arises of how up to date this conceptualization is and to what extent a focus on medical work was set.

This review aims to give an overview of digital health concepts, establish a framework for structuring them and provide a brief synthesis of research findings in this domain. Hence, the following research question serves as the overarching guideline for this paper's investigation: *Which concepts of DT in the context of HC and medical work have been researched so far and how can they be organized?*

By choosing the novel methodological approach of an umbrella review, we attempted to summarize the existing researched concepts of DT in HC. For this, a concept matrix has been developed upon which researched concepts have been systematized and potential relationships between existing concepts were suggested. The lack of research in certain concept areas was highlighted by discussing the different stages of research in these areas.

The remainder of this paper is structured as follows: First, a theoretical background on DT in HC will be given in section 2. On this basis, section 3 will describe the methodology and how this paper's umbrella literature review was conducted. After that, our findings will be presented in section 4. A discussion of the concepts under the framework that we developed will be presented in section 5, along with highlighting some limitations and possible future research directions. Finally, our conclusion will be drawn in section 6.

Theoretical Background on DT in HC and Medical Work

DT is leading to the embedment of digital technologies in all aspects of life (Stolterman & Fors, 2004) and is characterized by a high degree of simultaneous processes, which allow for the collection, analysis, and manipulation of data in real-time in any economic or social context (Trittin-Ulbrich et al., 2021). As society and industry change, companies increase their efficiency through DT by transforming their value creation process through digital technologies (Trittin-Ulbrich et al., 2021; Vial, 2019).

Digital health is about using digital technologies in the HC sector in order "to improve human health, HC services, and wellness for individuals and across populations" (Kostkova, 2015, p. 1). In turn, this could improve the quality of care and simplify access to it, leading to an increase in the overall efficiency of the HC sector, benefitting both patients and HC professionals (Angerer et al., 2022; Fatehi et al., 2020). Eventually, digital health will lead to a reduction of costs in the HC system for patients, but also for clinical research (Garcia-Perez et al., 2022). There are several components of digital health, including mobile Health (mHealth) or electronic Health (eHealth) (Iyawa et al., 2016).

In this regard, eHealth is "an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the Internet and related technologies" (Eysenbach, 2001, p. 1). It is seen as an enabler to the challenges in the HC system and is intended to counteract the problems of care (Kostkova, 2015). As a specific type of eHealth (Matusiewicz et al., 2018), mHealth is perceived as a technical intervention that relies on the use of mobile and wireless technologies in HC (Matusiewicz et al., 2018; World Health Organization, 2011). Various areas such as prevention, diagnostics, and even follow-up care are covered by mHealth devices. In addition, it also finds its use in wellness products and process optimization in hospitals and medical practices (Matusiewicz et al., 2018).

There are several challenges associated with the introduction of these digital tools, such as limited infrastructure or inadequate staff training (World Health Organization, 2019). For addressing them, the WHO released a guideline on digital health interventions (DHI) to enhance evidence-based decision-making. They define DHI as discrete functions of digital technologies that are used to achieve health objectives inside digital health applications and information and communication technologies (World Health Organization, 2019).

Moreover, digital health literacy has become an increasingly important factor alongside the DT in HC (Smith & Magnani, 2019). Health literacy refers to an individual's ability to access and understand health information and, accordingly, make reasonable decisions regarding their own health (Abel, 2008; Santana et al., 2021). Despite having some common ground with health literacy, digital health literacy can be seen as a more comprehensive concept (Smith & Magnani, 2019). It is defined as the ability "to search, select, appraise, and apply online health information and HC-related digital applications" (van der Vaart & Drossaert, 2017, p. 2) to solve health-related problems (Smith & Magnani, 2019).

In recent years, HC 4.0 has emerged as a term derived from Industry 4.0. It can be defined as the new era of data-driven health technologies (Jayaraman et al., 2020), where artificial intelligence (AI), real-time data collection, robotics, and data analytics transform HC for patients and HC providers (Al-Jaroodi et al., 2020; Tortorella et al., 2020; Wehde, 2019). As this transition occurs integrated HC systems not only link clinics, hospital suppliers, and long-term care facilities, but also equipment, devices, and patient homes (Tortorella et al., 2020). In this way, a smart health network along the entire HC value chain is created, which facilitates more effective interactions between HC service providers (Al-Jaroodi et al., 2020).

Methodology

Umbrella Literature Review

For this study an umbrella review, also called a "review of reviews" (Faulkner et al., 2022, p. 74), was conducted to identify concepts related to DT in HC, as well as to obtain evidence regarding its impact on medical work (Paré et al., 2015). In an umbrella review, multiple systematic reviews and meta-analyses are identified using systematic and explicit methods to contrast and summarize findings of different reviews (Faulkner et al., 2022). This approach was chosen for various reasons: Firstly, the number of primary studies on DT in HC and medical work of the past five years is too large to review them separately considering the capacity of this study. Secondly, this method is particularly valuable when the research question is wide in scope and a comprehensive overview through the conceptualization of research findings is desired (Faulkner et al., 2022). And lastly, this method supports targeted research by showing research gaps (Grant & Booth, 2009). However, since umbrella reviews "represent a relatively new research design, their guidelines and methods are still evolving" (Paré et al., 2015, p. 188).

Data Collection

To provide a broad overview of researched concepts of DT in HC six different databases were searched through: AISeL, IEEE Xplore, PubMed, Scopus, EBSCO, and Web of Science. The six databases chosen for this paper were selected because they are some of the most used databases for conducting systematic reviews and meta-analyses in the HC field. While PubMed mostly covers literature focused on HC, other databases such as AISeL and IEEE Xplore focus rather on information systems and technical literature. Web of Science, Scopus, and EBSCO are less sector-specific and were added as well to include papers that cover a wide range of disciplines and subjects. Considering the large number of new publications in the HC area every year and the fact that the results found in older papers often are outdated, we only included papers published in 2018 or later. The language was restricted to English. To keep the assessment of relevance facultative, two authors each assessed relevance independently, and in case of disagreement, the third author was consulted for evaluation as well.

A search strategy based on the two concepts of DT and HC in combination with the methodological approach of a review was developed. An overview of the conducted process and eligibility criteria is depicted in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) diagram in Figure 1. The database search yielded 1990 results in total, of which 778 were duplicates and therefore could be excluded. Based on a first screening of titles and abstracts, we identified 83 papers as preliminary relevant by excluding publications that were no reviews or had a non-thematic approach to digital health or work processes related to DT in HC. In a next step we used our eligibility criteria, 67 paper were excluded as they focused too much on technical content, only considered country outcomes, or lacked a strong focus on medical work. As a result of our primary literature, we identified 16 reviews. By applying the same procedure and inclusion criteria as already described to the reference lists of the included 16 reviews, we could identify nine additional papers. Thus, we were able to incorporate 25 reviews in our review in total.

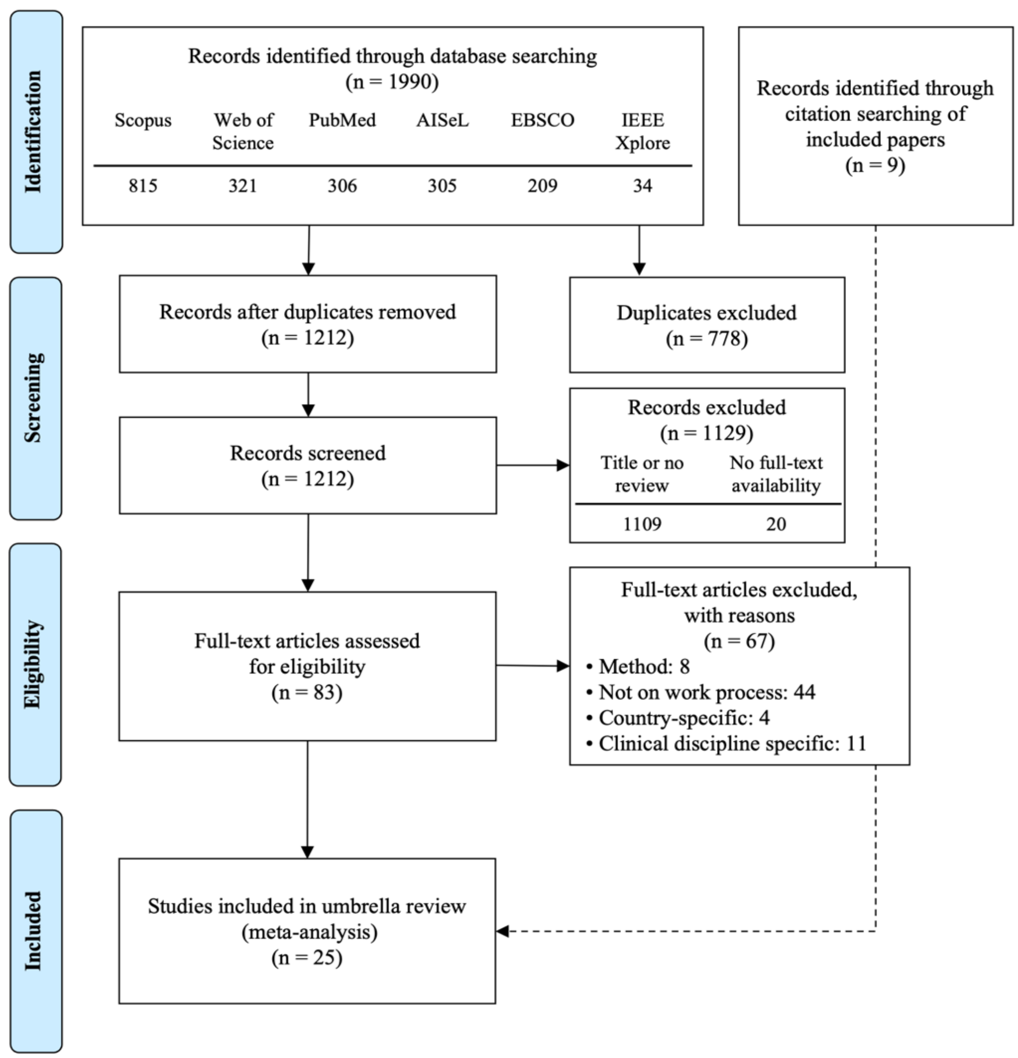

Figure 2. Visualization of the Umbrella Review Process Following the Guidelines of the PRISMA Statement by Moher et al. (2009)

For improved understanding of our exclusion criteria, the following will briefly describe an example of an excluded review for each criterion:

1. Method: Papers excluded because of their method, mostly conducted surveys, or used statistical methods etc., for example Arnold et al. (2022) conducted two cross-sectional surveys. Since we were following an umbrella review approach, those studies could not be considered.

2. Not on work process: Some results of our literature search were not relevant for us because of the topic of their research aims. For example, Kerr et al. aimed to “trace the evolution of mechanical objectivity from empirical studies of early anatomists” (Kerr et al., 2022).

3. Country-specific: The paper of Oshni Alvandi et al. (2021) only analyze how the concept of digital health is perceived and experienced by Australian citizens, which highly depends on the national circumstances of Australia.

4. Clinical discipline specific: Since we aim to provide an overall overview of research, some papers that only considered applications of very special medical fields were deemed not suitable for our research goal. One example is the paper of Joda and Zitzmann (2022) which discussed disruptions in dentistry, especially in the area of reconstructive dentistry.

Data Extraction and Synthesis

„Concepts determine the organizing framework of a review” (Webster & Watson, 2002, p. 16), which is why we created a data extraction form to obtain key information and concepts from the included reviews. In the first step, the reviews’ concepts related to DT in the HC area were identified by creating a concept matrix according to Webster and Watson in which each column of the matrix represents a key concept found in the reviews (see Table 1) (Webster & Watson, 2002). Therefore, findings of reviews that deal with the same or similar concepts were assigned to the same column. Hence, it was possible to identify linkages not only between researched concepts but also between reviews dealing with the same concept.

In order to make our data extraction synthesis more vivid, this short paragraph will give an exemplary assignment of a paper to different concepts on the basis of text excerpts. The paper of Cavallone and Palumbo (2020) is a good example of a paper that has been assigned to several concepts. Considering the concept of HC 4.0 the authors mention on page 863 the two diverging goals of HC organizations in times of DT: “1) the enhancement of the quality of health services and 2) the containment of health-related costs” (p. 863). In assessing the socio-economic aspects, the authors’ statement that the "applications [of HC 4.0] will be limited to the more affluent segments of health care delivery" (p. 862) is relevant. DT in the HC sector might lead to the “achievement of greater efficiency” (p. 862) though “a wiser management of health resources” (p. 862) leading to an attribution of the paper to the concept of operational efficiency.

As this paper elucidates several aspects which needs to be considered when designing HC 4.0, there are more concepts being addressed by the paper of Cavallone and Palumbo (Cavallone & Palumbo, 2020) and the above exemplary representation is not complete, but only serves the understanding of our concept assignment process. Building on this, we discussed and systematized the found concepts (see Table 4) and developed a framework that also illustrates potential relationships between different concepts.

Review on DT in HC

This section provides a summary of our review findings. As shown by the 25 included reviews from several countries, there is a wide range of existing concepts about DT in HC. Based on these results, we were able to identify six clusters, which summarize the existing research concepts of this domain.

HC 4.0

A key goal of HC 4.0 is to reconcile patient-centeredness and technological improvement to achieve two diverging strategies: the improvement of HC service and the containment of HC costs (Cavallone & Palumbo, 2020). In this respect, HC 4.0 redefines the traditional organizational and management models of HC systems, and by that facilitates structural change towards patient-centered care (Cavallone & Palumbo, 2020).

Authors	Publi-cation Date	Country	HC 4.0	Digital Health Technology				Socio-Economic Aspects	Goals of DT in HC		Key Requirements for DT in HC				Impacts of DT on HC-Actors	
				EHR	CDSS	other DHT	DHI		Patient-Centered Approach	Operational Efficiencies	Organizational factors and Managerial Implications	Digital Health Competencies	Digital Health Literacy	Human-AI Interaction & Collaboration	Impact on Workforce Practices	Patient-Provider Relationship
Angerer et al.	2022	GER								x	x					
Baines et al.	2020	GBR				x						x			x	
Brice and Almond	2020	AUS										x				
Brown et al.	2020	AUS									x	x			x	
Carboni et al.	2022	NLD			x				x	x	x				x	x
Cavallone and Palumbo	2020	ITA	x					x	x	x	x	x			x	x
González	2022	MEX		x		x			x						x	x
Haupeltshofer et al.	2020	GER										x	x		x	x
Jimenez et al.	2020	NLD and SGP										x	x			
Jun et al.	2018	CAN and IRL			x											
Knop et al.	2022	GER												x		
Konttila et al.	2018	FIN										x				
Kraus et al.	2021	FRA and ITA						x	x	x	x					x
Krick et al.	2020	GER		x	x	x										
Kruse and Ehrbar	2020	USA			x											
Longhini et al.	2022	ITA										x				
Marques and Ferreira	2020	PRT		x		x										
Palumbo et al.	2021	ITA						x		x		x	x			
Patterson et al.	2019	USA		x	x											
Peyroteo et al.	2021	PRT				x				x						
Reddy et al.	2018	AUS, GBR and USA			x				x	x	x			x		
Scott et al.	2018	AUS			x											
Sharma et al.	2019	IND	x		x				x						x	
Willis et al.	2022	USA		x	x	x	x									
Wurster et al.	2022	GER		x		x				x	x				x	

Table 3: Concept Matrix Following the Guidelines of Webster and Watson (2002)

Concepts:	Key Summary of Findings:	Articles:
(1) HC 4.0		
	- Empowerment of the patient as active participant in HC process → aim: value co-creation - Technologies: big-data analytic based technologies, wearable technology, cloud platform, AI and robotics	Cavallone and Palumbo, Sharma et al.
(2) Digital Health Technology		
EHR	- Advantages of EHR: better patient documentation, reduction in medical errors and increased efficiency, - Disadvantages of EHR: Focus shift towards computer	González, Krick et al., Marques et al., Patterson et al., Willis et al., Wurster et al.
CDSS	- Efficiency of CDSS shown through improved practitioners' performance and patient outcome	Carboni et al., Jun et al., Krick et al., Kruse et al., Patterson et al., Reddy et al., Scott et al., Sharma et al., Willis et al.
Other DHT	- For example: tele-monitoring, HC-recommender-System, tele consultation	González, Krick et al., Marques et al., Peyroteo et al., Willis et al., Wurster et al., Baines et al.
DHI	- Concrete medical interventions that incorporate DHT	Willis et al.
(3) Socio-Economic Aspects		
	- DT is associated with high costs → only rich countries and well-funded HC-system could implement DT in HC	Cavallone and Palumbo, Kraus et al., Palumbo et al.
(4) Goals of DT in HC		
Patient-Centered Approach	- Focus on the treatment of the patient is increased by DT - DT can also remove the focus from the patient	Carboni et al., Cavallone and Palumbo, González, Kraus et al., Reddy et al., Sharma et al.
Operational Efficiencies	- Aim of DT in HC is efficiency increase, reached through improved workflow, reduced costs, faster documentation - Digital systems can relieve HC professionals of tasks, but therefore sufficient competences are needed - Management should support training and skill	Angerer et al., Carboni et al., Cavallone and Palumbo, Kraus et al., Palumbo et al., Peyroteo et al., Reddy et al., Wurster et al.
(5) Key Requirements for DT in HC		
Human-AI Interaction & Collaboration	- Collaboration between AI-agents and humans is needed - Differentiation between human and technological factors - Moreover medico-legal factors are important	Knop et al., Reddy et al.
Digital Health Competencies	- A lot of competencies relate to digital health literacy, user experience and knowledge in ethical medical care - Key drivers of competencies: job position, working place, team climate and attitude towards technology - Nursing informatics as new job profession - Acquisition of digital skill does not automatically empower all stakeholders involved	Baines et al., Brice and Almond, Brown et al., Cavallone and Palumbo, Haupeltshofer et al., Jimenez et al., Konttila et al., Longhini et al., Palumbo et al.
Digital Health Literacy	- Change of role of patients and HC staff to a value co-creation relationship - Age and economic status as driver for low DH literacy - Difference between organizational and individual Factors	Haupeltshofer et al., Jimenez et al., Palumbo et al.
Organizational Factors and Managerial Implications	- DT is highly important for HC-organizations to face the upcoming challenges - Organizations: actively engage employees in the DT	Angerer et al., Brown et al., Carboni et al., Cavallone and Palumbo, Kraus et al., Reddy et al., Wurster et al.
(6) Impacts of DT on HC-Actors		
Impact on Workforce Practices	- Positive influence on workforce practice, e.g., through easier access on patient data and easier documentation - Reliance on quantitative data for medical therapy - Changing work roles and increased computer-related task - Overall improvement in quality of Care	Baines et al., Brown et al., Carboni et al., Cavallone and Palumbo, González, Haupeltshofer et al., Sharma et al., Wurster et al.
Impact on the Patient-Provider Relationship	- Onset of depersonalization by DT is possible - Digital offerings complement face-to-face communication	Carboni et al., Cavallone and Palumbo, González, Haupeltshofer et al., Kraus et al.

Table 4: Concept Summary

With the introduction of HC 4.0, the empowerment of the patient as an active participant in the HC process has been widely emphasized as a key feature (Cavallone & Palumbo, 2020; Sharma et al., 2019). Thus, patients can access their health information from anywhere (Sharma et al., 2019), anticipating their health needs and participating in the process of value co-creation (Cavallone & Palumbo, 2020), such as by using wearable devices (Sharma et al., 2019).

Cavallone and Palumbo (2020) divided the applications of HC 4.0 into two categories: 1) tools and devices aimed at improving resource management, and 2) interventions to improve the patient-provider relationship. Big data analytic-based technologies, wearable technology, cloud platforms, AI, and robotics are some of the tools that come with the introduction of HC 4.0 (Sharma et al., 2019).

Concerns have been raised which describe the dark sides of HC 4.0 that "needs to be illuminated and properly managed in order to realize the full potential of the digital turn in health care" (Cavallone & Palumbo, 2020, p. 862). The first concern is the lack of human touch in the design of HC 4.0 technologies, resulting in their possible misapplication and misuse (Cavallone & Palumbo, 2020; Sharma et al., 2019). Secondly, HC 4.0 changes caretakers' traditional roles, resulting in a possible loss of organizational identity and commitment (Cavallone & Palumbo, 2020). Moreover, the limited attention given to bioethics in designing HC 4.0 technologies, might lead to a conflict between the concepts of patient-centeredness and DT (Cavallone & Palumbo, 2020; Sharma et al., 2019).

Digital Health Technology

A growing body of literature has examined the potential of different digital health technologies (DHT). As Krick et al. (2019) point out, most studies investigate the effectiveness of care technologies (60%), followed by acceptance (59%) and only a few (5,8%) examined the efficiency, e.g., cost analysis. In this context information and communication technology, like computerized clinical decision support systems (CDSS), robots, EHR, and have been identified as major research topics in the hospital setting (Krick et al., 2019; Willis et al., 2022).

In recent years, EHRs have improved patient care by reducing possible errors, increasing efficiency, and distributing medical information through digital electronic documentation (González, 2022; Marques & Ferreira, 2020). Research has tended to focus on positive outcomes like better patient documentation (Wurster et al., 2022) and EHRs as a reliable data-source for researchers (Marques & Ferreira, 2020). Cordova et al. (González, 2022) have addressed some negative effects that come with the introduction of EHR, like security issues (González, 2022). Moreover, they argue that EHRs can be seen as the third actor in physician consultation, shifting the focus from the patient to the computer (González, 2022).

Several studies have taken place on how AI and digitalization can assist in medical decision-making (Jun et al., 2018; Krick et al., 2019; Kruse & Ehrbar, 2020; Marques & Ferreira, 2020; Patterson et al., 2019; Scott et al., 2018; Sharma et al., 2019; Willis et al., 2022). Overall, research emphasizes the efficiency of CDSS for practitioner performance and patient medical outcome (Carboni et al., 2022; Kruse & Ehrbar, 2020). In most cases, CDSS were taken to support medical diagnoses based on provided symptoms (Kruse & Ehrbar, 2020; Marques & Ferreira, 2020), to manage medications (Marques & Ferreira, 2020; Sharma et al., 2019), to evaluate possible treatments in accordance with clinical practice guidelines (Kruse & Ehrbar, 2020), and to determine the overall patient status (Kruse & Ehrbar, 2020; Marques & Ferreira, 2020). Improved practitioner performance and patient outcomes are likely to result from these capabilities (Kruse & Ehrbar, 2020). Organizations must have an appropriate infrastructure to support CDSS, training must be available for providers and administration need to ensure that the cost budget allows for its implementation (Kruse & Ehrbar, 2020).

A few of the reviews discuss the synergy between EHR and CDSS (Patterson et al., 2019; Scott et al., 2018), as the majority of DHT is implemented as a combination of different technologies (Willis et al., 2022). In addition to the DHTs presented, other authors focused on the use of tele-monitoring (Krick et al., 2019; Palumbo et al., 2022; Reddy et al., 2019; Willis et al., 2022), tele-medicine (Baines et al., 2020; González, 2022; Marques & Ferreira, 2020) and health-recommender-systems (Sharma et al., 2019).

Furthermore, Willis et al. (2022) took up the concept of DHI to demonstrate how digital technologies can be used for specific health interventions in the primary care setting. They showed that with the introduction of DHIs, like app-driven personal health tracking or digital medication management, health services could be elevated in terms of quality and effectiveness (Willis et al., 2022).

Socio-Economic Aspects

Since the implementation of digital technologies and tools is associated with high costs, the advantages and possibilities of DT might be limited to rich countries with well-funded HC systems and its affluent segments (Cavallone & Palumbo, 2020; Kraus et al., 2021). Therefore, the extensity of changes in medical work may vary globally. Moreover, different HC standards within the society of the same country may appear due to different socio-economic backgrounds, for example, because of different access to wi-fi, HC wearables, or treatment types (Cavallone & Palumbo, 2020; Kraus et al., 2021; Palumbo et al., 2022).

However, the relationship between socio-economic status and HC/medical work is bidirectional: not only the socio-economic status influences HC access and work but also medical work may influence the socio-economic status of individuals, e.g., by improving the prospects of social service health workers (Kraus et al., 2021).

Goals of DT in HC

Patient-Centered Approach

DT can lead to increased use of patient-centric digital technologies in HC, like EHRs, mHealth applications, or the use of AI as they focus on the patient by providing personalized medical services or supplying patients with individualized treatment plans (Kraus et al., 2021; Krick et al., 2019; Sharma et al., 2019).

There may be both positive and negative effects from the patient's perspective (Carboni et al., 2022; Cavallone & Palumbo, 2020; González, 2022; Kraus et al., 2021; Sharma et al., 2019). For instance, the EHR can elicit a renunciation of the patient-centered approach as clinicians constantly look at screens and spend an inappropriate amount of treatment time typing and documenting (González, 2022). This can result in diminished importance of patient care due to the change in documentation procedures (Carboni et al., 2022; Cavallone & Palumbo, 2020). On the other hand, DT can strengthen patient.

empowerment. New technologies evoke highly informed and interested patients, who consequently become active decision-makers regarding their treatment (Kraus et al., 2021; Sharma et al., 2019). Digital technologies allow the smallest differences between patients to be considered, thereby the patient-centered approach is strengthened and thus the reduction of inequalities and the achievement of more fairness are promoted (Cavallone & Palumbo, 2020).

Although it is mentioned that the principles of industry 4.0 and patient-centeredness are hard to align, as "they produce diverging pressures and conflicting issues for health care organizations" (Cavallone & Palumbo, 2020, p. 861), several researchers have highlighted the importance of patient-centeredness that comes with the introduction of HC 4.0 (Cavallone & Palumbo, 2020).

Operational Efficiencies

There are high hopes for efficiency increases due to DT in HC, which therefore states a researched concept mentioned in various papers (Angerer et al., 2022; Peyroteo et al., 2021; Wurster et al., 2022). Efficiency gains may be achieved, for example, through improved workflows, reduced costs, and faster documentation (Carboni et al., 2022; Kraus et al., 2021; Wurster et al., 2022). Through DT, however, it is also possible to increase efficiency by protecting the HC system from overloading (Peyroteo et al., 2021). Reddy et al. (2019) and Kraus et al. (Kraus et al., 2021) see one way of increasing efficiency in shortening the length of stay by using AI. DT can also make HC organizations more efficient as they allow a more intelligent use of HC resources (Cavallone & Palumbo, 2020).

Employees must have sufficient competence to avoid efficiency losses (Palumbo et al., 2022). Therefore, it is important to consider this at the management level when designing digital systems (Cavallone & Palumbo, 2020; Reddy et al., 2019).

Key Requirements for DT in HC

Human-AI Collaboration

With the rapid progress in AI in the last few years, such as natural language processing or deep neural networks, a variety of fields in HC and medical workers will be impacted, including patient monitoring, CDSS, HC interventions, and patient administration (Reddy et al., 2019). Hence, assessing the factors that influence the interaction with AI technologies and strengthening the collaboration between human actors and AI is of major importance (Knop et al., 2022; Reddy et al., 2019).

In their review, Knop et al. (2022) evaluated the human-AI collaboration in the context of CDSS and provide a framework for effective collaboration. Firstly, they describe technological characteristics, such as training data quality, system performance, transparency, and adaptability. Similarly, human factors are influencing effective AI-human collaboration, like medical and technological expertise, personality, cognitive biases, and trust.

Among these, Reddy et al. (2019) identified further factors influencing the human-AI interaction. As AI agents are increasingly providing HC services autonomously, it is important to evaluate medico-legal factors. For example, in situations like medical errors, it is often not clear where responsibility lies. Governments should address concrete strategies about how AI should be integrated into HC. Also, developers should include clinicians in the design and testing of AI tools, though they create a level of trust and user-friendliness in these systems.

Digital Health Competencies

Changing working environments in HC due to DT and the consequent embedment of medical informatics in all kinds of activities require new competencies of medical staff (Cavallone & Palumbo, 2020). Depending on the stage of digitalization of different HC infrastructures, the required competencies may differ (Longhini et al., 2022). A number of studies aimed to define and/or cluster digital health competencies into domains using different perspectives and different granularities (Baines et al., 2020; Brice & Almond, 2020; Haupeltshofer et al., 2020; Jimenez et al., 2020; Longhini et al., 2022; Palumbo et al., 2022).

A lot of the identified required competencies related to digital (health) literacy, which refers to knowledge of the use of digital applications, like EHR and the internet (Brown et al., 2020; Jimenez et al., 2020; Konttila et al., 2019). New skills regarding interaction and communication with patients are required (Konttila et al., 2019). Moreover, knowledge of management, administration, and changing working procedures, such as the implementation of online consultation, has also often been viewed as a competency domain (Baines et al., 2020). Some studies explicitly differentiated between competency requirements for specific fields of medical work, such as primary care, and outpatient settings, such as rural or metropolitan areas, or focused on specific types of medical staff (Baines et al., 2020; Brown et al., 2020; Haupeltshofer et al., 2020; Jimenez et al., 2020).

There is a research focus on competency requirements for nurses for which specific competency assessment tests have been developed (Haupeltshofer et al., 2020). While the term "nursing informatics" already appeared in 1976, this job profession gained more attention in recent years, and "the theory of technological competency as caring in nursing" (Haupeltshofer et al., 2020, p. 2713) has been developed, stressing the important interplay of caring, nursing, and technology.

However, not only new competency requirements are researched but also issues affecting their acquisition and strategies to support their integration (Brown et al., 2020; Konttila et al., 2019). Amongst the found factors influencing the requirement and adoption of new skills are "job position, working place, team climate and attitudes towards wireless communication devices" (Konttila et al., 2019, p. 756).

Digital Health Literacy

Poor digital health literacy of medical staff is one of the reasons why the implementation of digital tools and technologies has been slow in practice (Jimenez et al., 2020). Additionally, digital health literacy changes the role of patients and medical staff in HC systems towards a value and health service co-creation relationship (Haupeltshofer et al., 2020; Palumbo et al., 2022). However, to enable patients to obtain and record information with technologies and consequently make full use of them, patients must be empowered and educated by medical staff, above all nurses, which in turn extends the tasks of medical work (Haupeltshofer et al., 2020). The consequences of limited digital health literacy, e.g. unequal HC opportunities, have been researched and especially concern people with low digital literacy in general, wherefore age and economic background are two of the relevant factors (Haupeltshofer et al., 2020). For appropriate countermeasures, medical staff must be trained in the field of digital health literacy themselves, which is why specific components of digital health literacy have been researched (Haupeltshofer et al., 2020; Palumbo et al., 2022). Additionally, the similarities and differences between digital health literacy and health literacy and their implications have been studied (Palumbo et al., 2022). Furthermore, differentiations between organizational and individual digital health literacy have been made (Palumbo et al., 2022).

Organizational Factors and Managerial Implications

In the context of this work, the organizational and managerial implications of DT in HC represent another important research domain. In this area, it is highly relevant to implement digital technologies in HC to improve work processes and proactively prepare organizations for the accompanying changes (Angerer et al., 2022; Kraus et al., 2021; Reddy et al., 2019; Wurster et al., 2022). However, increased integration of digital technologies in HC should not neglect employees and take their challenges into account (Brown et al., 2020).

At the organizational level, employees should be given the freedom to actively shape the transformation process, rather than simply following the logic of the management (Carboni et al., 2022). Otherwise, implementation will have negative effects on the organization (Kraus et al., 2021). All employees should be considered, otherwise, some may adapt the system to their needs while others have to adapt to the system (Carboni et al., 2022; Kraus et al., 2021).

DT may lead to changes in legal frameworks, which must be considered by the organization and evaluated with all stakeholders (Cavallone & Palumbo, 2020).

Impact of DT on HC Actors

Impact on Workforce Practices

The impact of DT on HC staff's workforce practices is a reoccurring research topic. Digital technologies not only enable but also enforce a wide variety of reconfigurations: depending on the job position held and the accompanying different embedment of professional identity in technologies, professionals can tailor technologies to their individual use or have to adapt their work processes to them (Carboni et al., 2022). Improvements such as easier access to patient information or EHR-initiated reminder positively influence workforce practices and can enhance the overall quality of care (Brown et al., 2020; Carboni et al., 2022; Wurster et al., 2022). At the same time, there is an increased reliance on quantitative data which changes diagnostic and treatment practices (Carboni et al., 2022). This comes with multiple changes in work tasks: increased computer-related administrative tasks also referred to as "desktop medicine", as well as invisible work (Baines et al., 2020; Carboni et al., 2022). The latter refers to "necessary but unacknowledged" (Carboni et al., 2022, p. 6) tasks like explaining technologies to patients or reminding them to use them. Regarding the influence of DT on documentation practices and the amount of documentation needed, studies diverge in their findings (Carboni et al., 2022; González, 2022; Wurster et al., 2022).

The new workforce practices affect work roles, especially the variety of roles taken by nurses, and led to the new expertise field of "nursing informatics" (Haupeltshofer et al., 2020, p. 2707). However, also the role of patients changes since there is a tendency to delegate non-meaningful tasks which were previously fulfilled by medical staff to patients (Carboni et al., 2022). This may result in a relief of burden on medical practices, however, the empowerment of patients also leads to patients assuming to know what kind of disease they have and how it should be treated, which brings new challenges (Sharma et al., 2019).

Several studies found that the implementation of industry 4.0 in HC comes with higher job-related stress either due to operating procedures being new, replaceability of certain activities with digital tools, or higher workload (Carboni et al., 2022; Cavallone & Palumbo, 2020; Wurster et al., 2022).

Additionally, there are changes in modes of interaction with patients, leading to completely new service offers such as electronic consultations (Baines et al., 2020; Cavallone & Palumbo, 2020).

Impact on the Patient-Provider Relationship

Aside from the work environment for HC professionals, DT affects the relationship between patients and providers as well. Depersonalization can occur between the two parties since digital technologies distance the patient and physician from each other and may lead to disruptions of the communication relationship (Carboni et al., 2022; Cavallone & Palumbo, 2020; González, 2022). Kraus et al. (2021) stress that potential depersonalization must not create conflicts of interest between HC providers and patients that may negatively impact patient well-being.

On the other hand, it is also emphasized that digital offers and face-to-face communication do not have to exclude each other but can complement each other leading to an increase in communication between both parties (Haupeltshofer et al., 2020; Kraus et al., 2021).

At the same time, a development away from medical dominance toward technological dominance in the patient-doctor relationship can be observed (Cavallone & Palumbo, 2020).

Discussion

This work is the first umbrella review to present concepts related to DT in HC with a special focus on medical work. According to our inclusion criteria, we identified 25 reviews as relevant. In order to condense existing research, we were able to identify six main concept clusters, which are mostly in line with the concepts established by Kraus et al. (2021). For instance, we could adopt the following concepts: operational efficiency, organizational factors and managerial implications, patient-centered approach, impact on workforce practice, and socio-economic factors. In contrast to earlier reviews, we could identify additional important concepts, like digital health literacy, digital health competencies, DHT, HC 4.0, and the patient-provider relationship.

Since the identified concepts depend on each other, we aimed to illustrate possible relationships in Figure 2. As expected, we could highlight that DT in HC influences medical staff, patients, and HC institutions. Hence, our research concludes that digitalization will have a significant change in HC staff workforce practices (Brown et al., 2020; Carboni et al., 2022; Wurster et al., 2022), which will lead to changing work roles (Haupeltshofer et al., 2020) and new tasks (Carboni et al., 2022; Konttila et al., 2019). Whilst the patient-provider relationship will be strengthened by the possibilities of collaborative care that come with DT in HC (Carboni et al., 2022), practitioners should be aware that there is the potential to lead to a shift away from focusing on the patient and towards depersonalization of care (Kraus et al., 2021). In this respect, this would counteract the overall goal of digital health to strengthen patient-centered care and increase the overall efficiency of HC systems. Different DHTs, like EHR or CDSS, are the digital tools, that come along with the DT and change the way of patient documentation (González, 2022; Marques & Ferreira, 2020), clinical decision-making (Jun et al., 2018; Krick et al., 2019; Kruse & Ehrbar, 2020; Marques & Ferreira, 2020; Patterson et al., 2019; Scott et al., 2018; Sharma et al., 2019; Willis et al., 2022), and overall medical care. Socio-economic aspects, such as social background and financial status influence the implementation of these DHTs and show that the application of them is associated with high costs (Cavallone & Palumbo, 2020; Kraus et al., 2021). Moreover, different key requirements for a successful DT in HC could be identified.

To begin with, different organizational and managerial factors have been considered central to successful implementation. As DT is fundamental for HC institutions to cope with upcoming challenges, they need to be aware of the changes in their legal framework (Cavallone & Palumbo, 2020; Reddy et al., 2019) and how to prepare their employees for a successful DT (Brown et al., 2020). Likewise, the lack of digital health competencies threatens the DT in HC systems (Cavallone & Palumbo, 2020). Especially digital health literacy is a key competence and is strongly influenced by the age and economic status of individuals (Haupeltshofer et al., 2020). In addition to this, HC staff will be confronted with additional requirements with further emergence and development of HC 4.0, such as human-AI collaboration. In the new era of HC 4.0, data-driven technologies will empower the patient as an active participant in a new smart health network (Cavallone & Palumbo, 2020; Sharma et al., 2019), facilitating a more effective interaction between health care providers and patients (Al-Jaroodi et al., 2020).

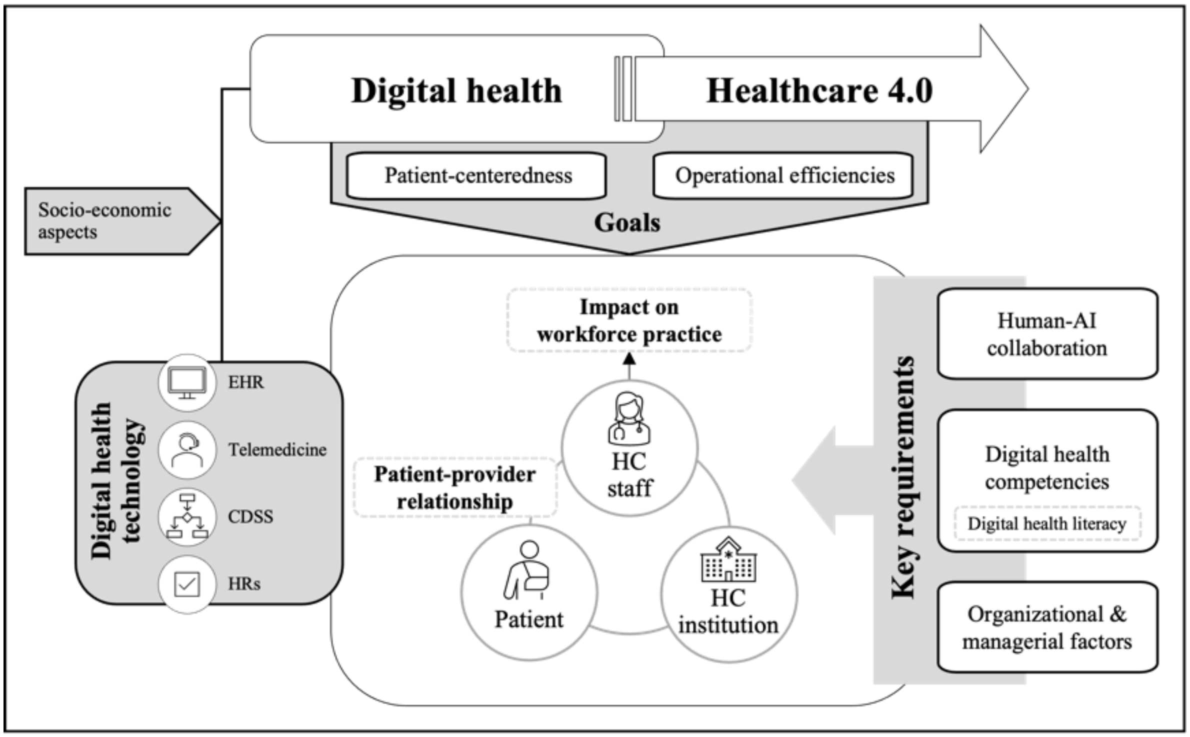

Figure 3. Research Concepts of DT in HC and Medical Work

We are aware that our research may have some limitations. Firstly, the umbrella literature review considered six databases, which provide a comprehensive but a not holistic representation of all relevant literature. Additionally, the specific search string used in this study included a wide range of different HC topics however, due to the scope of this topic, this search string cannot be considered a complete representation of all the relevant fields of DT in HC. The methodology used entails the limitation that only reviews were considered. As a result, some papers that may have shed light on interesting aspects were not considered in this study if they were not mentioned in reviews. The temporal selection starting from 2018 and the focus on English-language papers may have led to neglect of older aspects and omission of relevant papers in other languages. The restricted use of further criteria for evaluating the overall quality of the included reviews, such as journal quality or an examination of the methodological approach, could account for an overall lower study evidence.

Therefore, further conceptualizations related to DT in HC and medical work are required to validate the overall quality of our research findings. Additionally, we propose that HC 4.0, digital health literacy, human-AI collaboration, and the influence of socio-economic factors need further investigation since they are currently underrepresented in research. Additionally, the study of specific interrelationships of concepts could be an interesting future research topic. Apart from that, our findings also indicate that to accomplish goals such as patient-centeredness and digital health literacy, it is also important to acknowledge the patient's perspective. On a wider level, research should incorporate more umbrella reviews since they present a valuable tool for synthesizing knowledge in the digital health area (Faulkner et al., 2022).

Conclusion

As stated in the introduction, our main objective was to review researched concepts in the context of DT in HC, provide a framework for classifying them and present a synthesis of central research findings. We believe our results contribute to significant knowledge on the current state of DT in HC, especially its effects on medical work. By using the novel approach of an umbrella review we found an innovative solution for a fast and comprehensive way to summarize knowledge on digital health research.

Furthermore, our work provides a framework for a new way of organizing research on DT in HC, which can be summarized in six concept domains: (1) HC 4.0, (2) DHT, (3) socio-economic aspects, (4) key requirements for DT in HC, (5) goals of DT in HC, and (6) impact of DT on HC-actors.

Our reviews summary of occurring concepts related to DT in HC extends existing research with similar aims (Carboni et al., 2022; Kraus et al., 2021) by updating and focusing on concepts related to medical work. This might enable more effective and efficient implementation of research findings in practice and hence, contribute to the catch-up of the HC sector on DT. Hence, more studies on this topic are required in order to prepare the HC sector for the future and its upcoming challenges.

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Interview-Analysis of the Impact of Integrating Computer Vision Technology in Biomedical Imaging on the Organizational Identity of Healthcare Professionals

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Abstract

Background: *This study investigates the influence of computer vision (CV) technology in biomedical imaging on organizational identity (OI) within the healthcare industry.*

Objective: *The objective of this study is to explore the ways in which healthcare professionals (HP) adapt to and incorporate new CV technologies, and possible resulting changes to their organizational identity.*

Methods: *The study conducted five expert interviews to gather insights. It provided an introduction to the change in organizational identity in the context of CV technology adoption in healthcare and its impact on the roles and identies of HP.*

Results: *The findings indicate that while CV technology holds the potential to improve diagnostic capabilities, the current applications do not fully automate the process or replace the role of HP.*

Conclusion: *The study concludes that the results serve as a basis for exploring the impact of CV technology on HP. It provides insights for developing strategies to integrate CV technology into healthcare operations while maintaining core values.*

Keywords: computer vision, biomedical imaging, organizational identity, healthcare professionals, technology adoption.

Introduction

The implementation of new technologies in healthcare organizations can have a impact on their identity. This study aims to examine the effects of introducing computer vision (CV) technology in diagnostic practices on OI within the healthcare industry. Through expert interviews, the ways in which healthcare professionals (HP) in their organizations adapt and incorporate new technologies and the resulting changes to their OI will be explored. The findings of this research will provide insight into the process of OI change in the context of CV technology in healthcare.

Motivation

The research on OI is a crucial aspect which can significantly affect the efficacy and success of the transition to new digital systems and processes (Wessel et al., 2021). By understanding these changes, organizations can better support their employees and ensure a smooth adoption of new technologies.

There are several reasons why OI change is important to consider when studying digital transformation.

First, new technologies often require organizations to adopt new business models, processes, and ways of working, which can challenge their existing identities and values. This can lead to feelings of uncertainty and discomfort, as well as resistance to change. Understanding how organizations navigate these changes and how their identities evolve can help organizations better support their employees and ensure a smooth adoption of new technologies (Nadkarni & Prügl, 2021). Second, OI change can affect an organization's performance, reputation, and competitive advantage. For example, if an organization's identity is significantly altered by the introduction of new technologies, it may struggle to attract and retain top talent, or it may lose the trust and loyalty of its customers. On the other hand, if organizations are able to embrace their new identities and communicate their values and mission effectively, they may be more successful in attracting and retaining top talent and building strong relationships with their customers (Ashforth & Mael, 1989; Elving, 2005).

In this paper the authors investigate the influence of CV technology on the OI of HP. CV technology has the potential to enhance patient care and streamline internal processes. By providing doctors with the ability to accurately interpret medical images and data, CV can facilitate more accurate and efficient diagnoses and treatment plans, ultimately improving the reputation of hospitals as providers of high-quality care. In addition, the use of CV can help to increase efficiency and decrease the likelihood of errors within the hospital, potentially leading to a positive transformation of the organization's identity. The authors aim to understand the impact of CV on the roles and identities with characteristics like the mission, values and culture (Kraus et al., 2021). To guide the investigation, the following research question was formulated: "*In what ways does the integration of CV technology in biomedical imaging impact the OI of HP?*".

The paper is structured as follows. First, a theoretical background of OI and CV in healthcare diagnostics is provided. This section aims to provide a comprehensive understanding of the concepts and theories that underpin the research. Afterwards, the authors present the research approach. This section provides an overview of the main sub-objectives that will be reviewed in this paper, as well as the methodology. Chapter four then presents the results of the expert interviews. The authors exhibit their findings, highlighting the key themes and patterns that emerged from the interviews. Following the presentation of the results, the authors provide a discussion section. This section aims to contextualize the identified results within the broader theoretical framework of the study. Lastly, in the conclusion the authors summarize their key findings and contributions to the literature on OI and CV technology in healthcare.

Theoretical Background

This chapter examines the literature and theories relevant to the research topic, including the concept of OI and its significance in the healthcare sector, and how CV technology affects OI change. It covers both current and future uses of CV-based technology in various domains.

Organizational Identity

The concept of OI refers to the unique set of characteristics that distinguish an organization from others and provide it with a sense of cohesiveness and purpose. These characteristics may include the organization's mission, vision, values, culture, and reputation (Gioia et al., 2013a) which may impact not only the identity of HP but also the role they have in the organization. In healthcare, OI can encompass a hospital's mission and values, the services it offers, the patient demographic it serves, and the culture and environment of the hospital. A hospital with a strong OI may experience increased trust and loyalty from stakeholders, while a weak or unclear identity may have detrimental effects. Research has demonstrated that organizations with a positive and well-defined OI often exhibit better outcomes, such as higher patient satisfaction and employee engagement (Kang et al., 2020).

A study by Hospodková et al. (2021) examines how the implementation of digital technologies and emerging trends can lead to systemic changes in the healthcare industry. Their study evaluates the effectiveness of change management and the readiness for change in five Central European countries. The authors conclude that although there is a significant amount of research on the application of Artificial Intelligence (AI) in healthcare, there is a discrepancy between this research and its practical implementation in real-world settings. Furthermore, the study highlights that while AI has the potential to greatly innovate and improve organizational procedures, its sudden implementation may cause long-term difficulties for employees.

In a different study, Hermes et al. (2020) investigate the challenges faced by the healthcare sector in its adoption of new technologies. They identify complexity within the industry, including the presence of multiple interconnected stakeholders and strict regulations, as the primary reason for slower adoption. This complexity results in a lack of interoperability among stakeholders. Additionally, the patients' concerns over data confidentiality and willingness to share personal information further hinder the acceptance of innovation. This concept of patients' distrust towards new technologies is reinforced by a 2018 study that surveyed 2000 German citizens. While Hermes et al. (Hermes et al., 2020) examined the adoption of new technologies in general, this 2018 study by VMware specifically explored the extent to which potential users trust AI in relation to their health. The results of the study indicate that despite most respondents (86%) expressing support for the use of AI to assist in maintaining elderly family members' independence in their own homes, a substantial percentage (61%) of Germans would still choose a human surgeon over an AI, even if it prolongs the healing process. The study concludes that the main reasons for this mistrust are patients' reluctance to relinquish control over certain areas of their lives and their fear of a lack of data protection (Lieder, 2019).

In contrast, many proponents of AI in medicine have a completely different view of the issue. A meta-study published in the Lancet Digital Health in 2019, which evaluated over 20,000 medical studies, revealed that AI's accuracy in identifying diseases is comparable to that of medical professionals. The study identified that CV-based algorithms had an accuracy rate of 86% in correctly identifying diseases, while physicians had an accuracy rate of 87%. Furthermore, the study found that AI performed even better in correctly excluding diseases, with an accuracy rate of 93%, compared to 91% for physicians (*Künstliche Intelligenz Wenn Computer Röntgenbilder Auswerten*, n.d.). However, the findings of this meta-study should be viewed with caution, as only a small fraction of the initial studies were included in the analysis. As such, it is not possible to make a definitive statement about the results of the study.

CV Diagnostiv in Healthcare

CV, a type of AI, enables the analysis and interpretation of visual data such as images and videos (Szeliski, 2022). In healthcare, CV algorithms can be utilized to analyze medical images to identify abnormalities or other indications of disease (Lang et al., 2021). This can facilitate more precise and expeditious diagnoses and treatment plans, leading to improved patient outcomes. In addition to its use in medical imaging, CV technology can also be employed to analyze and interpret other types of medical data (Esteva et al., 2021). The use of CV technology in healthcare has the potential to significantly enhance the accuracy and speed of diagnoses and may reduce the risk of errors while improving patient outcomes (Milstein & Topol, 2020).

X-ray/MRI: Both MRIs and X-rays are medical imaging techniques that use electromagnetic radiation or magnetic fields to produce detailed images of the inside of the body (Buxton, 2009). These images can be analyzed using CV algorithms to identify abnormalities or other signs of disease. Both can be used to diagnose a wide range of medical conditions, including brain disorders, heart conditions, and tumors (Apostolopoulos & Mpesiana, 2020; Lu et al., 2021). Regarding the identity change potential for HP, a comprehensive information gain is listed, but this is always accompanied by a heterogeneity of technical interfaces and a lack of explainability in real use cases.

Computer Tomography (CT) scans: CT scans, or computed tomography scans, use a combination of X-rays and computer technology to create detailed images of the inside of the body. These images can be analyzed using CV algorithms to identify abnormalities or other signs of disease and can be used to diagnose a wide range of medical conditions, including cancer, heart disease, and injuries (Ozdemir et al., 2020). In terms of the potential for identity change of HP, CT scans and CV applications can identify systemic phenotypes that are not readily apparent to human interpretation. This leads not only to more information, but also new information in the diagnosis process (Maier-Hein et al., 2017; Mouhsine et al., 2007; Ozdemir et al., 2020).

Medical Videos: CV technology has been proposed for various surgical applications, such as enhancing surgeon performance through real-time contextual awareness, skills assessments, and training (Garcia-Peraza-Herrera et al., 2017; Maier-Hein et al., 2017).

These applications have been primarily studied in the field of video-based robotic and laparoscopic surgery, where methods for detecting surgical tools and actions, analyzing tool movement, and recognizing distinct phases of surgery have been proposed (Garcia-Peraza-Herrera et al., 2017; Vassiliou et al., 2005). Additionally, CV has been studied for its potential in open surgery settings and for recognizing human activity in physical spaces such as hospitals, for ambient intelligence applications such as patient monitoring and automated documentation (Luo et al., 2018; Núñez-Marcos et al., 2017b; Wang et al., 2016b). While the potential for CV to improve patient outcomes and increase access to healthcare is significant (Esteva et al., 2021). As for HP identity change potential, it could lead to a paradigm shift in healthcare by screening patients for eye disease and other conditions simultaneously (with the OCT scan) – something currently reserved for human physicians.

After an examination of each technology individually, Table 5 provides a summarizing overview of various medical technologies, their corresponding application fields, their potential to bring change to the organization, and the current challenges they face. This table serves as a strategic summary of AI methods and applications and facilitates a systematic progression towards the subsequent chapter.

Medical Technology	**Medical Application**	**Change Potential**	**Challenges and hurdles**
X-rays/ MRIs	Pathology; Cardiology; Cancer (Choy et al., 2018; Mazurowski et al., 2019; Saba et al., 2019)	The utilization of CV methods in healthcare can facilitate progress in image translation and reconstruction, thus providing HP with a more comprehensive information base for diagnosis .	Technical interfaces; different data situation as well as the quantity and its distribution. Explainability
CT scans	EchoNet (Ghorbani et al., 2020) (Cardiology)	Identifies systemic phenotypes not readily identifiable to human interpretation (i) overcome limitations of human visual perception and cognition (ii) develop new signatures of disease and therapy from morphological structures invisible to the human eye, and (iii) combine pathology with radiological, genomic, and proteomic measurements to improve diagnosis and prognosis. (Gaur et al., 2013; Papolos et al., 2016)	Data output formats are protected; Complexity of 3D scans; Explainability
Medical images/videos	Ophthalmology (P. A. Keane & Topol, 2018; P. Keane & Topol, 2019; Ting et al., 2019) Funduscamera, OCT scans Surgeries, Elderly care (Núñez-Marcos et al., 2017a; Wang et al., 2016a)	Video integration in healthcare can enhance diagnostic capabilities and decision-making processes for HP through real-time access to large amounts of data. Additionally, it can reduce workload for HP by automating tasks such as fall detection in elderly care settings, thus improving overall care for this population. It could lead to a paradigm shift in care, in which eye exams screen the patient for the presence of both ocular and nonocular disease—something currently limited for human physicians. (Brinker et al., 2019; Esteva et al., 2017; Haenssle et al., 2018)	Data privacy; Explainability

Table 5: Medical Technologies with AI Applications Compiled from (Esteva et al., 2021)

CV technology can also play a supporting role in the secondary use of health data. The secondary use of health data refers to the use of existing medical data for purposes other than the original purpose for which it was collected (Linder et al., 2010). CV algorithms can be used to analyze this data in order to identify patterns and trends, which can be useful for research, public health surveillance, or quality improvement efforts (Shickel et al., 2018).

Research Approach

Objectives

The purpose of this research is to examine the influence of CV technology on the shift of roles, and identities of HP and to determine any alterations in the OI of the healthcare organization resulting from the adoption of this technology. As OI encompasses various aspects, the authors chose to narrow the focus of the study by identifying four sub-objectives to facilitate the interviewees' responses. The following sub-objectives were used to detect any potential alterations resulting from the integration of CV technology in biomedical imaging and its impact on the OI of healthcare professionals:

1. *Analysis of the influence of CV Technology on the diagnosis process of HP:* This sub-objective aims to understand how the use of CV technology has affected the diagnosis process for HP, including any changes in their roles and tasks.
2. *Analysis to identify awareness of a possibly changed work task of HP:* This sub-objective aims to examine whether HP perceive changes in their work tasks as a result of the introduction of CV technology.
3. *Analysis of the impact of CV technology on the requirements of the qualification profile of HP:* This sub-objective aims to identify any changes in the skills and knowledge required by HP as a result of the adoption of CV technology.
4. *Analysis of the view of legal conditions through the introduction of CV technology:* This sub-objective aims to examine any (assumed) changes in legal or regulatory frameworks to HP that may have resulted from the adoption of CV technology in the healthcare industry.

These sub-objectives address the characteristics of OI: mission, vision, values, culture, and reputation of CV technology in biomedical imaging on the OI of healthcare professionals (Gioia et al., 2013b). By analyzing the impact on the diagnosis process, work tasks, qualification profile, and legal conditions, the authors believe they can understand in which ways the integration of CV technology in biomedical imaging impacts the OI of HP.

Methodology

This chapter outlines the methods and procedures that were employed in the study to address the research questions and achieve the research objectives (Kvale, 1994)[28]. To achieve this goal, semi-structured interviews were conducted with HP who have experienced the introduction of CV technology in their organizations (Kvale, 1994). A comprehensive summary of the research is presented in

, which provides a concise and structured overview of the subject matter.

A purposive sample of five HP from different healthcare organizations was recruited for this study (Patton, 2002). An important consideration in recruiting potential interviewees was medical knowledge of the diagnostic process before and after the use of CV technology (Corbin & Strauss, 2014). The Interviewees were selected based on their early adoption of CV technology and their willingness to participate in the study (Yin, 2009). The sample included doctors and medical computer scientists, who had direct experience with the implementation and use of CV technology in their organizations (Kvale, 1994).

Semi-structured interviews were conducted with the HP to gather in-depth information about their experiences with CV technology and the impact on OI (Kvale, 1994). The interviews were conducted by the authors and a brief overview of the interview partners' characteristics is shown in Table 6. The characteristics include the profession, the working environment at the employer, and then whether the interviewee has direct contact with patients. Finally, to get an impression of the interviews, the length of the interviews is listed as an indicator of the scope. Furthermore, a semi-structured interview guide was developed to ensure that all participants were asked the same questions, while allowing for flexibility to explore topics in more depth (Kvale, 1994). Another topic that was discussed was how a user's technical aptitude can influence the skill adjustments that a HP professional may need to handle. For this purpose, each participant was asked which technical skills they need to have on a scale of one to ten for uncomplicated use. The scale evolves from one being really easy to ten being really hard. The interviews were transcribed verbatim for analysis (Patton, 2002).

ID	Organization	Occupation	Patient Contact	Interview Length
1	Hospital	Doctor	Direct	24 min
2	Research	Manager	None	21 min
3	Hospital	Doctor/Reseacher	Direct	27 min
4	Research	Scientist	None	48 min
5	Start-Up	Data Reseacher	None	26 min

Table 6: Overview of Interview Partners

The transcribed interviews were analyzed using thematic analysis (Braun & Clarke, 2006). The authors coded the transcripts using the “f4analysis tool” (audiotranskription, 2023) and pursued with selective coding (Holton, 2007) according to the previously set sub-objectives. The themes were discussed and agreed upon by the research team (Corbin & Strauss, 2014). The data was analyzed using axial coding, in which codes and themes were compared and refined throughout the analysis process (Braun & Clarke, 2006), the detailed overview of the sub-objectives and quantitative representation can be found Table A 1.

All participants provided informed consent and were assured of the confidentiality and anonymity of their responses (Patton, 2002).

Results

As already described, the authors conducted interviews, coded the transcribed texts, and analyzed them based on the aforementioned (sub-)objective(s). Further prerequisites such as the description of the activity and thus the proof of knowledge were clarified at the beginning of the interview. To examine the impact of CV technology on diagnostic processes, the interviewees were asked to describe the initial diagnostic procedures. The next section presents the specific procedures and steps of the diagnoses as described by the interviewees.

Interview 1: The diagnostic process of the subject drawn from interview 1 is the detection of diabetic retinopathy in diabetic patients. This is an existing remote solution in a diabetes center of a clinic that does not have an affiliated eye clinic. The patients’ eyes are opened wide to provide an unobstructed view of the patients’ retinas. The physician can then look at the patients and assess whether acute action is needed due to retinal damage. After this decision is made, the basic diagnostic process is complete.

As evidenced by the initial interview, a diagnostic workflow, as depicted in Figure 4, was identified. This workflow, utilizing a CV method, enables a preselection process in which the probability of diabetes mellitus is determined in varying degrees, and only critical cases with an identified risk are forwarded to the treating physician. This approach enhances the quality of the physician’s work and allows for increased time allocated to individual patients.

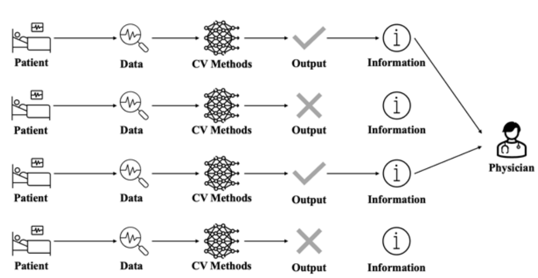

Figure 4: CV Technology in the Diagnosis as a Preselection

Interview 2: Interview 2 addressed a technological innovation in the field of radiology. More specifically, a software that enables CV analysis of X-ray data and classifies it according to possible types of cancer.

However, the software also incorporates the history and therapies stored in the patient's file and provides clues and reasons why the treating physician should refocus on certain regions. For the radiologist and the treating physician, this means more comprehensive information and discoveries on the images as supplementary evidence is provided through the implementation of CV technology.

Interview 3: As mentioned in Interview 1 or the chapter "CV Diagnostics in Healthcare" (2.2), there is a promising application area for CV in ophthalmology. In Interview 3, the interviewee described a potential solution to the problem of analyzing Optical Coherence Tomography (OCT) scans. The goal of the project is to predict and determine the likelihood of whether injection therapy (Anti-VEGF injection therapy (Schrader, 2006)) will result in vision prolongation. This prediction will be based on OCT scans before and after the initial treatments. The goal is to support the physician in his decision to perform the therapy and to recommend a course of action. In contrast, physicians currently make decisions based on experience and risk assessments.

Interview 4: Medical video data, as shown earlier, is a big point of potential innovation. One CV technology considered in Interview 4 deals with live video transmission of surgery to remove tumors. The current state of the art is to transmit a camera image using red, green, and blue wavelengths, as is the case with the human eye.

In the project, a conventional camera was replaced by a multispectroscope that covers between 10 and 100 variables and thus more wavelengths in a range beyond human vision. Through the use of machine learning, these images can be analyzed for oxygenation of tissue structures, for example, and decide whether a piece of tissue is perfused or not. The physician receives an additional image section with the corresponding information on the previously specified screen. In contrast to the first interview, a workflow was observed in the last three interviews, as depicted in Figure 5. The technologies employed in these cases do not perform any pre-selection. Instead, they process the data, augment it with supplementary information, including information that is not readily perceptible to human perception, and provide all the information to the attending physician along with an indication for decision-making. The technology in these cases facilitates the physician with additional or alternate information, thereby supporting decision-making.

Interview 5: The interviewee, an expert in generative adversarial networks, describes a European research project that is conducting a project of the development of a clinical decision support system that assists healthcare professionals in providing treatment methods for patients suffering from stroke attacks. The recommendations are being given by medical images that are analyzed with CV methods to detect symptoms or irregularities. The project is set to improve patient outcomes by providing clinicians with real-time access to relevant information.

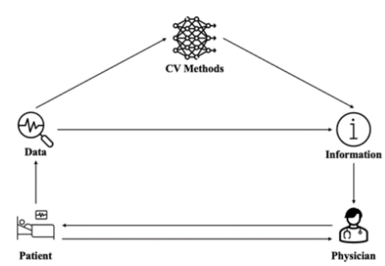

Figure 5: CV Technology in the Diagnosis as Information Enhancement

While Table 7 covers the statements from every interviewee regarding the formulated sub-objectives, the following only presents a brief summary of the results.

	Sub-objective 1 Diagnostic Process	Sub-objective 2 Work Task	Sub-objective 3 Qualification Profile	Sub-objective 4 Legal Conditions
Interviewee 1	Without a CV technology a HP must check every patient. With it only those patients, will be inspected by the HP, where a change was detected.	Work tasks will change, but not in as many scenarios as assumed that the HP would become obsolete. Rather, the AI-based device will help with repetitive and labor-intensive tasks.	Even though the focus and the time-management of the HP is changing, the qualification profile stays the same.	Upon approval, the manufacturer of CV tech will be held liable in a specific manner. It is crucial to ensure that the device is trustworthy through testing, as the question of whether "man or machine" makes more mistakes must be considered.
Interviewee 2	Primary aim is the systematization of working methods by guiding HP through different questions, resulting in comprehensive reports of findings.	HP will perceive the changing work tasks through the technical progress.	There is a legal challenge where AI can only assist HP and not be held accountable for the diagnosis. Therefore, there is no change regarding the qualification profile requirements.	High requirements due to various admissions for the medical tools result in high quality. At the end the HP is liable but depending on the case a reduced liability is possible. In addition, there are country-specific differences that give HP different levels of protection.
Interviewee 3	In many aspects, CV technology gives the HP evidence-based recommendations so that the diagnosis can change. Since the HP still bases their experience not only on the device but also on their perceptions. The diagnosis can remain the same but the process changes.	Once AI-based device has gained trust of the HP, he/her uses the device which results in awareness of a changed work task.	Since the HP already uses other measuring devices, they are already familiar with supporting data (systems).	HP will always remain accountable since in criminal law a natural person must be liable. At first this will always be the doctor. Depending on the case a reduced liability for the HP may be possible.
Interviewee 4	Because the HP gets additional information provided the process of the diagnosis changes.	HP will have more time for patients. If the device shows promising results, HP will move from a primary diagnostic role to a corrective role which results in recognized work task.	On a higher plane, with CV technology the balance shifts from technical expertise to social expertise as the AI will possess the technical expertise.	Not yet widely in use and therefore also still great uncertainty in this area. Cannot be answered at the time of the interview.
Interviewee 5	In the near future the diagnosis process especially for radiologists will change, since CV technology is better in detecting rare diseases.	With the help of CV technology, the HP will have access to a better diagnosis, which they will recognize.	The qualification profile should change, since from a technical perspective the HP should be aware of limitations and chances of CV technology	The CV technology will only be a diagnosis decision support, which results in no legal conditions change.
Summary	CV technology will become increasingly important for HP as a supporting function for additional Information incorporated in the decision-making process. That improves the HP decisions in the diagnostic process.	HP work tasks will become less repetitive and labor-intensive, allowing them to focus on more qualitative patient-centered care.	The interviews showed different views on whether and how the qualification profile changes. Some said it will be more social than technical, others said it will stay the same as HP already use complex equipment.	Interviewees disagreed on liability, with some suggesting reduced liability for HPs but continued accountability under the law. The use of CV technology as a diagnostic aid does not change legal conditions, but one interviewee with practical experience claimed the manufacturer would be liable.
	Legend:	No change reported	Change reported	No answer

Table 7: Interviewee Responses on the Impact of Computer Vision Technology Integration in Biomedical Imaging on the Organizational Identity of Healthcare Professionals, in Relation to the Formulated Sub-objectives.

Diagnosis Process: With the aid of CV technology, HP are now able to efficiently detect health alterations of patients and only inspect those patients where an alteration was detected. This has resulted in a more systematic working method for HP, who are guided through a series of questions to generate comprehensive reports of findings. Furthermore, the use of CV technology provides evidence-based recommendations to HP, which can potentially alter the diagnosis process. However, the process remains heavily dependent on the experience and perception of HP. While the incorporation of CV technology may lead to changes in the diagnosis process, the role of HP in the process remains vital. Additionally, the use of CV technology has also provided HP with additional information that has changed the process of diagnosis. As a result, the diagnosis process for HP, particularly for radiologists, is expected to change in the future, as CV technology is better equipped to detect rare diseases. Overall, most interviewees agree that the impact of CV technology on the diagnosis process of HP is significant and has an influence on the roles, identies, and tasks of HP.

Work Task: All interviews revealed that HP have become increasingly aware of the possibility of a changing work task due to the integration of CV technology. The experts mentioned that AI-based devices can help with repetitive and labor-intensive tasks, which will lead to a shift in the work tasks of HP. This change will allow HP to have more time for patients, and if the technology shows promising results, they will move from a primary diagnostic role to a corrective role.

In connection to identifying awareness of a possibly changed work task the interviewees indicate that the HP will recognize the changing work task as they become more familiar with the technology.

Qualification Profile: The interviews revealed a lack of consensus regarding a qualification profile change. One legal challenge with the use of AI in healthcare is the requirement that AI is used to assist HP rather than replace them in the diagnosis of patients. This legal requirement supports the notion that the qualification profile of HPs could remain largely unchanged. Others stated that since HP already use complex measurement equipment there might be no change in the qualification profile.

However, one interviewee mentioned that the introduction of CV technology could shift the balance of expertise required of HPs, as AI will possess much of the technical expertise, which may lead to a greater need for social expertise. Another interviewee noted that the incorporation of CV technology into healthcare practices creates the need for a better understanding of the potential benefits and limitations of these technologies.

In addition to the potential change in the qualification profile, all the interviewees noted the importance of technical aptitude (Figure 6) for the HP to effectively utilize CV technology in biomedical imaging.The technical aptitude was added to the questionnaire to get a better idea of the bias of each interviewee and to contextualize their responses accordingly. Moreover, technical aptitude can give an indication of the novelty of the introduced technology for the interviewee. And consequently, it fulfills the function of a more comprehensive picture for the evaluation of the possible identity change.

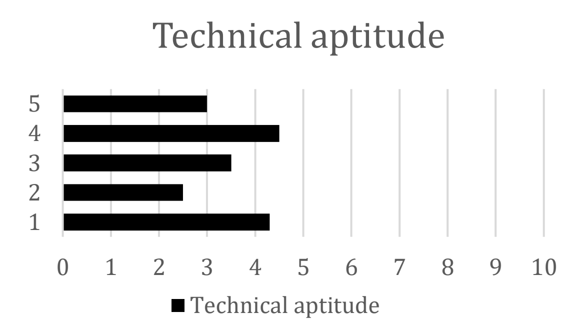

Figure 6: Technical Aptitude of Users Needed

The responses given were on a scale of one to ten, with zero indicating a lack of technical aptitude and ten indicating a high level of technical aptitude. The responses given by the interviewees were between two point five (2.5) and four point five (4.5), which indicates a beneficial characteristic for the acceptance and successful implementation of CV technology or AI technology in general among HP.

Legal Conditions: There was an unclear consensus among interviewees regarding liability. The majority of the interviewees acknowledged that depending on the case, HP could potentially mitigate liability, but they emphasized that legal accountability rests solely on natural persons in criminal law. This aligns with the statement that CV technology is intended to serve as a decision-making tool for diagnosis and will not alter the legal framework. However, the only interviewees who had experience with using CV technology in practice believed that the liability lies with the manufacturer.

Discussion

The results of the research indicate that the integration of CV technology in biomedical imaging for diagnostics impacts the OI of HP. While there is a common assumption that AI solutions could potentially replace HP, the majority of the interviewees did not express such concerns but rather viewed these technologies as complementary aids. The integration of CV technology in the *diagnosis process* could lead to improved accuracy, enabling HP to make well-informed decisions and reducing the risk of misdiagnosis (Ravi et al., 2017). Additionally, a streamlined diagnosis process could save time and effort, which would result in higher levels of patient satisfaction and trust, ultimately impacting the OI.

Furthermore, participants agreed that the use of AI in an assistive role would enhance the diagnostic *work task* of HP. Those HP who possess knowledge about the modifications in their job tasks and comprehend how such changes impact their work are more inclined to experience job satisfaction, perhaps due to their ability to adapt proactively to new tasks and exert greater control over their work (Grant & Ashford, 2008). Such job satisfaction is associated with better job performance and a more favorable work atmosphere, which in turn positively affects the OI (Judge et al., 2001).

Based on the results of the interviews, the authors found that the necessary technological expertise for operating CV technology would not require significant skill changes for HP who already use assistive technologies. Organizations that adopt CV technology should evaluate its impact on the *qualification profile* of HP to ensure optimal resource utilization (Aquino et al., 2023; Frank et al., 2019). This analysis can identify the need for additional training or resources for the existing workforce, or the creation of new roles to support efficient technology use, enabling informed decision-making to align technology integration with organizational vision while preserving core values and identity, and ultimately optimizing resource utilization and securing OI. Moreover, research suggests that incorporating AI education into medical curricula can enhance the understanding and utilization of technical solutions (Paranjape et al., 2019). Current studies indicate that interdisciplinary teams with diverse skill sets are crucial for developing effective solutions and enhancing the qualification profile of HP (Thevenot et al., 2018).

In regard to the last sub-objective, examining the impact of *legal conditions* on HP resulting from the adoption of CV technology, the findings of this study provide an intriguing insight. Specifically, it is noteworthy that only the participant who utilizes CV technology for assistive preselection believes that the technology provider covers any insured loss. This observation aligns with the statement made by another participant who noted that AI will remain an assistive enhancement technology as long as the current laws and regulations do not change. It is also worth mentioning that, as stated by legal expert (Schönberger, 2019), the law should clarify that the lack of explanation shall always be to the detriment of the decision-maker. These findings emphasize the importance of considering the legal and regulatory implications of implementing CV technology in healthcare. Ongoing monitoring and adaptation are also necessary to ensure the safe and compliant use of the technology. Effective communication and transparency between healthcare organizations and technology providers are crucial to ensure all parties are aware of and addressing potential legal liabilities. Compliance with legal regulations is not only important for avoiding legal liabilities, but it may also be crucial for maintaining an organization's values and identity. With the introduction of CV technology, concerns about data privacy and security must also be addressed to maintain an organization's reputation as a trusted healthcare provider. Both values and reputations distinguish one organization from another and are therefore worth considering in research on OI (Ravi et al., 2017). Furthermore, the study uncovered a consensus among participants that there is a disconnect between research and implementation in the field, which is consistent with current literature on the topic (Thevenot et al., 2018).

In general, digital technologies play a crucial role in various aspects of the diagnostic process, beyond the scope of this study which closely examined the impact of CV technology. Some examples of digital technologies in healthcare include capturing information about patients' clinical history, shaping clinicians' workflow and decision-making, and facilitating information exchange (Balogh et al., 2015). Furthermore, the effect of digital technologies on the OI of HP may fluctuate based on the particular technology employed. A conceivable example of this is the degree of reliance a medical practitioner places on a digital technology. Certain AI models that employ algorithms characterized as black boxes, whose operational mechanisms are ambiguous, may engender less confidence than those that are more comprehensible (Savage, 2022).

Conclusion

The incorporation of technology in healthcare organizations requires a comprehensive and well-designed strategy for OI, considering the complexity of the healthcare industry. The healthcare sector comprises a vast number of interrelated stakeholders and strict government regulations that make it challenging to implement new technologies, such as biomedical imaging (Maier-Hein et al., 2017). Additionally, patients' concerns over data confidentiality further impede the acceptance of technological advancements. In this study, the authors conducted interviews with experts from various backgrounds, including experienced physicians and computer scientists with knowledge in the field of CV and healthcare. Through interviews conducted, significant findings and observations were obtained.

Although the integration of CV technology holds the potential to significantly improve the diagnostic capabilities of HP, the current applications do not involve fully automating the process and replacing the role of physicians with AI. At present, AI in healthcare mostly concentrates on providing better access and representation of information for HP, thereby enhancing their job performance. The current applications are mainly supportive and do not necessarily make the daily tasks more efficient.

Nevertheless, one area where CV has already been successful in making a physician's daily routine more efficient and reducing time requirements is in the preselection process using a camera. The result is better quality of work for and more capacity for the physician.

Another aspect that can be inferred from the support function of CV is that of knowledge management. As the use of CV reduces the need for extensive professional expertise, the requirements for HP may change. If CV reduces the need for extensive professional knowledge, the human or social aspects of the job may become more prominent.

To create a more holistic perspective of how CV technology can lead to OI change, the authors formulated four sub-objectives about the following topics:

- *The diagnosis process*
- *The work task*
- *The qualification profile*
- *The legal conditions*

In conclusion, this study serves as a valuable starting point for further investigation into the impact of computer vision (CV) technology on the internal value proposition of healthcare professionals (HP). The insights gained from this study can guide the development of strategies aimed at optimizing the integration of CV technology into healthcare operations, while ensuring the preservation of core values and organizational identity.

Furthermore, it is crucial for researchers and healthcare organizations to collaborate on conducting larger and more diverse studies to gain a comprehensive understanding of the impact of this emerging technology on healthcare systems. With ongoing research and innovation, CV technology holds the potential to enhance patient outcomes and revolutionize the field of healthcare.

Acknowledgement

This study is faced with several limitations, one of which is the small sample size of only five interviewees, this could hinder the generalizability of the findings. Additionally, the selection bias is present as the choice of participants may influence the outcome of the study and the interviewees may not be representative of the entire population in the healthcare sector, which further limits the generalizability of the results. Furthermore, the discrepancy between the research on biomedical imaging and its practical implementation could be seen as a constraint. While research proposes a wide range of potential use-cases for CV technology, there is a lag in its practical implementation which results in the time of the interviews being too early to fully capture the OI change of CV technology use in the healthcare sector.

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Appendix

A.1 Overall Research Approach

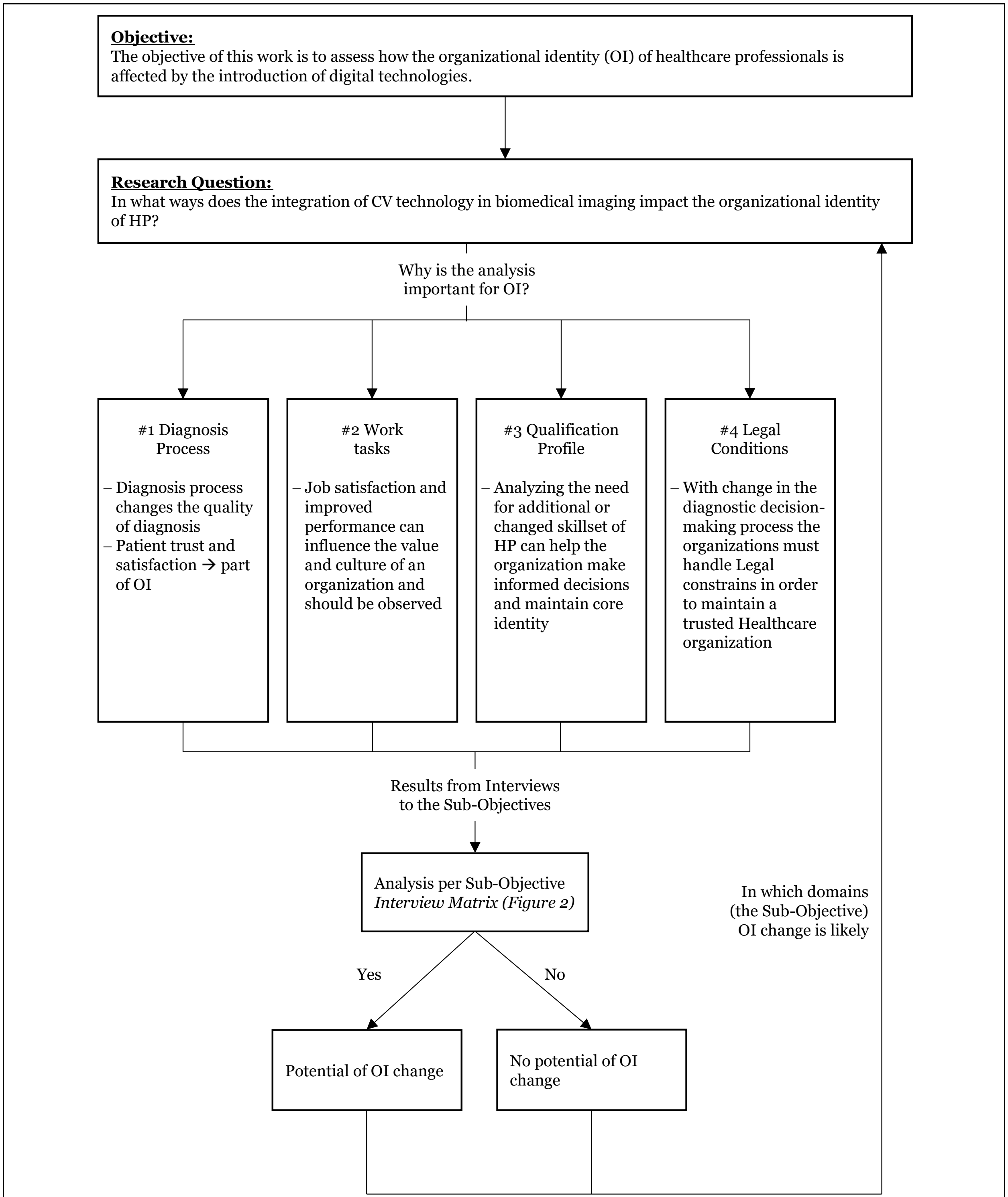

Figure A 1: Overview Research Approach

A.2 Coding Overview

Code No.	Name of the Code	Interview 1	Interview 2	Interview 3	Interview 4	Interview 5	∑
1	Personal Data and Introduciton	1	2	3	1	3	10
2	Problem that induced the Project of the interviewee	2	2	1	5	2	12
3	Diagnosis process change*	9	7	3	10	4	33
4	Awareness of change in the Work task*	3	8	5	10	2	28
5	Change in the Qualification profile or Skillset of HP*	2	2	3	6	3	16
6	Technical Aptitude	5	1	3	2	1	12
7	Legal Conditions*	8	6	1	6	1	22
8	Change of Role/Change of Identity	2	2	5	8	3	20
9	Technical issues of the implementation of CV technology in HC	2	4	2	5	0	13
	∑	34	34	26	53	19	166

Table A 1: Overview Coding; * *Sub-objectives which are described in 3.2 Objectives*

Examination of the Applications and Requirements of a Chatbot in Administrative Student Services

Selected Issues in Critical Information Infrastructures, Winter Term 22/23

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Abstract

Background: *The sentiment at the Karlsruhe Institute of Technology (KIT) among students reveals relatively low satisfaction with administrative support from student services (Studierendenservice). One potential solution is the implementation of chatbots based on positive experiences in other fields and companies, such as customer support services.*

Objective: *The literature is divided on the potential of chatbots in the administrative environment of universities. Therefore, this study examines the acceptance, potential application areas, and usage requirements for a chatbot in student services.*

Methods: *In a standardized online survey conducted with 58 students from various disciplines and study stages, the acceptance, potential application areas, and usage requirements were assessed through open-ended and closed-ended questions. The qualitative responses were coded based on the inductive category formation and deductive category application process model.*

Results: *The results indicate a tendency to use the chatbot for services that require minimal personal consultation, such as providing information and access to formal documents. The chatbot is intended to serve as the first point of contact for inquiries to student services, delivering complete, accurate, and prompt responses. Furthermore, it is evident that the willingness to use chatbots positively correlates with previous satisfaction with chatbot experiences.*

Conclusion: *The chatbot is not intended to replace student services but rather complement their existing work and, when necessary, redirect inquiries to personal contact persons.*

Keywords: chatbots, university, administrative support, questionnaire, survey, applications, requirements

Einleitung

Verschiedene Studien belegen, dass der Mangel an Unterstützung für Studierende zu einem geringeren Lernerfolg und einer höheren Unzufriedenheit im Studium führen kann (Annamdevula & Bellamkonda, 2016; Eom et al., 2006). Aus diesem Grund erfasst das Karlsruher Institut für Technologie (KIT) in regelmäßigen Abständen die Erfahrungen der Studierenden mit den administrativen Diensten (Pfeifer & Legrum-Khaled, 2022). In der Umfrage aus dem Wintersemester 2021/ 2022 schneidet der Studierendenservice – als zentrale Anlaufstelle für diverse Belangen – am schlechtesten im Vergleich zur Betreuung durch Fachschaften, Fakultäten und das Lehrpersonal ab (Pfeifer & Legrum-Khaled, 2022). Die Unzufriedenheit mit dem Studierendenservice wurde durch informelle Gespräche mit anderen Studierenden weiter bestätigt. Vor allem wurden die mangelnde Erreichbarkeit des Services sowie die Fehlerhaftigkeit der bereitgestellten Informationen als Gründe genannt.

Der Einsatz eines Chatbots stellt für dieses Problem eine mögliche Lösung dar, weil er eine rund um die Uhr verfügbare, skalierbare und durch natürliche Sprache steuerbare Interaktion bieten kann. In der Literatur finden sich positive Erfahrungen mit Chatbots im Kundenservice (Xu et al., 2017), im Gesundheitswesen (Nadarzynski et al., 2019) sowie erste Anwendungen von Chatbots an Hochschulen (Wollny et al., 2021). Insbesondere mit den technologischen Fortschritten wie ChatGPT haben Chatbots in den letzten Monaten eine breite Akzeptanz und Anwendung gefunden (Browne, 2023).

Die Frage nach der Akzeptanz der Studierenden für den Einsatz von Chatbots im administrativen Umfeld ist allerdings uneinheitlich beantwortet: Einige Studien attestieren vielversprechende Potenziale (Hien et al., 2018; Meyer von Wolff et al., 2020), andere Arbeiten sind skeptischer (Han & Lee, 2022). Der Gegensatz innerhalb der gesichteten Literatur erfordert die Sinnhaftigkeit eines Chatbots für den Studierendenservice am KIT in Hinblick auf die Akzeptanz der Studierenden, die Einsatzgebiete und zugrundeliegenden Anforderungen zu untersuchen. Auf Basis dieser Überlegung wurden folgende beiden Forschungsfragen abgeleitet:

Forschungsfrage 1: Wo eignet sich der Einsatz von Chatbots im Studierendenservice?

Forschungsfrage 2: Welche Nutzungsanforderungen haben Studierende an einen Chatbot im Studierendenservice?

Anhand einer Online-Umfrage unter 56 Studierenden wurde eine Tendenz zur Nutzung eines Chatbots im Studierendenservice festgestellt. Der Chatbot soll hauptsächlich Auskunft und Zugang zu Informationen/ Dokumenten ermöglichen, die ein niedriges oder mäßiges Maß an persönlicher Beratung und damit einhergehendem Vertrauen benötigen (zum Beispiel Anträge/ Formulare/ Bescheinigungen oder Termine/ Fristen). Der Chatbot soll die Arbeit des Studierendenservices nicht ersetzen, sondern ergänzen, indem das Anliegen bei unzufriedenstellender Antwort an eine persönliche Ansprechperson weitergeleitet wird.

Die Arbeit ist wie folgt aufgebaut: Kapitel 2 beschäftigt sich mit dem bisherigen Einsatz von Chatbots an Hochschulen und dem Studierendenservice am Beispiel des KITs. Im darauffolgenden Kapitel 3 wird Methodik und die Datengrundlage erläutert, gefolgt von der Analyse der Umfrageergebnisse in Bezug auf die beiden Forschungsfragen in Kapitel 4. Die Arbeit endet mit einer zusammenfassenden Diskussion in Kapitel 5.

Grundlagen

Einsatz von Chatbots an der Hochschule

In der Geschichte der Informatik ist der Gedanke, durch die Nutzung von Computern Fragen zu beantworten, nicht neu. Bereits in den 1960er Jahren entstand diese Idee. Der erste Chatbot namens ELIZA wurde 1966 von Joseph Weizenbaum entwickelt (Weizenbaum, 1966). Allerdings konnte sich das Konzept von Chatbots erst durch die Verwendung und Verbesserung von Messenger Diensten durchsetzen, sodass sich inzwischen der Einsatz von Chatbots einer zunehmend großen Beliebtheit erfreut (Gentner et al., 2020).

Durch die Verwendung natürlicher Sprache ermöglichen Chatbots die unkomplizierte Interaktion zwischen Menschen und technischen Systemen. Chatbots können Informationen sammeln, fungieren als Übersetzende oder vereinfachen geschäftliche Transaktion (Aditya et al., 2022) und können somit viele unterschiedliche Aufgaben übernehmen. So gibt es diverse Anwendungsbereiche, in welcher der Einsatz von Chatbots vorteilhaft sein kann: zum Beispiel im Kundenservice wie im E-Commerce, Bankensektor oder Tourismus (Savanur et al., 2021), aber auch im Gesundheitswesen (Nadarzynski et al., 2019).

Während Chatbots in den genannten Bereichen schon erfolgreich implementiert und genutzt werden, sind sie im Bildungswesen noch wenig im Einsatz. In der Studie von Wollny et al. (2021) werden drei Domänen im Bildungswesen identifiziert, in denen bereits die Nutzung von Chatbots stattfinden: Diese umfassen Learning Chatbots, Mentoring Chatbots und Assisting Chatbots. Ein bekanntes Beispiel für Learning Chatbots ist Duolingo, einer der bekanntesten Online-Dienste zum Erlernen von Fremdsprachen. Duolingo ermöglicht es den Nutzenden durch die Interaktion mit Chatbots Fremdsprachendialoge zu üben (Duolingo, 2023). Während Learning und Mentoring Chatbots aber dazu beitragen können, interaktivere Lernplattformen zu gestalten, können Assisting Chatbots bei der Durchführung von administrativen Tätigkeiten Unterstützung bieten (Wollny et al., 2021). Insbesondere bei Aufgaben in der Administration entstehen Vorteile wie bessere Kommunikation (Sandu & Gide, 2019), Beschleunigung von Arbeitsprozessen und eine daraus resultierende Nutzerzufriedenheit (Aditya et al., 2022). Durch die Verwendung von Chatbots kann die administrative Arbeit reduziert werden (Lee et al., 2019).

An Hochschulen, welche einen bedeutenden Anteil an administrativer Arbeit aufweisen, könnte der Einsatz von Chatbots von besonderer Relevanz sein (Hien et al., 2018; Meyer von Wolff et al., 2020). Jedoch besteht in der Forschung keine einheitliche Position zu diesem Thema. In der Studie von Han und Lee (2022), bei der eine Umfrage mit 120 Studierenden durchgeführt wurde, wird die Nutzung von Chatbots an Hochschulen hingegen als weniger erfolgversprechend im Vergleich zu FAQ-Seiten betrachtet (Han & Lee, 2022).

Die Berücksichtigung von Anforderungen seitens der Nutzenden ist ein unerlässlicher Faktor für den Erfolg von Chatbots (Winkler & Soellner, 2018). In den genannten Studien Hien et al. (2018), Meyer von Wolff (2020), und Han und Lee (2022) wurden Nutzungsanforderungen identifiziert, jedoch sind diese spezifisch für die jeweilige Hochschule. Folglich können die Ergebnisse dieser Studien nicht ohne Weiteres auf die Entwicklung von Chatbots für andere Hochschulen übertragen werden. Es ergibt sich daher ein Bedarf zur Durchführung von universitätsspezifischen Umfragen zur Identifikation von Nutzungsanforderungen.

Auch wenn die Forschung zum Einsatz von Chatbots in Hochschulen noch am Anfang steht, gibt es einige Universitäten, die bereits Chatbots zur Klärung von administrativen Fragen nutzen. Zum Beispiel wird an der Goethe-Universität in Frankfurt am Main ein Chatbot für Fragen zum Studienbeginn eingesetzt (Goethe Universität, 2023). Anliegen zum Thema COVID-19 werden an der Universität von Sydney ebenfalls von einem Chatbot beantwortet (Matchett, 2020). Anhand dieser Beispiele wird deutlich, dass sich die Anwendungsfälle auf einen spezifischen Bereich fokussieren und sich folglich in ihren Anforderungen unterscheiden müssen.

Der Studierendenservice am Beispiel des Karlsruher Instituts für Technologie

Der Studierendenservice am KIT ist eine zentrale Anlaufstelle für diverse Belangen in unterschiedlichen Zeitabschnitten des Studiums. Bewerbende für ein Studium am KIT können sich bezüglich Fragen zur Bewerbung, Zulassung oder auch zur Studienberatung an den Studierendenservice wenden. Während des Studiums sind Anliegen hinsichtlich der Studienberatung oder anderen organisatorischen Themen relevant. Auch nach dem Studium ist der Studierendenservice der Kontakt für Themen wie die Ausstellung von Abschlussdokumenten oder auch die Exmatrikulation. Die hier genannten Themen bilden aber lediglich einen Ausschnitt aus dem umfangreichen Aufgabenbereich (Karlsruher Institut für Technologie, 2023).

Es ist ersichtlich, dass der Studierendenservice ein breites Themenspektrum abdeckt, was dazu führt, dass die Bearbeitung von Anfragen für mehr als 22.000 Studierende eine herausfordernde Aufgabe darstellt. Aufgrund der hohen Nachfrage können dringende Anfragen nicht zeitnah bearbeitet werden, was zur Überlastung der Mitarbeitenden des Studierendenservices führt und möglicherweise die Qualität ihrer Arbeit beeinträchtigt.

Dieser Umstand wird durch eine Umfrage unter Studierenden zur Zufriedenheit mit der Beratung im Studium aus dem Wintersemester 2021/ 2022 deutlich (Pfeifer & Legrum-Khaled, 2022). Die Ergebnisse dieser Umfrage zeigen, dass die Kategorie „Betreuung und Beratung am KIT Insgesamt" den geringsten Wert unter allen anderen Bereichen aufweist. Die Unzufriedenheit der Studierenden wird auch außerhalb dieser Umfrage sichtbar. Bei der Google Kundenbewertung erzielt der KIT Studierendenservice nur 2,8 Sterne auf einer Bewertungsskala von 1 bis 5 (Stand: 15.03.2023). Während einige Bewertungen sich positiv zum Studierendenservice äußerten, existieren zahlreiche negative Kommentare bezüglich der langen Bearbeitungszeit, der Korrektheit vermittelter Informationen sowie der zeitlich beschränkten Erreichbarkeit. Auch durch individuelle Erfahrungen der Autoren und persönlichen Austausch mit Mitstudierenden kann dieses Stimmungsbild bestätigt werden. Zusammenfassend kann die Situation beim Studierendenservice sowohl für Studierende als auch für Mitarbeitende als herausfordernd bezeichnet werden.

Methodik

Konzipierung der Umfrage

Zur Beantwortung der beiden Forschungsfragen wird eine standardisierte Umfrage als Forschungsmethode herangezogen. Das Forschungsdesign gliedert sich in drei Phasen: 1) Konstruktion des Fragebogens, 2) Durchführung der Umfrage und 3) Auswertung der Umfrageergebnisse (siehe Abbildung 1).

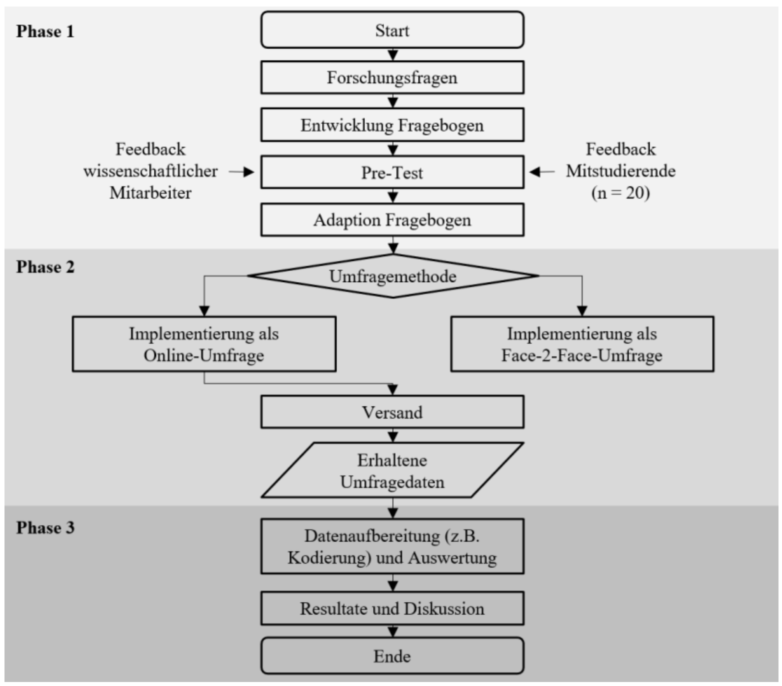

Abbildung 1. Ablaufplan Forschungsdesign

Phase 1 – Konstruktion des Fragebogens: Das Grundgerüst des strukturierten Fragebogens wurde auf Basis vergleichbarer Studien entwickelt (Han & Lee, 2022; Hien et al., 2018; Meyer von Wolff et al., 2020). Im Anschluss erfolgte eine Adaption des Fragenkatalogs im Rahmen eines Pre-Tests mithilfe von 20 Mitstudierenden und eines wissenschaftlichen Mitarbeiters des KITs. Dabei führte das Feedback der Mitstudierenden zu einer Anpassung der Verhältnisse zwischen offenen und geschlossenen Fragen sowie zu einer Verkürzung des Gesamtumfangs des Fragebogens, um die Teilnahmehürde zu verringern. Zudem wurde der Ablauf des Fragebogens optimiert und formulierungsbedingte Missverständnisse behoben.

Der resultierende Umfragebogen gliedert sich in vier Blöcke: 1) Demographische Fragen, 2) Bisherige Erfahrungen mit dem Studierendenservice, 3) Bisherige Erfahrungen mit Chatbots und 4) Chatbots im Kontext des Studierendenservices (siehe Anhang A-1). Die demographischen Fragen über Geschlecht, Studiengang und Studienabschnitt dienen zur Sicherstellung der Qualität der Stichprobe. Der zweite Block sammelt Informationen über die Häufigkeit, den Zeitpunkt und die Gründe für die Nutzung des Studierendenservices. Für letztere Frage wurde eine offene Fragenformulierung gewählt, um den vielfältigen Aufgabenbereichen des Studierendenservices gerecht zu werden. Innerhalb des dritten Blocks wird das derzeitige Nutzungsverhältnis von Chatbots und die damit einhergehende Zufriedenheit der Studierenden jeweils anhand einer fünf-stufigen Likert-Skala erfragt. Im vierten und letzten Block werden die beiden Forschungsfragen konkret gestellt: Für welchen Bereich des Studierendenservices können sich die Studierenden einen Chatbot vorstellen und welche Anforderungen haben die Nutzenden an diesen. Die Entscheidung, die erste Frage offen zu stellen, resultiert erneut aus dem Umstand, die Antwortmöglichkeiten im Hinblick auf die Vielfalt des Studierendenservices nicht einzuschränken. Die Frage nach den Nutzungsanforderungen ist ebenfalls aus zwei Gründen offen gestellt: Erstens, es können studierenden- oder sogar universitätsspezifische Anforderungen, die im Voraus nicht bekannt sind, erfasst werden. Zweitens, die Nutzungsanforderungen hätten auch auf Basis bereits in der Literatur definierter Merkmale in einer geschlossenen Frage umgesetzt werden können. Dieses Vorgehen hätte jedoch dem Feedback der Studierenden aus dem Pre-Test widersprochen, die Umfrage möglichst kurz zu halten, da Definitionen für die spezifischen Anforderungen zum Verständnis hätten mitgeliefert werden müssen. Letztendlich wird die geplante Nutzung eines Chatbots im Studierendenservice anhand einer fünf-stufigen Likert-Skala erfragt.

Phase 2 – Durchführung der Umfrage: Zunächst stand die Entscheidung über die Umsetzung als Online- oder Face-2-Face-Umfrage aus. Die empirische Forschung schreibt den Ergebnissen von Face-2-Face-Umfragen eine bessere Datenqualität zu (Heerwegh & Loosveldt, 2008), da zum Beispiel die direkte Interaktion zwischen Befragtem und Interviewer Unklarheiten beseitigen kann. Demgegenüber steht jedoch der erhöhte zeitliche Aufwand durch die Befragung an sich und der nachfolgenden Digitalisierung und Konsolidierung der erhobenen Daten. Die Abwägung dieser Vor- und Nachteile führte zu der Entscheidung, eine Online-Umfrage durchzuführen. Zur Implementierung wurde die Umfrageverwaltungssoftware „Google Formulare" gewählt. Über den Zeitraum vom 30.12.2022 bis zum 19.01.2022 wurde die Umfrage über private Kanäle (zum Beispiel über Messenger Dienste) und öffentliche Kanäle (zum Beispiel in den KIT-Gruppen der Lernplattform „Studydrive") zugänglich gemacht.

Phase 3 – Auswertung der Umfrageergebnisse: Die Kodierung der qualitativen Antworten (entsprechend in Fragenblock 2 und 4) orientiert sich am Ablaufmodell für induktive Kategorienbildung und deduktiver Kategorienanwendung (Mayring, 2000).

Die Antworten in Bezug auf die bisherigen Gründe für den Kontakt sowie die gewünschten Einsatzgebiete für einen Chatbot wurden durch ein induktives Vorgehen kodiert: Insgesamt wurden 87 Antworten zu Gründen für den bisherigen Kontakt und 98 Antworten zu Einsatzgebieten für den Chatbot in Zukunft in zwei Kategorien mit jeweils sieben und sechs Subkategorien zugeordnet (siehe Tabelle 1). Da die Mehrheit der Antworten nicht als umfangreich beschrieben, sondern eher als „einfache Nennungen" bezeichnet werden kann, wird auf das exemplarische Zitieren von Antworten verzichtet.

Die Kodierung der Anforderungen des Chatbots erfolgte in einem deduktiv-induktiv-gemischten Verfahren. Zunächst wurden die Antworten in *funktionale* und *nicht-funktionale* Anforderungen unterteilt. Als *funktionale* Anforderungen werden Funktionen bezeichnet, die ein System oder eine Systemkomponente ausführen muss (IEEE Standards Committee, 1990). Hierbei bezieht sich die Kategorisierung auf spezifische Funktionen des Chatbots, die für den Einsatz im Gebiet des Studierendenservice ausführbar sein sollten. Unter *nicht-funktionalen* Anforderungen werden jene Anforderungen beschrieben, welche sich primär auf die Qualität der ausgeführten Aufgaben des Chatbots beziehen, auf Basis unterschiedlicher Bewertungskriterien. Der Fokus liegt somit darauf „wie gut" der Chatbot seine Aufgabe erfüllt, im Gegensatz zu *funktionalen* Anforderungen, die sich darauf konzentrieren, „was" der Chatbot ausführen soll (Paech & Kerkow, 2004). In einem ersten Schritt wurden 75 Antworten den *nicht-funktionale* Anforderungen zugeordnet und deduktiv anhand der Strukturierungsdimensionen nach ISO 25010 in sechs Qualitätsmerkmale und acht Teilmerkmale unterteilt (siehe Tabelle 3). An dieser Stelle ist anzumerken, dass lediglich mit unseren Ergebnissen konsistente Merkmale präsentiert werden und aus diesem Grund zu manchen Qualitätsmerkmalen nur ein Teilmerkmal erwähnt wird. Als internationale Norm eignet sich diese aufgrund ihrer allgemeingültigen Struktur zur Bewertung der Qualität von Softwareprodukten, unter anderem auch für Chatbots. Die übrigen 23 Antworten wurden den *funktionalen* Anforderungen zugeordnet und induktiv in sechs Kategorien eingeordnet (siehe Tabelle 2).

In allen Fällen kodierten zunächst zwei Personen unabhängig voneinander, bevor im Anschluss eine Konsolidierung und Besprechung von Einzelfällen in der Gruppe erfolgte. Die anschließende Analyse und

Darstellung der Häufigkeitsverteilungen wurde mithilfe der Tabellenkalkulationssoftware Microsoft Excel durchgeführt und dient als Basis für die folgenden Kapitel.

Datengrundlage

Insgesamt nahmen 58 Studierende an der Umfrage teil, wovon 72,4 % männlich, 25,9 % weiblich und 1,7 % divers sind. Auch wenn die Mehrheit der Befragten (67,2 %, n= 39) Wirtschaftsingenieurwesen studiert, können Teilnehmende aus zehn weiteren Studiengängen verzeichnet werden: Maschinenbau (13,8 %, n= 8), Bauingenieurwesen und Mathematik mit jeweils zwei Teilnehmenden sowie je eine teilnehmende Person der Studiengänge Physik, Wirtschaftsinformatik, Informatik, Medizintechnik, Chemie, Bioingenieurwesen und Mechatronik. Über alle Studierenden hinweg ordnen sich etwa 77,6 % einem Masterstudiengang zu. Die Überrepräsentation der Studierende des Wirtschaftsingenieurwesen und Masterstudiengänge lässt sich damit begründen, dass die Umfrage auch über private Kanäle verteilt wurde und sich im Umfeld der Autoren (ebenfalls alle Studierende des Masterstudiengangs Wirtschaftsingenieurwesen) ein höherer Anteil dieser Gruppen befindet. Jedoch impliziert ein hoher Anteil an Masterstudierenden auch, dass diese Personen bereits die administrativen Pflichten eines Bachelorstudiums durchliefen und somit auch Erfahrungswerte mit dem Studierendenservice aufweisen (sofern sie ihr Bachelorstudium am KIT ablegten). Diese Aussage lässt sich auch im bisherigen Kontakt mit dem Studierendenservice erkennen: Die Kontaktaufnahme findet vor allem im letzten Semester statt (43,1 %, n= 25). Vor dem Studium und im ersten Semester hatten circa 19 % beziehungsweise 12,1 % den häufigsten Kontakt. Rund 25,9 % der Befragten gaben an, am häufigsten nach dem ersten und vor dem letzten Semester die Leistungen des Studierendenservice in Anspruch genommen zu haben. Die meisten Studierenden treten bisher im Durchschnitt ein- bis zweimal pro Semester mit dem Studierendenservice in Kontakt (62,1 %, n= 36), gefolgt von gar keinem Kontakt (20,7 %, n= 12) und drei- bis viermal pro Semester (17,2 %, n= 10). In dieser Stichprobe beansprucht keine Person die Dienstleistungen des Studierendenservices mehr als viermal pro Semester.

Auswertung und Resultate

Die Ergebnisse der Datenauswertung werden im folgenden Kapitel anhand der beiden Forschungsfragen sowie der Betrachtung der Nutzeneinschätzung vorgestellt.

Einsatzfelder für einen Chatbot

Die Ergebnisse der Kodierung über die Einsatzfelder für einen Chatbot sind in Tabelle 1 zusammengefasst. Die Kategorie *Studienberatung* umfasst dabei alle Subkategorien, welche einen starken Anteil an persönlicher Beratung erfordern. Der Bedarf an Beratung ergibt sich aufgrund der Existenz sehr individueller Aspekte, die eine gründliche und differenzierte Betrachtung erfordern. Durch die Kategorie *Studienorganisation* sind Subkategorien zusammengefasst, welche weniger Individualcharakter vorweisen. Anliegen, welche der Subkategorie *Studienorganisation* zugeordnet sind, können meist ohne persönliche Beratung, sondern durch eigenständiges Recherchieren auf den diversen Informationsportalen der Universität gelöst werden. Basierend auf den beschriebenen Umfrageergebnissen kann folgendes Zwischenfazit beschrieben werden: Die potenziellen Einsatzfelder von Chatbots im Studierendenservice liegen besonders bei Anliegen/ Fragen, welche ein niedriges oder mäßiges Maß an persönlicher Beratung und damit verbundenen Vertrauen benötigen. Besonders relevant ist der Einsatz von Chatbots bei Anliegen, welche auf das schnelle Auffinden von Informationen abzielen. Im Folgenden wird vor diesem Hintergrund auf die einzelnen Subkategorien eingegangen.

Studienberatung

Die Subkategorie *Allgemeine Studienberatung* bezieht sich auf Beratungsleistungen des Prüfungssekretariats, welche (meist) vor dem Studium stattfinden und den persönlichen Auswahlprozess des geplanten Studiums unterstützen sollen. Basierend auf dem Delta der Nennungen zwischen Frage A und B (5 zu 0 Nennungen) ist diese Subkategorie kein geeignetes Einsatzfeld für Chatbots, da es sich hierbei um hochgradig individuelle Beratungsleistungen mit hoher Wichtigkeit handelt. Die *Immatrikulation/ Exmatrikulation* ist die am häufigsten gezählte Nennung als Grund für das Aufsuchen des Studierendenservices (n= 44) derzeit, dies wird auch durch die Frage bestätigt, wann Studierende den

Studierendenservice am meisten verwenden: 43% gaben an, den Studierendenservice im letzten Semester (also Exmatrikulation) am meisten verwendet zu haben. Ein Chatbot im Bereich *Immatrikulation/ Exmatrikulation* ist weniger stark nachgefragt (n= 7), da es hierbei ebenfalls um äußerst individuelle Beratungsleistungen von Bedeutung handelt. Die Subkategorie *Studienfinanzierung* bezeichnet Beratungsdienstleistungen, welche ebenfalls aufgrund ihrer Individualität und Wichtigkeit, sowie Komplexität weiterhin persönlich von Sachbearbeitenden anstelle von einem Chatbot angefragt werden würden. Nennungen der Subkategorie *Mastervorzug* beziehen sich auf einen Anerkennungsprozess, welcher einen Spezialfall abbildet. Bei diesem Anerkennungsprozess werden erbrachte Leistungen innerhalb des Bachelorstudiums, welche im Mastercurriculum vorgesehen sind, im ersten Semester des entsprechenden Masters geltend gemacht. Der hierbei erforderliche Prozess ist zwar komplex, aber standardisiert. Das Aufklären über diesen Prozess könnten auch von einem Chatbot durchgeführt werden. Die Subkategorie *Auslandssemester* bezieht sich speziell auf individuelle Beratungsleistungen zum Klären von Fragen in diesem Kontext. Informationen zu standardisierten Prozessen könnten hierbei von einem Chatbot angefragt werden. Die Nennungen zu *Modulplanung* beziehen sich zum Großteil auf einen Prozess des Studiengangs Maschinenbau, bei welchem ein Vertiefungsmodul gewählt und eingetragen werden muss. Da es sich hierbei um eine zentrale und persönliche Angelegenheit handelt, erscheint diese Subkategorie nicht als geeignetes Einsatzfeld für Chatbots. Zu *Prüfungsanerkennung* wurden Nennungen zugeordnet, welche auf komplexe Fragen zur Anerkennung von externen Leistungen (beispielsweise Prüfungsleistungen eines vorherigen Studiums) abzielen. Die zugehörigen Fragen sind sehr individuell und eignen daher nur bedingt als Einsatzfeld von Chatbots.

Kategorie	**Subkategorie**	**#**	**%**	**#**	**%**
Studienberatung	Allgemeine Studienberatung	5	5,7%	0	0,0%
	Immatrikulation/ Exmatrikulation	44	50,6%	7	7,1%
	Studienfinanzierung	5	5,7%	1	1,0%
	Mastervorzug	2	2,3%	1	1,0%
	Auslandssemester	3	3,4%	2	2,0%
	Modulplanung	6	6,9%	1	1,0%
	Prüfungsanerkennung	2	2,3%	1	1,0%
# Studienberatung		**67**	**77,0%**	**13**	**13,3%**
Studienorganisation	Anträge/ Formulare/ Bescheinigungen	10	11,5%	37	37,8%
	Abschlussarbeit	2	2,3%	1	1,0%
	Termine und Fristen	1	1,1%	23	23,5%
	Bearbeitungsstände	2	2,3%	3	3,1%
	Allgemeine Fragen/ Sonst	5	5,7%	9	9,2%
	Navigation	0	0%	12	12,2%
# Studienorganisation		**20**	**23,0%**	**85**	**86,7%**
Gesamtanzahl		**87**	**100%**	**98**	**100%**

Frage A: „Aus welchem Grund haben Sie bisher den Studierendenservice kontaktiert?“

Frage B: „Zu welchen spezifischen Themen des Studierendenservices würden Sie sich von einem Chatbot Auskunft wünschen?“

Tabelle 1. Vergleich der Gründe für das Aufsuchen von Leistungen des Studierendenservices, n=58

Studienorganisation

Antworten zu *Anträge/ Formulare/ Bescheinigungen* beziehen sich auf das Suchen von entsprechenden Dokumenten und die Unterstützung beim Ausfüllen dieser. Ein Beispiel hierfür ist das Formular zur

Anerkennung eines Praktikums im Studienverlauf. Da sehr viele verschiedene Dokumente existieren, ist die Suche nach diesen aufwendig: „Soll mit helfen mich zurechtzufinden bei der Informationsflut, die es über alle Portale und Stellen gibt“. Ein Chatbot könnte hierbei assistieren und stellt ein interessantes und gefragtes Einsatzfeld dar (n= 37). Das Anmelden von Abschlussarbeiten ist ein standardisierter Prozess, welcher allerdings mehrere Instanzen (Studierende, Prüfungssekretariat, prüfende- und betreuende Person) tangiert. Da es sich bei der *Abschlussarbeit* um ein zentrales Dokument des Studiums handelt, sollten Informationen zum zugrundeliegenden Prozess persönlich verifizierbar sein und eignet sich daher nur bedingt für den Einsatz von Chatbots. Nennungen zu *Termine und Fristen* beziehen sich auf den Umstand, dass Informationen hierzu über verschieden Portale der Universität (Webseite des jeweiligen Instituts, Wiwi-Portal, ILIAS Kurs, Webseite der Fachschaft, Webseite der Universität) verstreut sind. Ein Chatbot würde hierbei die Informationsfindung beschleunigen und ist demnach sehr gefragt (n= 23). Die Nennungen zu *Bearbeitungsstände* beziehen sich auf bereits eingereichte Formulare sowie Anträge und stellt ebenfalls ein aussichtsreiches Anwendungsfeld für den Einsatz von Chatbots dar: „vielleicht könnte man ja abchecken, ob man zu Klausuren angemeldet ist und den Semesterbeitrag bezahlt hat etc. “. *Allgemeine Fragen/ Sonst* beinhaltet Antworten, welche auf Randfälle und ausdrücklich „Allgemeine Informationen“ abzielen, wie beispielweise den Speiseplan der Mensa. Ein Chatbot wäre geeignet, um Studierende bei dem zeitsparenden Finden dieser Informationen zu unterstützen. Auffallend ist die letzte Subkategorie *Navigation*, da diese gerade nicht im Leistungsbereich des Studierendenservice liegt und bisher nicht nachgefragt wird, aber ein Bedarf bei dieser zu erkennen ist (n= 12). Antworten zu *Navigation* beziehen sich auf das schnelle Finden von Informationen, wie beispielsweise „auch wäre es gut, wenn mir der Chatbot beantwortet, von wem ich überhaupt welche Information erhalte“, „Chatbot soll zeigen, wo ich Infos herbekomme“ und „Ich schätze, es sind schon alle Infos detailliert irgendwo auffindbar, aber meistens finde ich nicht die passende Information. Der Chatbot sollte mir dann einfach den Link schicken.“. Die Subkategorie *Navigation* ist daher ein Einsatzfeld für Chatbots, welches sehr gefragt von Studierenden wäre und gleichzeitig das Serviceportfolio des Studierendenservices erweitern würde.

Nutzungsanforderungen an einen Chatbot

Die Entwicklung und der mögliche Einsatz eines Chatbots am Fallbeispiel des Studierendenservices verlangt einen detaillierten Überblick über die Anforderungen der Nutzenden, die ein Chatbot *funktional* sowie *nicht-funktional* beinhalten sollte. Auf Basis der zweiten Forschungsfrage wurden die Umfrageteilnehmenden im Format der offenen Frage mit Freitextantworten nach ihren individuellen Nutzungsanforderungen an einen Chatbot im Kontext des Studierendenservices gefragt. Die Ergebnisse und Kategorisierung für *funktionale* Anforderungen sind in Tabelle 2 und für *nicht-funktionale* Anforderungen in Tabelle 3 abgebildet.

Insgesamt wurden 23,5 % (n= 23) aller gegebenen Antworten den *funktionalen* Eigenschaften des Chatbots zugeordnet. Die Umfrageteilnehmenden wünschten sich innerhalb dieser Kategorie mehrheitlich mit 56,5 % (n= 13) den Chatbot als *Erstkontakt*. Darunter versteht man die Funktion, dass der Chatbot als Schnittstelle zwischen den Mitarbeitenden des Studierendenservice und dem Nutzenden agiert. Der Chatbot sollte bei Fragen und Anliegen die erste Anlaufstelle sein und „bei unzureichender Antwort bitte direkt an „echte“ Mitarbeitende weiterleiten“ oder „den richtigen Ansprechpartner“ über „Mail bzw. Telefon“ vermitteln.

Mit 13,0 % (n= 3) wurde *Navigation* als *funktionale* Anforderung am zweithäufigsten erwähnt. Hierbei sollte der Chatbot als Koordinator und Vermittler für den Informations- und Auskunftspool des Studierendenservice dienen. Spezifischer sollten „Formulare oder Informationsseiten […] verlinkt […] oder zum Download bereitgestellt werden, sodass […] nicht […] danach gesucht werden muss“ und bei vorhandenen „Informationsfluten“ sowie „verstreuten Informationen“ den Studierenden helfen, diese zu konsolidieren und direkt zur Verfügung zu stellen. Anzumerken ist bei dieser funktionalen Anforderung die Schnittmenge der Antworten bezüglich der Einsatzfeld-Kategorie *Navigation*. Folglich ist *Navigation* als Einsatzfeld und gleichzeitig auch als funktionale Anforderung zu betrachten. Die direkte Bereitstellung von Dokumenten als Download durch den Chatbot wurde gesondert als *Dokument-Downloads* (8,7 %, n= 2) gefordert.

In Bezug auf die kommunikative Interaktion mit dem Chatbot wurden als weitere Funktionen *Mehrsprachigkeit* (8,7 %, n= 2) sowie die technische Möglichkeit zur *Sprachsteuerung* (4,3 %, n= 1) genannt, ähnlich zu bereits etablierten Bots wie „Amazon Alexa“ oder „Apple Siri“. Als *Menü- und Button-*

basierter Chatbot (8,7 %, n= 2) könnte alternativ oder ergänzend zu einem sprachbasierten Chatbot durch vorgefertigte Antwortoptionen im Chatbot-Nutzer-Interface die Kommunikation erleichtert werden.

Die oberhalb aufgeführten Ergebnisse der Umfrage zeigen, dass die Studierenden den Chatbot viel mehr als eine erste Instanz sehen, die ihnen alle nötigen Informationen, insbesondere die direkte Vermittlung zu zuständigen Mitarbeitenden des Studierendenservices, im Falle von individuellen Anliegen liefert. Vergleicht man die in der ersten Forschungsfrage beleuchteten Berührungspunkte der Studierenden mit dem Studierendenservice, wird die individuelle Beratungsdienstleistung nicht als direkte Funktion des Chatbots gewünscht. Darunter fallen zum Beispiel die allgemeine Studienberatung, Informationen zur Studienfinanzierung, Bearbeitungsstände oder die individuelle Modulplanung. Diese funktionale Anforderung an den Chatbot könnte den Mitarbeitenden des Studierendenservice zusätzliche Kapazitäten ermöglichen, da fast 80 % der Teilnehmenden mindestens einmal pro Semester mit dem Studierendenservice in Kontakt treten (siehe Kapitel Datengrundlage). Folglich wären weniger Koordinationsaufwand in der Erstaufnahme und Bearbeitung der Anliegen von Studierenden nötig.

Qualitätsmerkmale	**Teilmerkmale**	**#**	**%**
Erstkontakt	Der Chatbot soll die erste Anlaufstelle für Fragen sein. Nur falls der Chatbot nicht weiterhelfen kann, wird an das Personal des Studierendenservices weitergeleitet.	13	56,5%
Mehrsprachigkeit	Der Chatbot soll nicht nur deutsche Sprache verstehen, sondern auch die englische Sprache.	2	8,7%
Sprachsteuerung	Der Chatbot soll sich über natürliche Sprache steuern lassen, ähnlich zu bekannten Anwendungen wie Siri von Apple oder Alexa von Amazon.	1	4,3%
Navigation	Der Chatbot soll die Nutzenden bei Bedarf zu den entsprechenden Informationen weiterleiten/ dort hin navigieren, zum Beispiel über einen Link.	3	13,0%
Dokumenten-Download	Der Chatbot soll den direkten Zugang beziehungsweise Download von Dokumenten ermöglichen. Das heißt der Chatbot stellt den Nutzenden im Chat das Dokument (zum Beispiel einen Antrag) zum Download bereit.	2	8,7%
Menü-/ Button-basierte Chatbots	Der Chatbot soll vordefinierte Antwortoptionen angeben, aus welchen die Nutzenden auswählen können. Infolge der Auswahl interagiert der Nutzende mit dem Chatbot und erhält eine Antwort.	2	8,7%
Gesamtanzahl		**23**	**100%**

Tabelle 2. Funktionale Anforderungen an einen Chatbot im Studierendenservice

Die freigewordene Kapazität könnte somit effizient für die individuellen Bedürfnisse der Studierenden als Zweitinstanz genutzt werden. Diese Beobachtung findet sich auch in der aktuellen wissenschaftlichen Literatur wieder. Nach Lee et al. (2019) reduziert sich die Arbeitsbelastung von Verwaltungsorganen mit der Einführung des Chatbots deutlich, besonders die eingehenden Anfragen als *Erstkontakt* zum Beispiel in Form von E-Mails (Lee et al., 2019). Des Weiteren kann durch den Einsatz von Chatbots die Zeit- und Ressourcenersparnis für individuelle sowie persönliche Anliegen effizienter genutzt werden (Majumder & Mondal, 2021).

Darauf aufbauend zeigt die hohe Nachfrage nach *Navigation*, dass der Chatbot im Studierendenservice besonders die Koordinationskomponente übernehmen soll. Der Fokus auf die *Navigation* zu Dienstleistungen, Seiten, Links und Dokumenten deckt sich mit den Ergebnissen aus der ersten

Forschungsfrage. Der größte Anteil der Studierenden hatte in der Vergangenheit Kontakt mit dem Studierendenservice in den Bereichen Immatrikulation/ Exmatrikulation sowie Anträge, Formulare und Bescheinigungen. Auch in der Zukunft werden diese Auskünfte, sowie Informationen zu Terminen und Fristen mehrheitlich gewünscht. Verbindet man diese Beobachtung mit den bisherigen Ergebnissen, so lässt sich die Tendenz ableiten, dass Chatbots nicht die persönliche, individuelle Beratung des Studierendenservice ersetzen sollen, allerdings eine hohe Bereitschaft für die Informationsvermittlung vorhanden ist. Allgemeingültige Informationen sowie Dokumente, die bereits existieren, können durch den Chatbot zur Verfügung gestellt werden, um zum Beispiel den Suchaufwand zu minimieren. Hjerpbakk et al. (2021) nennt hierfür das bisherige mangelnde Vertrauen der Nutzenden als Ursache. Trotz der Verfügbarkeit von Informationen auf Webseiten, werde der Chatbot weiterhin eingesetzt, um einfache Fragen zu beantworten (Hjerpbakk et al., 2021). Mit Bezug auf den Bildungssektor machten Molnár und Szüts (2018) die ähnliche Beobachtung, dass Chatbots weniger für inhaltliche Problemlösungen genutzt werden, sondern für vorhandene und ergänzende Informationen (Molnár & Szüts, 2018).

Qualitätsmerkmale	**Teilmerkmale**	**#**	**%**
Funktionale Tauglichkeit	Funktionale Vollständigkeit	14	18,7%
	Funktionale Korrektheit	24	32,0%
	Funktionale Angemessenheit	6	8,0%
Kompatibilität	Interoperabilität	6	8,0%
Effizienz	Zeitverhalten	12	16,0%
	Ressourcennutzung	3	4,0%
Zuverlässigkeit	Verfügbarkeit	3	4,0%
Benutzerfreundlichkeit	Erlernbarkeit	6	8,0%
Sicherheit		1	1,3%
Gesamtanzahl		**75**	**100%**

Tabelle 3. Nicht-funktionale Anforderungen an einen Chatbot im Studierendenservice

Die Mehrheit der von den Studierenden genannten Anforderungen (76,5 %, n= 75) bezog sich auf die *nicht-funktionalen* Anforderungen des Chatbots. Innerhalb dieser Kategorie forderten mehr als die Hälfte der Teilnehmenden (58,7 %, n= 44) eine hohe *funktionale Tauglichkeit* des Chatbots. Dabei stehen vor allem die *funktionale Korrektheit* (32,0 %, n= 24) und *funktionale Vollständigkeit* (18,7 %, n= 14) im Vordergrund. Die Studierenden erwarten vom Chatbot, dass er alle inhaltlichen Aufgaben und Nutzerziele im Rahmen der Dienstleistungen des Studierendenservice technisch erfüllt und die resultierenden Ergebnisse der Anfragen fehlerfrei sind. Ein gut funktionierender Chatbot spart den Studierenden in diesem Kontext vor allem Zeit und Mühe, ihre Anliegen wie beispielsweise Anträge, Formulare und Bescheinigungen zu suchen (siehe Tabelle 1). Schnelligkeit und Effizienz scheinen hierbei von großer Bedeutung zu sein, um den Nutzen des Chatbots bei der Kontaktaufnahme mit dem Studierendenservice zu erhöhen. Des Weiteren ist die große Nachfrage nach *funktionaler Korrektheit* auffällig. Ein Chatbot, der nicht funktional ist oder falsche Informationen liefert, kann den Studierenden mehr Probleme bereiten als helfen. Mangelnde *Korrektheit* kann dazu führen, dass Studierende wichtige Informationen verpassen oder falsch informiert werden. Die gezielte Forderung nach *Korrektheit* könnte demzufolge auf eine gewisse Form der Skepsis gegenüber Chatbots gewertet werden, die man im Vergleich zum persönlichen Kontakt mit den Mitarbeitenden des Studierendenservice nicht aufweist. Vergleicht man die Forderung nach *Korrektheit* und *Vollständigkeit* mit der Zufriedenheit der bisherigen Nutzung von Chatbots, so fällt folgendes auf: Die Mehrheit ist unter diesem Aspekt „weder zufrieden noch unzufrieden“ (36,8 %, n= 14), gefolgt von „eher unzufrieden“ (23,7 %, n= 9) und „eher zufrieden“ (21,1 %, n= 8). Obwohl das Ergebnis unter diesen drei Kategorien einigermaßen balanciert ist, sind lediglich 5,3 % (n= 2) „sehr zufrieden“. Die mehrheitlichen Forderungen im Bereich der *Tauglichkeit* des Chatbots könnten daher eine einen Einfluss darauf haben, die Zufriedenheit der Nutzende im Umgang mit Chatbots auf „sehr zufrieden“ zu erhöhen.

Das am zweithäufigsten geforderte Hauptqualitätsmerkmal nach ISO 25010 ist die *Effizienz* (20 %, n= 15). Den Studierenden ist bei der Nutzung des Chatbots in dieser Kategorie das *Zeitverhalten* besonders wichtig

(16 %, n= 12). Eine kurze Reaktionszeit mit geringen Verarbeitungszeiten und hohen Durchsätzen steht im Fokus. Diese Beobachtung gleicht den Ergebnissen von Meyer von Wolff et al. (2020), die eine hohe Nachfrage nach kurzen Reaktionszeiten bei Chatbots im universitären Umfeld festgestellt haben (Meyer von Wolff et al., 2020). Nach Gnewuch et al. (2022) hat eine verzögerte Antwortzeit bei Chatbots negative Auswirkungen auf das Nutzererlebnis. Dies tritt überwiegend bei erfahrenen Chatbot Nutzenden auf (Gnewuch et al., 2022). Im Gegensatz dazu nehmen die Nutzende Chatbots als menschenähnlicher und sozialer wahr, wenn die Antworten dynamisch verzögert und nicht sofort gesendet werden (Gnewuch et al., 2018). Auf Basis dieser Beobachtungen könnte man darauf schließen, dass den Studierenden die soziale und menschenähnliche Komponente des Chatbots eventuell weniger von Bedeutung ist. Der Fokus liegt auf kurzen Reaktionszeiten und Effizienz. Vergleicht man dies mit den *funktionalen* Anforderungen des Chatbots, wie beispielsweise der Navigationskomponente, so unterstützen vor allem schnelle Antworten die Informations- und Wissensbeschaffung. Als zweite Anforderung in der Kategorie *Effizienz* wurde die *Ressourcennutzung* genannt (4%, n= 3). Unter *Ressourcennutzung* versteht man den Grad der zur Verfügung stehenden Ressourcen bei der Nutzung des Systems. Hierbei ist auffällig, dass verhältnismäßig wenig Studierende diese Anforderung thematisiert haben. Dies steht im Kontrast zu den Ergebnissen aus der ersten Forschungsfrage und der damit verbundenen hohen Nachfrage nach Ressourcen des Studierendenservice wie zum Beispiel Anträge, Formulare, Bescheinigungen, Termine und Fristen. Damit der Chatbot diese Mengen an Informationen korrekt und effizient zur Verfügung stellen kann, benötigt er einen hohen Grad an *Ressourcennutzung*.

Die *Interoperabilität* wurde als weitere *nicht-funktionale* Anforderung an den Chatbot von 8 % (n= 6) der Studierenden gefordert. Darunter versteht man den Grad, in dem zwei oder mehr Systeme Informationen austauschen und diese wiederum nutzen können. Im Fallbeispiel des Chatbots bezieht sich dies primär auf die Anwendung in mehreren Systemen. So forderten die Studierenden die Nutzung von Chatbots als App oder die Integration in Messenger Dienste wie WhatsApp. Des Weiteren wurde vorgeschlagen, die Integration in von der Universität bereits bereitgestellten Systeme wie den Campus Navigator zu ermöglichen. Die Bedeutung der *Interoperabilität* im universitären Umfeld zeigt in diesem Kontext ebenfalls die Beobachtung von Meyer von Wolff et al. (2020), in deren Umfrage sich die Mehrheit der Studierenden eine Integration des Chatbots in die Messenger Plattform WhatsApp wünscht (Meyer von Wolff et al., 2020).

Insgesamt 8 % (n= 6) der genannten *nicht-funktionalen* Anforderungen an den Chatbot bezogen sich auf die *Benutzerfreundlichkeit*, genauer auf die Subkategorie der *Erlernbarkeit*. In diesem Kontext bezieht sich die nach ISO 25010 benannte Subkategorie darauf, wie einfach es für die Studierenden ist, die Software zu erlernen, zu verstehen und anzuwenden. Betrachtet man die Bedeutung der *Erlernbarkeit* in der wissenschaftlichen Literatur, so wird diese teilweise als wichtigste Anforderung im Bereich Softwarenengineering betitelt (Nielsen, 1994). Die Ergebnisse der Umfrage belegen das nicht. Hierfür könnte die Rolle des Chatbots verantwortlich sein. Obwohl die *Erlernbarkeit* ein wichtiger Faktor für viele Arten von Software ist (Nielsen, 1994), ist sie für Chatbots möglicherweise nicht entscheidend. Auf Basis der Umfrageergebnisse im Bereich *nicht-funktionaler* Anforderungen scheint die funktionale *Tauglichkeit* und die *Effizienz* im Fokus zu stehen. Die Benutzererfahrung bei der Interaktion mit dem Chatbot wird laut Umfrageergebnissen mehrheitlich durch Faktoren wie einen hohen Grad an nützlichen (58,7 %, n= 44) und schnellen (16 %, n= 12) Antworten bestimmt. Des Weiteren ähnelt die Interaktion mit einem Chatbot, im Kontrast zu komplexen Softwareanwendungen, dem Frage-Antwort-Schema ähnlich zu Messenger Diensten wie zum Beispiel WhatsApp. Die gezielte Forderung der Studierenden nach einer *Interoperabilität* mit Messenger Diensten zeigt, dass sie hier mögliche Schnittstellen sehen und diese Art der Bedienung vermutlich beherrschen. Durch diese Ähnlichkeit könnte die *Erlernbarkeit* im Vergleich zur Literatur eher eine untergeordnete Rolle spielen.

Unter dem Aspekt der *Zuverlässigkeit* als Qualitätsmerkmal wurde von 4 % (n= 3) eine dauerhafte *Verfügbarkeit* des Chatbots gefordert. Nach Jenneboer et al. (2022) ist eine 24/7-Verfügbarkeit des Chatbots für einen hohen Grad an Systemqualität und zur Erfüllung der Kundenerwartung unerlässlich (Jenneboer et al., 2022). Im Gegensatz hierzu zeigen die Ergebnisse der Umfrage, dass eher eine geringe Menge der Studierenden dies explizit als Anforderung wünscht. Allerdings impliziert dies nicht direkt, dass die 24/7-Verfügbarkeit eine weniger wichtige Rolle spielt, sondern die Nutzende erwarten bereits von den Chatbots eine hohe *Verfügbarkeit* (Trivedi, 2019).

Lediglich 1,3% (n= 1) der *nicht-funktionalen* Anforderungen an den Chatbot bezogen sich auf die *Sicherheit*. Damit ist gemeint, inwieweit die Informationen und Daten der Nutzende geschützt sind und ein Zugriff nur nach Autorisierung beziehungsweise Zustimmung möglich ist. Nach Zumstein und Hundertmarkt (2017) ist der Datenschutz beim Einsatz von Chatbots sowohl für Anbieter als auch für Nutzende ein wichtiges Thema. Dabei sollte ein angemessener Schutz im Umgang mit Nutzerdaten gewährleistet werden (Zumstein & Hundertmark, 2017). Die geringe Anzahl an Forderungen nach *Sicherheit* in der zugrundeliegenden Befragung könnte verschiedene Ursachen haben. Eine mögliche Ursache im universitären Umfeld sind häufig Defizite im Datenschutzbewusstsein und -handeln der Studierenden (Moallem, 2019). Eine weitere Ursache könnte der Anwendungsbereich und Informationscharakter des Chatbots im Kontext des Studierendenservice sein. Nach Hasal et al. (2021) ist die *Sicherheit* – insbesondere der Datenschutz – bei der Nutzung von Chatbots in der Kommunikation mit Banken, Gesundheitsassistenten, Online-Shops, Autos, Versicherungen, Flughafengesellschaften und vielen anderen Themen unabdingbar (Hasal et al., 2021). Demgegenüber könnte die Forderung nach frei verfügbaren und personenneutralen Informationen wie Formularen, Anträge und Fristen für die Studierenden einen weniger starken Personenbezug haben. Dies könnte sich entsprechend auf die Bedeutung des Sicherheitsaspekts auswirken. Welche Rolle die *Sicherheit* bei personenbezogenen Daten wie der Studienfinanzierung oder der Studienberatung spielt, ist in diesem Zusammenhang unklar.

Einschätzung der Nutzungsbereitschaft

Die Bereitschaft der Studierenden zur Nutzung von Chatbots im Kontext des Studierendenservice stellt eine zentrale Determinante dar, um die wahrscheinliche Akzeptanz dieser Technologie in der Praxis einschätzen zu können. Abbildung 2 fasst hierzu die Bereitschaft zur Nutzung eines Chatbots im Studierendenservice nach Häufigkeit der Nutzung von Chatbots allgemein zusammen, während Abbildung 3 die Bereitschaft zur Nutzung eines Chatbots im Studierendenservice nach Zufriedenheit im Umgang mit Chatbots repräsentiert.

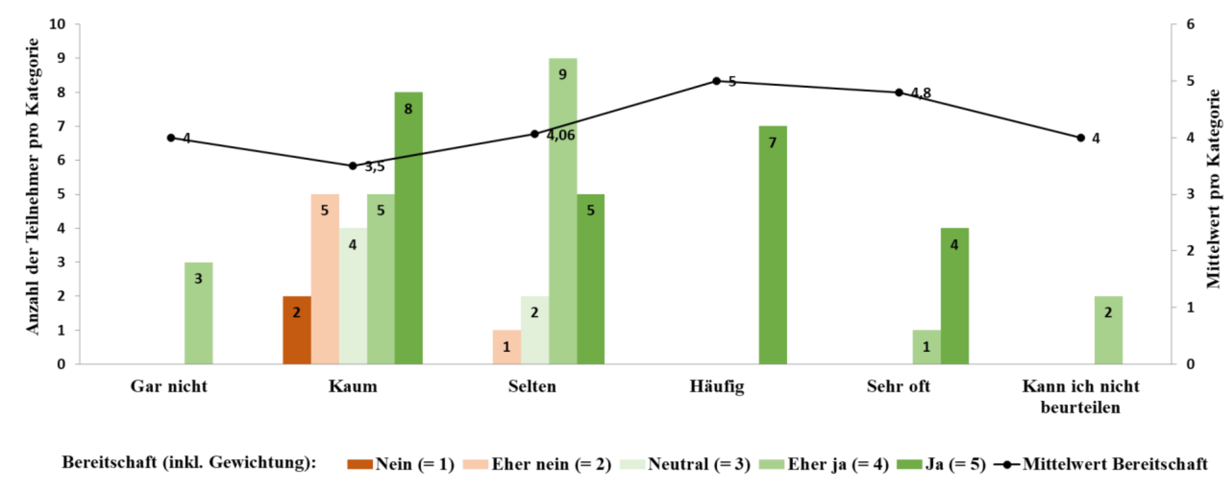

Abbildung 2. Bereitschaft zur Nutzung eines Chatbots im Studierendenservice nach Häufigkeit der Nutzung von Chatbots allgemein

Im Durchschnitt äußerten die Teilnehmenden der Studie eine Zustimmung zur Anwendungsbereitschaft mit der Antwortoption "eher ja". Dies zeigt eine Tendenz unter den Befragten, einen Chatbot im Bereich des Studierendenservice nutzen zu wollen. Bei einer detaillieren Analyse der Nutzbereitschaft konnte ein weiterer auffälliger Trend festgestellt werden. Hierbei wurde die Nutzungsbereitschaft für einen Chatbot im Studierendenservice der bisherigen Nutzfrequenz von Chatbots im allgemeinen Kontext gegenüberstellt (siehe Abbildung 2). Die Ergebnisse zeigen, dass mit höheren Nutzfrequenzen von Chatbots allgemein eine höhere durchschnittliche Nutzungsbereitschaft zur Anwendung im Studierendenservice einhergeht. Unter den Befragten verwenden 20,6 % (n= 12) Chatbots häufig bis sehr häufig, wobei eine sehr hohe durchschnittliche Nutzungsbereitschaft festzustellen ist. Eine Mehrheit von 70,6 % (n= 41) der befragten Studierenden gibt an, Chatbots selten bis kaum zu nutzen. Diese Gruppe zeigt eine Tendenz zur

Nutzungsbereitschaft, die im Bereich „eher ja“ anzuordnen ist. Darüber hinaus konnte in der Gruppe der Studierenden, die bisher keine Chatbots genutzt haben, eine Nutzungsbereitschaft im Bereich „eher ja“ festgestellt werden. Dies könnte auf eine gewisse allgemeine Erwartungshaltung an die Fähigkeiten der Chatbot-Technologie hinweisen.

In einer zweiten Analyse wurde die Nutzungsbereitschaft für einen Chatbot im Studierendenservice der bisherigen Zufriedenheit im Umgang mit Chatbots gegenübergestellt (siehe Abbildung 3). Hierbei ist ein eindeutiger Trend zu beobachten, der eine höhere Nutzungsbereitschaft mit steigender Zufriedenheit aufzeigt. Die Mehrheit der Studierenden (48,3 %, n= 25) sind mit ihrer bisherigen Erfahrung mit Chatbots eher unzufrieden beziehungsweise weder zufrieden noch unzufrieden. Trotz der bisher fehlenden Zufriedenheit im Umgang mit Chatbots zeigt diese Gruppe eine Tendenz auf, den Chatbot im Bereich des Studierendenservice dennoch nutzen zu wollen. Eine deutlich ausgeprägtere Nutzungsbereitschaft verzeichnen die Studierenden, die eher zufrieden beziehungsweise sehr zufrieden mit Chatbots sind (22,6 %, n= 12). In dieser Gruppe ist ein eindeutiger Trend zu einem „ja“ in Bezug auf die Nutzungsbereitschaft zu erkennen. Hierzu stehen schlechte Nutzerfahrungen im Kontrast. Eine Minderheit der Studierenden (5,2 %, n= 3) ist mit ihrer bisherigen Chatbot-Erfahrung sehr unzufrieden. Dies resultiert in einer geringen Nutzungsbereitschaft und einer eher ablehnenden Haltung gegenüber dem Chatbot und dessen Einsatz im Studierendenservice.

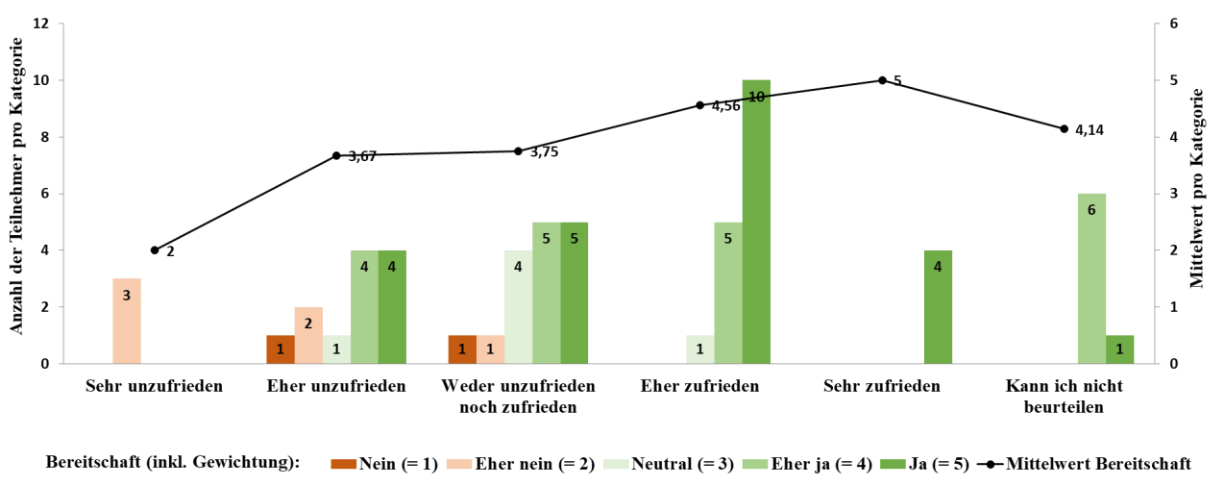

Abbildung 3. Bereitschaft zur Nutzung eines Chatbots im Studierendenservice nach Zufriedenheit im Umgang mit Chatbots

Zusammenfassung und Diskussion

Zusammenfassung

Die geringe Zufriedenheit der Studierenden am KIT gegenüber dem Studierendenservice stellt eine Herausforderung dar. Jedoch ist die Einführung von Chatbots eine Möglichkeit, dieser Herausforderung entgegenzuwirken. Um die Sinnhaftigkeit von Chatbots im Studierendenservice zu untersuchen, wurde eine Online-Umfrage unter 56 Studierenden durchgeführt. Dabei wurden die möglichen Einsatzgebiete, Anforderungen und Akzeptanz der Studierenden betrachtet und analysiert.

Basierend auf den Ergebnissen lässt sich festhalten, dass eine Integration von Chatbots im Bereich der Studienberatung und Studienorganisation als sinnvoll erachtet werden kann. Insbesondere ist zu bemerken, dass Chatbots bevorzugt bei Anliegen zum Einsatz kommen sollen, die ein niedriges oder mäßiges Maß an persönlicher Beratung und Vertrauen erfordern, beispielsweise bei der Suche nach Formularen, Anträgen oder Bescheinigungen. Die Hauptaufgabe eines Chatbots soll darin bestehen, den Suchaufwand nach Informationen zu reduzieren.

Hinsichtlich der Anforderungen an einen Chatbot wurden die Ergebnisse der Umfrage in *funktionale* und *nicht-funktionale* Anforderungen kategorisiert. Bei den *funktionalen* Anforderungen wird viel Wert daraufgelegt, dass der Chatbot als erste Anlaufstelle genutzt werden kann, um relevante Informationen zu erhalten oder an Mitarbeitende des Studierendenservices weitergeleitet zu werden. Der Chatbot sollte hauptsächlich koordinative Aufgaben übernehmen und den Nutzenden vorhandene Informationen bereitstellen, anstatt individuelle Beratung durchzuführen. Bei persönlicheren Anliegen bevorzugen die Studierenden nach wie vor den direkten Kontakt mit den verantwortlichen Personen.

Hervorzuheben ist unter den *nicht-funktionalen* Anforderungen, dass die funktionale *Tauglichkeit* am häufigsten genannt wurde. Die Effektivität des Einsatzes von Chatbots hängt entscheidend davon ab, ob Nutzende ihre Ziele erreichen können, indem ihre Anfragen inhaltlich korrekt beantwortet werden und der Chatbot während der Nutzung keine technischen Probleme aufweist. Eine weitere wesentliche Anforderung ist eine kurze Reaktionszeit des Chatbots. Im Gegensatz dazu wurde die Sicherheit als Anforderung nur geringfügig genannt.

Die Ergebnisse verdeutlichen, dass die Nutzungsbereitschaft von Chatbots im Studierendenservice im Allgemeinen positiv ist. Es ist hervorzuheben, dass Personen, die bereits Erfahrungen mit Chatbots gesammelt haben, tendenziell eher bereit sind, diese auch im Studierendenservice zu nutzen. Darüber hinaus ist zu erkennen, dass die Nutzungsbereitschaft mit der bisherigen Zufriedenheit mit Chatbots korreliert.

Die vorliegende Arbeit belegt auf Basis empirischer Daten das Potential des Einsatzes von Chatbots im Studierendenservice des KIT. Vor allem die Nutzungsbereitschaft durch Studierende unterstreicht die mögliche Einführung und Verwendung von Chatbots im Studierendenservice. Insbesondere bei der Abwicklung von standardisierten Anfragen sowie der Bereitstellung von Informationen können Chatbots effektiv eingesetzt werden. Um die Nutzung von Chatbots durch Studierende zu gewährleisten, ist es essenziell, dass diese funktional einwandfrei sind.

Wissenschaftlicher und Praktischer Beitrag

Die Ergebnisse dieser Arbeit tragen sowohl zur wissenschaftlichen als auch zur praktischen Diskussion bei. Während der Forschungsstand bezüglich der Sinnhaftigkeit von Chatbots im Hochschulwesen uneinig ist, liefern unsere Ergebnisse konkrete Erkenntnisse über den vielversprechenden Einsatz von Chatbots im Studierendenservice am KIT. Zudem werden praxisrelevante Einsatzbereiche und Anforderungen an einen Chatbot im Kontext des Studierendenservices identifiziert, auf welchen eine künftige Implementierung basieren kann.

Limitationen und Zukünftige Forschung

Es ist anzumerken, dass diese Studie aufgrund der eingesetzten Umfragemethoden und deren Design Einschränkungen aufweist. Im Fragebogen wurden einige Antwortbeispiele gegeben, die konsequenterweise auch häufiger von den Studierenden erwähnt wurden. So wurden beispielsweise unter der Frage nach den Gründen für den Kontakt mit dem Studierendenservice oftmals die Themen Immatrikulation/ Exmatrikulation genannt. Gleiches gilt für die Frage nach den Themen, zu denen sich die Befragten von einem Chatbot Auskunft wünschen. Hierbei wurden vermehrt Termine und Fristen genannt. Die Gültigkeit dieser Subkategorien soll daher noch weiter validiert werden. Des Weiteren wurden die Anforderungen in dieser Arbeit nicht spezifisch mit bestimmten Anwendungsfällen in Verbindung gebracht. Daher kann man auch keinen direkten Zusammenhang zwischen den Anforderungen und den möglichen Einsatzgebieten von Chatbots herstellen.

Im Rahmen dieser Arbeit wurde die Umfrage unter anderem auf der Sharing-Plattform Studydrive geteilt. Obwohl die Umfrage explizit in den Gruppen des KITs geteilt wurde, kann nicht garantiert werden, dass nur KIT-Studierende an der Umfrage teilgenommen haben. Darüber hinaus wurde die Umfrage hauptsächlich unter Studierenden der Wirtschaftswissenschaften geteilt, was zu einer Überrepräsentation dieser Gruppe führt. Um aussagekräftigere Ergebnisse zu erhalten, ist es daher ratsam, die gesamte Studierendenschaft des KIT zu berücksichtigen. Darüber hinaus waren nur aktuell eingeschriebene Studierende als Zielgruppe der Umfrage definiert. Es wäre sinnvoll, auch Studieninteressierte zu befragen, da sie den Studierendenservice nutzen würden, um sich über Studiengänge, Unterkunftsmöglichkeiten oder Freizeitangebote zu informieren.

In der Literatur wird der Einsatz von Chatbots vorwiegend in den Bereichen E-Commerce und Gesundheitswesen behandelt. Es gibt derzeit nur wenige Forschungsarbeiten zu Chatbots im administrativen Bereich von Hochschulen. Die Ergebnisse unserer Umfrage deuten jedoch darauf hin, dass eine Bereitschaft zur Nutzung von Chatbots in diesem Umfeld vorhanden ist. Die Ergründung dieses Forschungsfelds bleibt der zukünftigen Wissenschaftsgemeinschaft überlassen.

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Anhang

Block 1: Demographische Fragen
▪ **Geschlecht** Antwortmöglichkeit(en): Weiblich, Männlich, Divers ▪ **Was studieren Sie?** Antwortmöglichkeit(en): Offene Frage ▪ **In welchem Studienabschnitt befinden Sie sich gerade?** Antwortmöglichkeit(en): Bachelor, Master
Block 2: Bisherige Erfahrungen mit dem Studierendenservice
▪ **Wie oft treten Sie mit dem Studierendenservice im Semester im Durchschnitt in Kontakt?** Antwortmöglichkeit(en): 0 mal, 1-2 mal, 3-4 mal, mehr als 4 mal ▪ **Wann haben Sie den Studierendenservice am meisten bisher in Ihrem Studium verwendet?** Antwortmöglichkeit(en): Vor dem Studium, Im ersten Semester, Im letzten Semester, Sonst ▪ **Aus welchem Grund haben Sie bisher den Studierendenservice kontaktiert? (zum Beispiel Studienberatung, BAföG-Bescheinigung, Immatrikulation/ Exmatrikulation)** Antwortmöglichkeit(en): Offene Frage
Block 3: Bisherige Erfahrungen mit Chatbots
▪ **Wie oft interagieren Sie mit Chatbots?** Antwortmöglichkeit(en): Gar nicht, Kaum, Selten, Häufig, Sehr oft, Kann ich nicht beurteilen ▪ **Wie zufrieden sind Sie über all Ihre Erfahrungen hinweg mit Chatbots gewesen?** Antwortmöglichkeit(en): Sehr unzufrieden, Eher unzufrieden, Weder unzufrieden noch zufrieden, Eher zufrieden, Sehr zufrieden, Kann ich nicht beurteilen
Block 4: Chatbots im Kontext des Studierendenservices
▪ **Zu welchen spezifischen Themen des Studierendenservices würden Sie sich von einem Chatbot Auskunft wünschen? (zum Beispiel Termine und Fristen, Anträge und Formulare, Beurlaubung)** Antwortmöglichkeit(en): Offene Frage ▪ **Welche Anforderungen stellen Sie an einen Chatbot, welcher im Studierendenservice eingesetzt werden würde?** Antwortmöglichkeit(en): Offene Frage ▪ **Würden Sie beabsichtigen sich über den Chatbot Informationen zum Studierendenservice zu beschaffen?** Antwortmöglichkeit(en): Nein, Eher nein, Neutral, Eher ja, Ja, Kann ich nicht beurteilen
Tabelle A-1. Umfragebogen