# Co-designing Customizable Clinical Dashboards with Multidisciplinary Teams: Bridging the Gap in Chronic Disease Care

Diogo Branco
djbranco@fc.ul.pt
LASIGE, Faculdade de Ciências, Universidade de Lisboa
Lisboa, Portugal

Margarida Móteiro
margaridapmoteiro@gmail.com
LASIGE, Faculdade de Ciências, Universidade de Lisboa
Lisboa, Portugal

Raquel Bouça
raquelbouca@gmail.com
CNS—Campus Neurológico, Faculdade de Medicina, Universidade de Lisboa
Lisboa, Portugal

Rita Miranda
ritanmiranda@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Tiago Reis
tpamareis@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Élia Decoroso
eliadecoroso@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Rita Cardoso MSD, SLP
ritasicardoso@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Joana Ramalho
j.a.ramalho12@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Filipa Rato
filipa.ac.rato@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Joana Malheiro
joanamalheironutri@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Diana Miranda
diana.santos.miranda@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Verónica Caniça
canica.veronica@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Filipa Pona-Ferreira
filipaponaferreira@campus.ul.pt
CNS—Campus Neurológico
Torres Vedras, Portugal

Daniela Guerreiro
daniela.d.guerreiro@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Mariana Leitão
marianaleitao.ft@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Alexandra Saúde Braz
alexandra.saude.901@gmail.com
CNS—Campus Neurológico
Torres Vedras, Portugal

Joaquim Ferreira
joaquimjferreira@gmail.com
CNS—Campus Neurológico, Faculty of Medicine, University of Lisbon
Lisboa, Portugal

Tiago Guerreiro
tjvg@di.fc.ul.pt
LASIGE, Faculdade de Ciências, Universidade de Lisboa
Lisboa, Portugal

## ABSTRACT

Providing care to individuals with chronic diseases benefits from a multidisciplinary approach and longitudinal symptom, event, and disease monitoring, in and out of clinical facilities. Technological advancements, including the ubiquitous presence of sensors and devices, present opportunities to collect large amounts of data and extract evidence-based insights about the patient and disease. Nevertheless, practical examples of clinical utility of those technologies remain sparse, and in specific focus areas (e.g, insights from a single device). This paper explores the challenges and opportunities of multidisciplinary clinical dashboards to support clinicians caring for people with chronic diseases. We report on a focus group and co-design workshops with a multidisciplinary team of clinicians and HCI researchers. We offer insights into how technological outcomes and visualizations can enhance clinical practice and the intricacies of information-sharing dynamics. We discuss the potential of dashboards to trigger actions in clinical settings and emphasize the benefits of customizable dashboards.



*CHI '24, May 11–16, 2024, Honolulu, HI, USA*

ACM ISBN 979-8-4007-0330-0/24/05
https://doi.org/10.1145/3613904.3642618

## CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; **Participatory design**; **User centered design**; **User interface design**.

## KEYWORDS

chronic diseases, dashboards, sensors, co-design, customization, multidisciplinary

**ACM Reference Format:**

Diogo Branco, Margarida Móteiro, Raquel Bouça, Rita Miranda, Tiago Reis, Élia Decoroso, Rita Cardoso MSD, SLP, Joana Ramalho, Filipa Rato, Joana Malheiro, Diana Miranda, Verónica Caniça, Filipa Pona-Ferreira, Daniela Guerreiro, Mariana Leitão, Alexandra Saúde Braz, Joaquim Ferreira, and Tiago Guerreiro. 2024. Co-designing Customizable Clinical Dashboards with Multidisciplinary Teams: Bridging the Gap in Chronic Disease Care. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11–16, 2024, Honolulu, HI, USA.* ACM, New York, NY, USA, 18 pages. https://doi.org/10.1145/3613904.3642618

## 1 INTRODUCTION

Chronic diseases (CD) affect an ever-increasing proportion[1] - 90% increase expected in deaths by 2050 - of the global population. The prevalence of these conditions, often accompanied by a complex interplay of comorbidities, has placed an enormous burden on healthcare systems worldwide [23]. Notably, their significance becomes even more apparent during times of crisis, as witnessed during the COVID-19 pandemic, where individuals with underlying chronic conditions faced higher risks and poorer outcomes [60]. The imperative to improve chronic disease management and care delivery has never been more pressing.

One key approach to addressing the multifaceted nature of CD is the adoption of multidisciplinary care teams [63, 83]. These teams comprise professionals from various healthcare domains, each contributing their unique expertise to provide holistic and patient-centered care. To illustrate the potential impact of such an approach, consider the case of Parkinson's disease (PD), a neurodegenerative condition affecting millions globally[2]. Traditionally, PD management has primarily revolved around the expertise of neurologists. However, the comprehensive care of PD patients requires a broader perspective. Physical therapists, nurses, occupational therapists, and other specialists bring essential insights to the table [83], collectively improving patient outcomes and quality of life [55]. The communication challenges within these multidisciplinary teams arise from available mechanisms to share information, often consuming valuable time for clinicians [10].

Technological advancements, notably the proliferation of sensors and devices, have revolutionized our ability to monitor chronic conditions [50, 59, 81]. These innovations enable the continuous collection of vast patient data , such as self-reported (e.g., digital questionnaires) and objective (e.g., sensor-derived gait metrics) measurements offering unprecedented opportunities for understanding disease progression and tailoring interventions [41]. However, there is a gap in translating these technological capabilities into tangible clinical benefits [67]. Despite the wealth of data generated, evidence supporting the clinical utility of this information in improving patient care is scarce [75]. This gap between data generation and clinical utility is a significant challenge that needs to be addressed.

In this context, clinical dashboards emerge as a promising solution [35]. These dashboards have the potential to serve as a bridge, summarizing complex data and revealing patterns that might otherwise remain hidden [31, 85]. When considering dashboards for multidisciplinary teams new challenges arise related to the need to customize visualizations according to the unique interests of each team (or clinician) and facilitate information sharing between them [10]. Nevertheless, current efforts in this direction have been limited in their scope, focusing on synchronous team communication [42] or having a limited exploration of how to facilitate information sharing of multiple data sources in dashboards [36].

Given their current but sparse exposition to specific dashboards (e.g, single device), clinicians have both the domain knowledge(s) - i.e. from different disciplines - as well as dashboard-utility perceptions and aspirations to be able to contribute more actively to the design of future dashboards - a unique set of expertises that has been overlooked in clinical visualization [16].

Our work explores the challenges and opportunities of multidisciplinary clinical dashboards as tools to support clinicians caring for people with chronic diseases. We sought to address the following research question: *How do multidisciplinary teams of clinicians perceive, adapt, and ideate dashboards for long-term multidisciplinary care?* To address this question, we enacted a collaboration between a multidisciplinary team of clinicians from diverse backgrounds and expertise and HCI researchers to co-design clinical dashboards tailored to monitor chronic conditions, with a particular focus on neurodegenerative diseases such as PD . Our collaborative process encompassed two essential phases: a focus group aimed at characterizing current practices and defining the types of information desired for PD monitoring, followed by six co-design sessions with distinct groups of professionals, ranging from physiotherapy to nursing. Together, we designed and discussed more informed and comprehensive dashboards, leveraging the collective wisdom of these diverse healthcare professionals.

Our findings revealed distinct priorities of clinical areas when evaluating patients while uncovering shared interests. Drawing upon the knowledge gained from previously evaluated areas could prove beneficial in developing more informed and comprehensive dashboards. Our study underscores the critical role of co-designing and involving clinicians from the outset of the design process, ensuring that technological solutions align closely with their specific requirements and preferences.

This study contributes to the HCI field by (1) providing design guidelines for future multidisciplinary dashboards in monitoring chronic conditions; (2) delving into the intricate dynamics of information-sharing within multidisciplinary teams; (3) emphasizing the empowering potential of personalization in allowing clinicians to customize visualizations to suit their unique needs and preferences. Additionally, our study contributed to the more general body of work on mapping and better understanding the challenges surrounding technology integration in clinical practice.

## 2 RELATED WORK

This section presents a comprehensive overview of related work in three primary areas: monitoring of chronic conditions, particularly related to data collection and availability, visual analytics and dashboards in healthcare, and the importance of involving stakeholders in the design process.

[1]https://news.un.org/en/story/2023/05/1136832
[2]https://www.who.int/news-room/fact-sheets/detail/parkinson-disease

## 2.1 Continuous Monitoring in Chronic Diseases

Chronic Diseases (CD) may have multiple definitions and encompass many conditions, such as arthritis and diabetes. In our context, we adopt the approach outlined by Bernell et al. [9], which defines chronic diseases as those that manifest recurrently over extended periods. CDs have long-term health implications that significantly impact an individual's quality of life [55]. Additionally, these factors can also exert a burden on healthcare systems [23], given the frequent need for regular patient check-ups. In some chronic diseases, a multidisciplinary approach can benefit the patients [63, 83]. Tosserams [83] suggests that optimizing functional mobility involves a complex interaction between motor and non-motor symptoms, which must be addressed through collaboration across various professional areas. Nevertheless, sharing information about their patients can be hard and a burden in multidisciplinary teams leading to more time spent by each clinician [10].

While appointments serve as important moments for CD patients to receive assistance from their clinicians, the effective management of CDs necessitates ongoing and close monitoring, which often extends beyond clinical appointments [65]. For instance, managing conditions like diabetes require patients to make significant behavioral changes related to their diet and exercise routines, even though clinicians can offer recommendations and periodically assess progress [17]. These changes often entail patient-driven activities such as monitoring blood sugar and consistent medication adherence [32]. For individuals with chronic neurological and psychiatric conditions like Alzheimer's disease and attention deficit hyperactivity disorder, distinct challenges arise, and they often benefit from close monitoring by family members or caregivers who provide support [80, 89]. In some cases, individuals seeking to modify their behaviors may require participation in therapeutic interventions or support groups. Consequently, continuous monitoring is pivotal in tracking health-related metrics and supporting effective disease management [41].

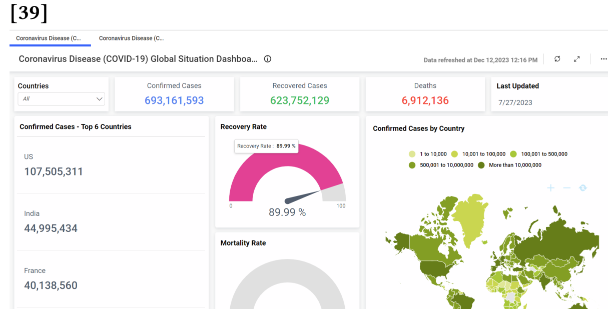
In recent years, there has been an increase in the use of technological tools to manage CD, enabling continuous monitoring. [31, 50, 59]. Accelerometers and gyroscopes that are present in smartphones, smartwatches, or bracelets [7, 19, 20, 74], are non-invasive and continuous data collection methods for monitoring and tracking symptoms. Furthermore, desktop [13, 33, 51], and mobile [2, 4, 44] applications are used for disease management. Regarding techniques, machine learning has demonstrated efficacy in predicting disease stages [34, 46, 68] diagnose diseases [5, 8, 56], and detecting disease symptoms [49, 77]. However, determining the most effective digital indicators for capturing disease symptoms and fluctuations remains challenging.

While many sensors and algorithms have been applied in CD to track symptoms and detect the disease, these approaches focus on a subset of activities within clinical environments. Additionally, studies conducted in free-living often face challenges as patients tend to stop using the technology [24]. While monitoring patients during clinical evaluations is crucial, the availability of information is limited in free-living environments where clinicians have reduced oversight. On top of that, it is necessary to explore the integration of these outcomes into clinical practice.

## 2.2 Visual Analytics in Healthcare

The availability of subjective and objective data collected using mainstream devices is increasing [31]. However, a gap exists in effectively utilizing this data within the healthcare environment, particularly for patients and clinicians [61]. Creating usable visualizations is pivotal for enhancing the understandability of data collected from mainstream devices [70]. While many studies primarily focus on extracting outcomes from these devices, there are noteworthy examples that emphasize the importance of providing meaning to raw data [14, 22, 57, 58]. Usable visualizations can bring significance and opportunities to clinical practice[35, 38, 39, 78, 93]. There are high-fidelity prototypes (Figure 1a) and real-world deployment of dashboards that are already being available for clinical practice (Figure 1b).


**(a) Example of a high-fidelity prototype of a clinical dashboard [39]**




**(b) Example of a real-world deployment of a clinical dashboard to analyse the coronavírus disease situation [3]**

**Figure 1: Examples of the dashboards.**

Visualization techniques, such as dashboards, play a pivotal role in uncovering patterns in patient data [31, 33]. Dashboards facilitate continuous monitoring of changes in patient symptoms [22, 39, 76] and can contribute to enhancing decision-making [34]. Visuals within these dashboards simplify the identification of outliers from typical data patterns. Moreover, they can contribute to stimulating patient-clinician discussions [58]. Beyond enhancing individual interactions, visualizations can also serve as a crucial bridge, facilitating effective communication and data exchange among multidisciplinary healthcare teams and enhancing the collaborative approach to patient care. Two studies explored dashboards in the context of multidisciplinary care. Lai et al [42] delve into the role of a dashboard in aiding multidisciplinary teams but narrow their scope to a particular moment of these teams' activities (multidisciplinary

[3]https://samples.boldbi.com/solutions/healthcare/coronavirus-disease-dashboard

rounds), where clinicians collectively discuss patient progression and plan next steps. Janssen et al [36] explore iteratively clinicians' dashboard interests but with a small sample (n=5) and do not delve into how different types of patients' data could be presented. To the best of our knowledge, no studies have sought to understand how dashboards may support multidisciplinary teams longitudinally, particularly in how these tools enable clinicians to assess the specific information they generate and need while also supporting information-sharing.

## 2.3 Involving Stakeholders in Healthcare Research

Involving stakeholders in the design process has been successfully used to elicit and demonstrate how technology can serve people's needs[1, 71, 79]. In HCI and healthcare research, co-design has been employed to gather insights from domain experts and stimulate discussions [12, 14, 39, 53, 84, 92]. Co-design facilitates close collaboration and discussion among researchers, patients, clinicians, and designers. Previous co-design studies have explored patient perspectives [12, 53], collaborations between clinicians and researchers [14, 39, 92], and interactions between clinicians and PD patients [58, 84]. Although within the context of multidisciplinary care for chronic diseases, multiple stakeholders exist, our study primarily focused on understanding clinicians' perceptions. Through co-designing dashboards, we aimed to explore their potential contributions in enhancing the comprehension of patients' outcomes and fostering information sharing among multidisciplinary teams.

# 3 METHODOLOGY

With the goal of exploring the role of technology and visualizations in facilitating multidisciplinary clinical practice, we conducted a two-phase study. Healthcare professionals who participated in both study phases have experience with a multitude of CDs, such as dementia, stroke, and PD. Both phases of the study were conducted at a tertiary private clinical institution focusing on neurological conditions that operate with a multidisciplinary disease monitoring and rehabilitation approach [4].

Given all participants' shared experiences evaluating PD, our study focused on both phases within the context of PD multidisciplinary care scenarios. We started with a focus group to characterize current practices and establish the types of information desired for PD monitoring. Subsequently, we conducted six co-design workshops to collaboratively design and discuss more informed and comprehensive dashboards, as well as to envision future scenarios where technology could play a significant role. We started with a focus group discussion followed by co-design workshops.

## 3.1 Phase I: Focus Group

Our first goal in exploring how technology can support clinical practice for continuous monitoring of chronic diseases was to understand the type and detail of information desired by clinicians.

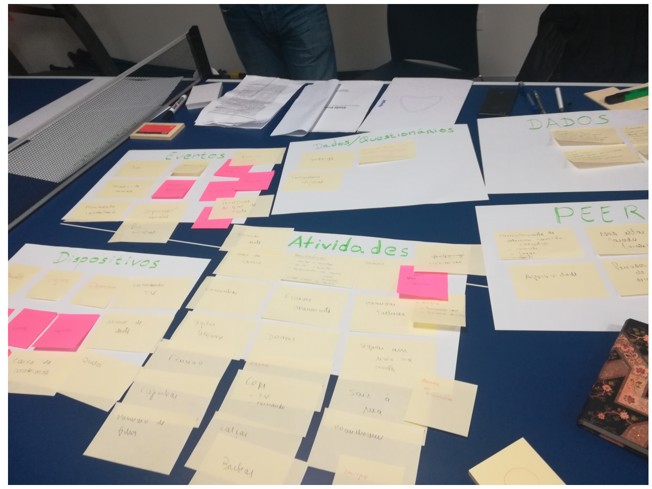



**Figure 2: The setup in the focus group, with the different boards and outputs produced.**

We performed a focus group study and post-session asynchronous activities with a multidisciplinary team of clinicians.

*3.1.1 Participants.* Five clinicians (two physiotherapists, two nurses, and one neurologist) participated in the focus group session. They were aged 34-53 (M=39.25; SD=9.18), with 11-35 (M=17.75; SD=11.53) years of experience, and 2-8 years working at the clinic (M=6.5; SD=3.00). Additionally, six more participants (four physiotherapists, one speech therapist, and one nutritionist) aged 30-33 (M=30.83; SD=1.17), with 7-11 (M=8.83; SD=1.72) years of experience, and 5-7 years working at the clinic (M=6.5; SD=8.84) engaged in post-session asynchronous activities. All participants were working at the tertiary clinical institution and had experience with chronic disease care. Table 1 provide additional details.

*3.1.2 Procedure.* The co-located session lasted around two hours and started by explaining the study goals and tasks. Participants were engaged with the researchers in defining the workflows and data for a data-driven platform. For that, we prepared a set of boards (A3 paper sheets) to represent the more relevant devices, activities, and data outcomes for clinicians. Throughout the session, the boards were iteratively filled with examples (written on post-its). Further details can be found in Figure 2.

We asked participants to write down daily **activities** and **events** that held relevance for inclusion in a free-living assessment framework. Then, participants identified the **devices** or **objects** they consider relevant for assessing patients in the clinical routine and to have, over time, an overview of disease progression. Then, they write down on **data** and **peer** boards and discuss the most relevant outcomes from the aforementioned activities and devices.

To foster further discussions and consolidate information beyond the session, we translated the final state of the paper boards into a digital format using Trello[5]. Participants were encouraged to fill in all available information and prompted with questions to elicit action (e.g., "You mention a couple of objects (e.g., a book). What

[4]Our country's healthcare system is founded on universal coverage, ensuring that all residents have access to comprehensive medical services funded through general taxation. It iis publicly funded, providing healthcare as a fundamental right to its citizens without requiring direct payments for most services. Additionally, to complement public healthcare people may have additional complementary insurances that reduce the cost when going to private hospitals and clinics.

[5]https://trello.com/

type of useful data you see being collected from those objects that can inform on the status of a person with PD?"). Additionally, we introduced a new board titled "Scenarios" to capture real-world scenarios pertinent to the diseases, aiming to extract further data from these examples.

*3.1.3 Analysis.* We started by thoroughly examining the contents generated on each board. Following this, we collated the results derived from the six boards (activities, events, devices, data, peers, and scenarios). We categorized information based on the underlying connections and relationships identified. Subsequently, three researchers began the exploration of the study data and collated information to construct our initial affinity diagram. Following this, our affinity diagram underwent discussion and refinement involving four researchers until we achieved a final consensus. Subsequently, the affinity diagram was integrated into the themes that originated from phase II.

## 3.2 Phase II: Workshop

We performed co-design and group discussion sessions with a multidisciplinary team of clinicians (Figure 3). Our goal was to design and discuss more informed and comprehensive dashboards, while also envisaging future scenarios in which technology could play a significant role.

*3.2.1 Participants.* We recruited 15 participants aged 25-35 (M=29.93; SD=3.28), with 1.5-12 (M=6.17; SD=3.75) years of experience, and 1-7 years working at the clinic (M=3.73; SD=2.38). To ensure a wide variety of valences and experiences, we included a broad representation of healthcare professions in the design process. The professionals represented are two psychologists, three physiotherapists, four speech therapists, two occupational therapists, two nutritionists, and two nurses. Table 1 provides additional details.

Our participants were from the same clinical institution as the focus group, operating with a multidisciplinary disease monitoring and rehabilitation approach. In this clinic, professionals have access to technological devices that, in some clinical teams, are used to evaluate a patient state. On top of that, they use applications to store general patient information (PRIME[6]), to continuously monitor the disease (DataPark [13]), and to exchange notes between them (email). However, some areas and professionals do not use any particular digital health technology.

*3.2.2 Co-Design Workshop.* We conducted six co-design sessions, one with each clinical team. Each session, lasting approximately 45 minutes, consisted of a group discussion, co-design activity, and debriefing discussion. We asked participants to consider both clinical and free-living scenarios in all segments. Additionally, we provided them with personas representing patients of different ages, disease duration, and varying disease stages (e.g., first visit versus a more longitudinal case).

*Group Discussion.* We initiated focus group discussions by inquiring about the daily routines of healthcare professionals in a typical appointment setting. We presented three personas for the following stages. The first persona represented an individual of eighty years with an advanced disease stage, low autonomy, residing in a care home, and undergoing treatment at the clinic. The second persona represented a seventy-year-old recently diagnosed individual, living with family and preparing for their first clinic appointment. The third persona depicted a sixty-year-old with an initial disease stage, having a caregiver, and occasionally attending clinic appointments. We sought to understand the technologies currently used to evaluate and monitor PD patients and their impact on patient evaluations. Given a scenario of a world without financial and technological constraints, participants were asked to ideate solutions to overcome their current limitations in patient evaluation. Participants were prompted to contemplate how technology could augment data availability in their clinical practice. Furthermore, they were encouraged to consider their desired outcomes for future endeavors.

**Figure 3: Clinicians designing a dashboard with researchers at the clinic**

*Co-Design Activity.* After the group discussion activity, we asked them to develop their ideal dashboards, incorporating the information they believed should be displayed (Figure 3). To facilitate this process, we provided whiteboards, markers, and magnets containing examples of visualizations (e.g., textual information, progression charts, and comparisons). We also prepared blank magnets if participants wanted to add a new visualization type. The idea behind the magnets was to help them with different visualization possibilities to facilitate the design of the dashboards and modification. Participants used these tools to visually design their interfaces, representing the desired data and the preferred visualization methods.

Some participants adeptly embarked on the dashboard design process, actively exchanging information as they made headway. Conversely, some exhibited hesitancy, expressing apprehension about their proficiency in dashboard design. To alleviate their anxieties, we clarified that we focused solely on comprehending their priorities regarding patient monitoring outcomes rather than assessing their design abilities. Without any constraints, participants were encouraged to contemplate their current data collection practices in both clinical and daily living contexts. Moreover, they were prompted to identify the information they aspire to collect but currently overlook.

*Debriefing.* At the end of the study, we prompted patients to engage in a reflective exercise concerning their dashboard designs. This led to the presentation of their respective designs, followed

[6]https://primedev.pt/solucoes/

| ID | Area | Age | Gender | YE | YC | P1 | P1A | P2 |
|---|---|---|---|---|---|---|---|---|
| P1 | Physiotherapy | 35 | Female | 11 | 2 | X | X | X |
| P2 | Physiotherapy | 31 | Female | 10 | 7 | | X | X |
| P3 | Physiotherapy | 25 | Female | 2 | 2 | | | X |
| P4 | Physiotherapy | 32 | Female | 10 | 6 | X | X | |
| P5 | Physiotherapy | 28 | Female | 6 | 3 | | X | |
| P6 | Physiotherapy | 28 | Female | 9 | 5 | | X | |
| P7 | Physiotherapy | 29 | Female | 5 | 4 | | X | |
| ST1 | Speech Therapy | 33 | Female | 10 | 7 | | X | X |
| ST2 | Speech Therapy | 26 | Female | 1.5 | 1.5 | | | X |
| ST3 | Speech Therapy | 31 | Female | 7 | 6 | | | X |
| ST4 | Speech Therapy | 30 | Female | 2 | 2 | | | X |
| N1 | Nutrition | 28 | Female | 5 | 1 | | | X |
| N2 | Nutrition | 30 | Female | 7 | 7 | | X | X |
| PS1 | Psychology | 27 | Female | 2 | 2 | | | X |
| PS2 | Psychology | 26 | Female | 4 | 3 | | | X |
| OT1 | Occupational Therapy | 28 | Female | 2 | 2 | | | X |
| OT2 | Occupational Therapy | 30 | Female | 8 | 4.5 | | | X |
| NS1 | Nursing | 34 | Male | 12 | 7 | X | X | X |
| NS2 | Nursing | 33 | Female | 11 | 6 | X | X | |
| NS3 | Nursing | 35 | Female | 9 | 2 | | | X |
| NL1 | Neurology | 51 | Male | 33 | 6 | X | X | |

**Table 1: Characteristics of the participants.**
**Each participant is identified with numerical codes. The first letter refers to the area they belong to: P refers to physiotherapist; OT to occupational therapist; ST to speech therapist; N to nutritionist; PS to psychologist; NS refers to nurse. YE means years of experience, YC means years working at the clinic, P1 represents phase 1, P1A represents phase 1 asynchronously, and P2 represents phase 2**

by discussions highlighting the diverse approaches adopted and consolidating on an ideal dashboard for the area.

*3.2.3 Analysis.* The sessions conducted were recorded and subsequently transcribed for analysis. Thematic analysis (TA) was employed, utilizing both inductive and deductive coding. We followed the six phases of TA [15]. Initially, we took a deductive approach to generate a list of codes based on our pre-defined concepts of interest, including tools, methods for data collection, data visualization, and clinical specialties. We used a design space [72] to categorize the intent of the dashboards and a taxonomy [11] to classify the different visuals used on the dashboards produced. Subsequently, two researchers began the exploration of the study data , which led to the inductive enrichment of the codebook with additional concepts such as instruments and data. Independently, both authors coded all the sessions, generating codes for further analysis. The generated codes were then extensively discussed among the researchers to ensure a thorough examination and understanding of their implications. Subsequently, we derived themes from the relationships and patterns observed among the codes. Multiple sessions were dedicated to further discussion and refinement of the themes, ultimately leading to our research findings.

## 4 FINDINGS

Our participants provide care for a heterogeneous group of patients characterized by differences in disease stage, age (typically skewed towards older individuals), and gender. Although we presented personas, clinicians indicated in all sessions that the outcomes of interest would not be influenced by patients' individual characteristics, such as age and disease stage. Instead, they emphasized that these outcomes would primarily be shaped by patients' interests and the initial assessment, which determines the target areas of focus. We commence by outlining the existing procedures employed by each clinical team. Subsequently, we describe the technological and visualization components currently in use and those with potential applications in their clinical practice. Finally, we unveil the insights derived from embracing a multidisciplinary strategy for disease monitoring involving the collaborative sharing of knowledge. In subsequent sections when we use the term "data", we are referring to patients' information available to clinicians that captures disease-related details. This encompasses both self-reported data and data generated from sensors and devices.

### 4.1 Current Clinical Practices and Technological Tools [F1]

This clinical institution follows a multidisciplinary approach to monitoring chronic diseases. Specifically, the professionals in these studies evaluate people with Parkinson's Disease, among other neurological and neurodegenerative conditions. The areas covered are Nursing, Speech Therapy, Nutrition, Physiotherapy, Psychology, and Occupational Therapy. Patients are divided into three categories - according to the period of stay in the clinic - inpatients, outpatients, and those who follow a rehabilitation program. Clinicians gather

**Current Clinical Practices and Technological Tools**

- Workflow
  - There are asymmetries in technology usage between areas [F1a]
- Multidisciplinary
  - Clinicians face challenges when collecting information from patients outside clinical appointments [F1c.2]

**Values in Technology**

- Current Technology Support
  - Clinicians already use established technology in their assessments [F2a.2]
- Looking to the future
  - Technology is important for monitoring at-home scenarios [F2b.3]
- Barriers to technology adoption
  - Lack of adaptation to user needs [F2c.1]
  - Time [F2c.2]
  - Limited budget [F2c.3]
  - Unawareness [F2c.4]

**The Role of Visualization**

- Dashboard Structure
  - Two-level dashboards. One with a summary and then navigate for the details [F3a.1]
  - Dashboards should be modular to facilitate the change of information components and support templates import to promote reusability [F3a.2]
  - Customization to change pre-defined templates according to their needs [F3a.3,F3a.4]
  - Dynamic dashboards allow real-time data visualization, editing, and updating [F3a.6]
- Dashboard Relevant Features
  - Incorporate data from third parties (family and caregivers) [F3c.3]

**Sharing in Multidisciplinary Teams**

- The relevance of sharing
  - Clinicians benefit from using information from other areas [F4a.1]
- Support for direct and indirect sharing [F4b, F4c]

**Table 2: Summary of the findings**

data during clinical visits and in domestic settings, whether under supervision or independently.

#### 4.1.1 *Workflow.*

During appointments, clinicians endeavored to pinpoint the challenges and underlying factors that prompted the patient's visit to the clinic. To achieve this, they employ validated tools, such as questionnaires or specialized devices [30, 43], and engage patients in dialogue. Subsequently, they formulate an intervention plan for the patient to implement within their home environment.

Upon a patient's hospitalization or upon embarking on a rehabilitation program, the Nursing team oversees the patient's admission and conducts an initial assessment. Subsequently, comprehensive evaluations are conducted across various domains, guided by the challenges identified or reported by the patients. Following this, clinical teams curate an individualized plan based on the outcomes of these assessments. Throughout the patient's stay at the clinic, continuous monitoring is carried out in alignment with specific focus areas to enhance the identified aspects needing improvement. As the patient's discharge approaches, each team reevaluates the patient's condition. The formulation of the discharge summary entails a comparative analysis of admission and discharge results, which aids clinicians in summarizing the patient's journey effectively.

Both admission and discharge notes are documented within their electronic health record system (PRIME). Excluding Nursing, clinicians utilize a dedicated platform (DataPark) to collect and visualize the data collected during assessments [F1a] . Some clinicians also mention the use of professional email to exchange daily updates about patients [F1b] . Teams collaborate to provide a more personalized and comprehensive treatment for patients. Below, we outline key areas:

#### 4.1.2 *Nursing.*

This team conducts a comprehensive assessment of the patient's overall health. This includes identifying food habits, cognition challenges, and the level of autonomy in performing Activities of Daily Living (ADL). Captured data encompasses demographic details, allergies, vaccination history, and medical background. The patient responds to inquiries regarding their well-being, recent issues encountered, and Parkinson's disease symptoms. Clinicians employ direct observation and structured questionnaires to gauge the patient's disease status and progression. In addition to this assessment, measurements such as blood pressure, heart rate, and blood analyses are conducted. Should the need arise, clinicians may request a 24-hour cardiac frequency monitoring examination. Traditionally, nurses record all collected information in prose format on paper, utilizing a structured format known as

SOAP[7](Subjective, Objective, Assessment, and Plan). Subsequently, this data is transcribed into PRIME. As the culmination of their assessment, clinicians develop an intervention plan encompassing admission notes, identified needs, and patient objectives. This plan is relevant to other areas that will periodically assess the patient. This team is responsible for detailing the patient's hospital stay and their status upon discharge.

*4.1.3 Speech Therapy.* When assisted by this team, patients' evaluation focuses on language-related aspects: cognitive features, speech, and swallowing. Then, by consulting the medical history and asking questions to the patients, clinicians pinpoint primary symptoms and their impact on ADL. During inpatient care, speech therapists closely observe patients while they eat. They utilize audio and video recording during acoustic assessments to analyze speech patterns. Then, a software program (e.g., PRAAT[8]) generates an image to identify potential problems to discuss with the patients. The remaining facets are assessed through the utilization of questionnaires.

*4.1.4 Nutrition.* The assessment begins with measurements of height, weight, body circumferences (mid-arm, calf, abdominal - if applicable), hand-grip strength (measured using dynamometry), and body composition (determined through bioimpedance). Subsequently, clinicians inquire patients about food allergies, intolerances, and dietary habits. In cases of inpatient care, nutritionists closely observe patients during their meals. This practice aids in gauging food group consumption, identifying swallowing difficulties, and noting choking episodes. Following this observation, an intervention plan detailing meal-specific food intake and hydration instructions is formulated. Regular checks are conducted during the internment to monitor any changes. Upon discharge or during a follow-up appointment, the patient undergoes a re-evaluation, following the same protocols as the initial assessment. The information gathered is integrated into DataPark, while the intervention plan and discharge notes find their place within the PRIME.

*4.1.5 Physiotherapy.* This team focuses on assessing motor complications. Patients are evaluated using relevant questionnaires, including the MDS-UPDRS [30], the golden standard for evaluating PD severity. This is a comprehensive rating scale that evaluates motor and non-motor symptoms. A physical evaluation occurs on a subsequent day, involving exercises to evaluate motor elements such as balance and gait. Patients utilize sensors to obtain objective measures to complement clinicians' observations during these assessments. Upon discharge, a parallel procedure is conducted, repeating the same assessments. The values obtained during admission and discharge are subsequently juxtaposed for comparison. The discharge summary is then composed and integrated into PRIME. The remaining data is inputted into DataPark. Patients are also provided access to a concise summary report detailing the outcomes of their assessments.

*4.1.6 Psychology.* The clinical team conducts assessments encompassing the patients' cognitive and physiological aspects. When feasible, patients complete questionnaires utilizing tablets, pens, paper, or specialized materials. Throughout their stay, cognitive stimulation tasks are incorporated. Upon discharge, patients undergo a re-evaluation. DataPark serves as the platform for completing all the required questionnaires.

*4.1.7 Occupational Therapy.* This team's assessment focuses on clinical observations and comprehensive depictions of challenges faced by PD patients while engaging in ADL, which encompass tasks like bathing and showering, dressing, self-feeding, personal hygiene, toileting, and maintaining posture. The underlying issues can stem from either motor or cognitive impairments. To pinpoint the root causes, clinicians inquire about patients' daily routines and potential architectural barriers within their living spaces that might hinder these routines. Afterward, clinicians observe patients as they perform these activities. Questionnaires are employed to gauge their level of independence and manual dexterity. When needed, they resort to dynamometers to measure muscle strength. Throughout the evaluations, information is documented on acetates. Post-session, the gathered data is transferred to DataPark.

*4.1.8 Multidisciplinary.* Clinical teams focus on different aspects of the disease [F1c.1] . Depending on their patient assessment requirements, these specialties often use technology for assistance. However, clinicians face challenges in gathering data when patients are at home [F1c.2] . To facilitate information exchange, technology is also employed among healthcare professionals.

## 4.2 The Potential and Challenges of Future Technologies in Clinical Practice [F2]

By technology, we mean all the devices and applications currently in use, potentially accessible or desired by clinicians, to bolster clinical practice. It encompasses tools employed before, during, and after clinical appointments. We divided our findings into three categories: clinicians' current technology usage, challenges, and envisioned future technology applications (more details on Table 3). The outcomes of technological integration can extend beyond assessment, potentially unveiling patterns within patients' daily lives through continuous monitoring. This, in turn, could aid in uncovering concealed health issues.

*4.2.1 Current Technology Support [F2a].* Clinicians employ a set of assessments to assess the present condition of a PD patient. They value data obtained from validated instruments [F2a.1] . Examples are specialized questionnaires such as the MDS-UPDRS, considered the benchmark for disease evaluation, or targeted questionnaires designed to evaluate specific aspects of the patient's condition. In the current clinical framework, clinicians already incorporate established technology into patient assessments [F2a.2] . Typically, this happens in areas needing to measure biomarkers (e.g., blood pressure, weight).

All the clinical teams use PRIME and email to share information about patients' evaluations. Except for the Nursing team, the remaining areas use DataPark, a digital platform that centralizes their assessments, aids in the evaluation process, and facilitates data visualization. Some areas use devices in their clinical routine evaluation. Nutrition resorts to dynamometry, bioimpedance, and weighing scales. Speech Therapy employs software for speech

[7]https://www.ncbi.nlm.nih.gov/books/NBK482263/
[8]https://www.fon.hum.uva.nl/praat/

| Area | Type of Patients' Data | Type of Device or Application | Mandatory | Optional | Desired | Phase |
|---|---|---|---|---|---|---|
| Common | patients' admission and discharge notes | Prime | X | X | | 1,2 |
| Common | patients' daily changes | email | X | X | | 1,2 |
| Common | digital questionnaires clinical and free-living data | DataPark | | X | | 2 |
| Common | medication reminders | medicine box | | | X | 1 |
| NS | heart rate blood pressure | heart rate monitor sphygmomanometer | X | X | | 1,2 |
| NS | sweating urinary incontinence | sensor, not explicitly mentioned | | | X | 1 |
| ST | voice analysis | specific software | X | X | | 2 |
| OT | muscle strength | dynamometers | X | X | | 2 |
| P | gait energy expenditure sleep analysis | accelerometer sensors smartphones | | X | | 1,2 |
| P, PS | support data collection in clinical appointments | tablets | | X | | 2 |
| N | identify food intake | eye camera | | | X | 2 |
| OT | architectonics barriers | 3D map of patients' house | | | X | 2 |
| N, P, OT | daily difficulties and routines location of body problems | sensors automatic diary | | | X | 2 |
| PS | attention level anxiety level | not explicitly mentioned | | | X | 2 |
| ST | detect cough vocal volume | sensors | | | X | 2 |

**Table 3: Clinicians' valued insights from various technological aspects. Area denotes each clinician's area concerning patients' data, including OT (Occupational Therapy), ST (Speech Therapy), N (Nutrition), PS (Psychology), N (Nursing); Type of Patients' Data encompasses both self-reported and device-generated data that clinicians currently have or would like to access; Type of Device or Application signifies the tools used for collecting patients' data; Mandatory and Optional represents patients' data that clinicians already have access; Desired represents patients' data that clinicians would like to have access; Phase refers to the study phase where these findings were mentioned.**

analysis, while Occupational Therapy employs dynamometers for measuring muscle strength. Physiotherapy uses accelerometer sensors, smartphones, and tablets to better understand the patient's current status.

Conversely, the nursing team predominantly relies on observation and patient inquiries for their evaluation approach. Nevertheless, they also incorporate heart rate and blood pressure measurement devices. The value of these additional tools lies in their ability to provide more comprehensive insights into the patient's condition. Psychology uses tablets instead of paper whenever possible for patients to use while performing tasks. Overall, all teams turn to technology, albeit selectively, to enhance and complement their evaluation procedures.

*4.2.2 Looking to the future [F2b].* Participants mentioned the value they attribute to technology and expressed aspirations to harness it for gathering more comprehensive patient information [F2b.1] . Additionally, some mention measurements beyond current practice. To illustrate, Nutritionists expressed a desire for eye cameras on patients to record eating activities, along with software that can automatically analyze nutrition plans and issue alerts when deviations occur, *"Access to beautiful photographs taken with an ocular camera or on the head, ready before starting the meal and after, for three days."* (N1). There are approaches already available, like CalorieMama [6], that provide the same output. This application tracks calorie and nutritional information through photo recognition upon logging meals. Nevertheless, it requires user interaction. Another example is to identify attention and anxiety levels: *"For us, anxiety is relevant. Identifying that in a person's daily life would be wonderful."* (PS1).

Despite not being part of a clinical routine, professionals recognized the value of monitoring patients' daily lives regarding specific aspects pertinent to each clinical domain [F2b.2] . This includes the use of wearable sensors for continuous patient monitoring. *"There are aspects that patients cannot identify while in their homes, and we do not capture them because we only have contact with them at a specific time. So, passive monitoring of symptoms would be ideal"* - P3. An important consideration is ensuring that wearables are ergonomically designed (P1). In unfortunate scenarios (as reported by physiotherapists), patients who experienced psychotic episodes might discard their devices. Furthermore, when gathering data via smartphones, given that patients typically do not carry their phones at home, it leads to potential interference with data accuracy. Wearables also allow nutritionists to monitor patient body weight fluctuations over time, providing awareness of changes.

In uncontrolled environments, like at-home scenarios, clinicians require more comprehensive information to understand patients' difficulties better [F2b.3] . In that sense, there are several activities they would like to monitor. These activities encompass various aspects of daily life, including basic routines like dressing, personal hygiene, and sleeping; leisure activities like dancing, reading, and writing; and exercise-related activities like walking and swimming. Depending on the activity being monitored, the devices they are interested in using range from more general options such as smartphones, sensors, and smartwatches to more specific ones like toothbrushes, shoes, and glasses. Clinicians' specific interests align with their respective areas of specialization [F2b.4] . For instance, Neurology emphasized summary metrics that provide an overall view of patients' experiences at home, such as sleep quality or the number of daily steps (NL1). Conversely, areas like Physiotherapy and Nursing focused more on the details, such as the intensity of movements when patients wake up at night to go to the bathroom (NS1-2).

The Nursing, Physiotherapists, and Speech and Occupational therapists desire sensors capable of measuring and monitoring patients within their homes. This could include an automatic diary to discern patients' daily routines and challenges, sensors positioned on specific body locations to aid in identifying potential issues - *"We would like to have a sensor to identify cough episodes during the day"* - ST1, and wearable technologies that can map locations or capture images of the environment can prove valuable in identifying obstacles within a patient's home that hinder their daily activities - *"When I mentioned architectural barriers, it would be the person bringing photos of the house and the bathroom"* - OT2. Moreover, in connection with vocal volume, there is a shared aspiration to detect fluctuations and offer visual or vibratory feedback to patients when their vocal volume is not optimal.

Hence, these indications underscored the potential that clinicians envision for technology in shaping the future of their clinical practice. Nevertheless, existing limitations must be addressed to transform these possibilities into reality.

*4.2.3 Barriers to technology adoption [F2c].* Some areas desired technology to be better aligned with their needs [F2c.1] . For example, the Nutrition team highlighted that the data available on their digital platform may not consistently be aligned with their particular interests. Conversely, essential information for their reports is sometimes absent from the platform, leading to information dispersion. This results in scattered information and diminishes professionals' motivation to engage with digital platforms.

NS1 explained that the Nursing team is currently not using the platform because it is too time-consuming and lacks some essential features they require, *"We have not used Datapark yet, due to the lack of time to insert everything. We are doing it in paper format."*. Moreover, NS1 highlighted that the platform's lack of direct contribution to its evaluation process – primarily centered on observation and overall assessment – led to perceived limited advantages in its use. This underscores the significance of a technology's cost-effectiveness [F2c.2] [28] emphasizing the necessity for meaningful outcomes that address clinicians' needs while minimizing the time investment for data input, preferably through automated means.

Moreover, an additional barrier to adopting technology is the constraint imposed by budget limitations [F2c.3] . For instance, N1 conveyed their enthusiasm for indirect calorimetry machines. They resorted to estimating energy expenditure; however, the appropriate technology would enable precise quantification of patients' energy needs, optimizing nutritional support. Nonetheless, financial restrictions have prevented them from pursuing such solutions at the current juncture.

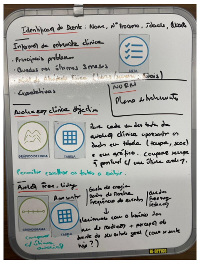
We discerned that, at times, the reluctance of practitioners to integrate more technology into their assessments can be attributed to their lack of awareness regarding whether the device they need even exists [F2c.4] . As expressed by P2, *"Many things could still be developed in the scope of memory, but I confess that I am not into what already exists"*.

## 4.3 The Role of Visualization [F3]

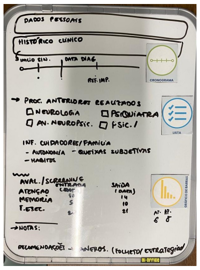
In this section, our primary focus is to describe the outcomes of the design sessions in which participants engaged in discussions about data visualizations. In two of the six sessions (Nursing and Occupational Therapy), participants refrained from providing insights about how they would like to visualize data or the organization of the dashboards. Instead, they enumerated the components they wished to have in a clinical dashboard, as depicted in Figures 4f and 4d. These could be linked to their limited exposure to technology within their clinical routines and the anticipated benefits they envisage technology could offer. Nevertheless, they identify the value of a *"more interactive approach"* (NS1) to explore patients' data. The remaining clinical teams used the magnets to help them communicate what the outcomes might symbolize when visualized, such as comparisons, progressions, simple values, or highlighted values. The outcomes were organized into interest categories: patient information, internment details, clinical evaluations, and at-home data. These can be observed in Figures 4a, 4c, 4b, and 4e.

*4.3.1 Dashboard Structure [F3a].* Participants would like access to a two-level dashboard [F3a.1] . In the first one, all clinical teams shared general information about a patient, the internment, and a summary of the most relevant results for each area - defined by each area. A second one, with the details of each clinical assessment by area. They discussed the need to customize the data available according to the patient they will be evaluating - each patient has different needs - and the most relevant aspects for each area (and individually for each clinician). This is relevant for the first level of the dashboard to define the relevant outcomes from each area that should appear in the summary. Furthermore, for the detailed view, being able to customize according to their preferences can save them time and allow them more flexibility - even during data visualization.

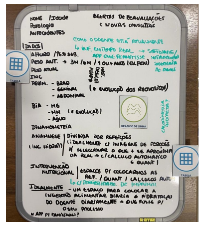
*Customized templates.* Incorporating templates designed to promote data presentation's easiness can significantly enhance these dashboards' effectiveness [F3a.2] . Moreover, the option to customize these templates impacts the flexibility of use for clinicians [F3a.3] . Thus, they can capitalize on templates devised by others



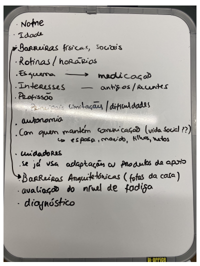
**(a) Example of a Physiotherapy Dashboard**



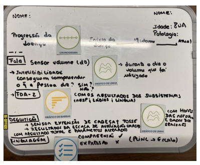
**(b) Example of a Psychology Dashboard**



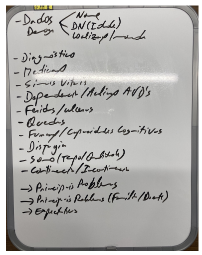
**(c) Example of a Nutrition Dashboard**



**(d) Example of an Occupational Therapy Dashboard**



**(e) Example of a Speech Therapy Dashboard**



**(f) Example of a Nursing Dashboard**

**Figure 4: Examples of the dashboards designed by clinicians during the session. Figures 4f and 4d showcase dashboards presenting a list of desired patients' data by clinicians in these respective areas. On other hand, Figures 4c, 4a, 4b, and 4e offer a clearer insight into the preferred organizational layout and visual components for their respective dashboards. These assymetries could be related to each clinical team regular exposure to technology during patients' assessments. While each clinical area prioritizes distinct patient data, these dashboards share a general structure.**

(established upon application creation), experimenting and tailoring them to align with their needs [F3a.4] .

*Categorical Organization.* All clinical teams shared the same vision about the general structure of the dashboard, organized into four categories [F3a.5] . The first encompassed general patient information, including their name, age, and clinical history. The second category was the internment details, incorporating the date of admission and treatment plans. The third one entailed patients' characterization specific to the evaluated area. Lastly, there was a desire to include data spanning the inter-appointment period, which could encompass information from the clinic stay beyond clinical assessments and their daily life. Depending on the respective clinical domain, additional supplementary visualizations were envisaged. These would entail data from patient evaluations, encompassing observations, questionnaire outcomes, and performed exercises. Participants were also interested in incorporating information from relatives and caregivers (N1, N2, PS2).

*Dynamic Dashboard.* Including free-living data in dashboards would prove advantageous in garnering additional patient information upon arriving at the clinic (Physiotherapy, Speech Therapy, and Psychology), *"For people with anxiety, having a sensor to monitor heart-rate or to identify the activities when anxiety is predominant could help us to identify the causes"* - PS2. If data is collected in real-time, clinicians could remotely monitor patients. This holds potential for scenarios such as blocking symptoms like Freezing of Gait [27] (described by participants as one of the relevant scenarios in Phase I), where clinicians could receive notifications and attempt to assist patients in overcoming the situation without necessitating patient's initiative.

Participants emphasized the need for direct modification of information within the dashboard during clinical assessments so that they can retrieve current and past outcomes while inputting the latest data and additional notes. This underscores the demand for a dynamic dashboard that allows real-time data visualization, editing, and updating [F3a.6] . This dynamic aspect should extend beyond the dashboard, enabling external applications or professionals to modify and update information [F3a.7] . Such adaptability serves to enhance flexibility during and beyond assessments.

*4.3.2 Dashboard Characterization [F3b].* The subsequent findings are anchored within Sarykaya et al. [72] conceptual framework. All dashboards revealed a predominant static operational motivation, implying they delivered real-time data with low visualization literacy [F3b.1] . Nonetheless, they also possessed nuances associated with decision-making, rendering them with interactive tools employed to comprehend the subject of study (in this case, patients' information), either in real-time (operational) or over extended periods (strategic) [F3b.2] . Concerning their purpose, it is primarily operational and the intended audience, is typically organizational [F3b.3] ; these dashboards share common attributes such as the requirement for low visual literacy, domain expertise, and being single-paged [F3b.4] . Some dashboards demonstrated interactive visual elements (P1, P3, PS2) [F3b.5] , and highlighting features (P2) [F3b.6] . While not immediately apparent in the dashboard designs, participants underscored the importance of visual and data customization and the integration of data from other areas [F3b.7] . While the semantics of all data should ideally be adaptable, only one dashboard (N1) indicated the need for notifications and benchmark indicators [F3b.8] .

*Valued visuals.* Most participants valued objective dashboards that can provide meaningful visual insights about outcomes [F3b.9] . They highly prioritized the ability to compare different evaluation periods within a single dashboard [F3b.10] . This comparison might involve overlaying current data or displaying the previous assessment alongside the latest one. This also extends to comparing patients and similar assessments of different areas. Furthermore, participants expressed a strong desire for visuals that provide a holistic perspective of metrics by employing progressions [F3b.11] , *"It would be essential to have a progression here. If we could obtain this data, the weight of the user three months ago, six months ago, and one year ago, we could have a kind of graph with the evolution, and in all our reassessments, it would be possible to add the weight and get a more visual perception of the patient's weight"* - N2. To help uncover the patterns in data, participants emphasized the significance of highlighting variations (defined based on certain benchmark thresholds) and identifying the most relevant metrics [F3b.12] . This proactive approach assists in detecting potential variations in a patient's disease stage.

*4.3.3 Dashboard Relevant Features [F3c].* Participants expressed a desire for dashboards to include a printable version (N1). This feature would enable them to share the generated reports with their patients, fostering future discussions guided by patient-generated data [F3c.1] . Additionally, providing patients with a summary of the outcomes from all conducted assessments would be rewarding for them [F3c.2] .

*Family and Caregivers.* Some participants mentioned the value of including data from family or caregivers (N1, N2, PS2) on dashboards [F3c.3] . This additional data would serve to complement the existing information by offering an alternative perspective, including events occurring at home. This proves particularly significant given that patients might not always recall all events or perceive them in the same way as a third party, such as a caregiver, would. Among the most commonly sought outcomes, captured at home, by clinicians are levels of autonomy and daily habits. Clinicians highlighted the advantages of involving others who can use applications to report on these daily routines (N1) or biomarkers (N2).

## 4.4 Sharing in Multidisciplinary Teams [F4]

Clinical teams evaluate and monitor different disease dimensions. On top of that, areas such as psychology, occupational therapy, or nutrition primarily rely on observational data. On the other hand, areas such as physiotherapy involve more objective data collection. This discrepancy underscored the need for information sharing to augment the data availability to each specialized area. This section delves into the insights concerning the information-sharing workflow, categorizing it into direct and indirect communication.

*4.4.1 The Relevance of Sharing [F4a].* Enabling effective information sharing is pivotal in supporting clinicians to acquire patient data. For instance, nursing assumes the primary role during the initial interaction with the patient at the clinic. This area collects personal information and conducts an overarching assessment to discern patients' areas of focus. The data compiled during these interactions must be centralized, *"and it would be beneficial if they had some application to introduce the information. That way, we could access what the patient has already done"* - N2.

Clinicians benefit from reusing the information collected in other areas [F4a.1] . For example, Nutritionists find it beneficial to access clinical outcomes from assessments conducted by speech therapists. This enables them to tailor patients' meal plans to their specific limitations. That way, they *"do not need to repeat the procedure"* (N1). Similarly, Occupational therapists, whose intervention is primarily based on the patient's daily barriers, express the value of accessing data from physiotherapists. This data, which includes metrics such as the number of falls, freezing episodes, or motor deficits, allows them to *"adapt the interventions to patients' needs more effectively."* (OT1).

Given that patients are followed over long periods and not always assessed by all areas, it is important that the clinician is notified whenever new information has been added since the previous checks. This enables a shared understanding of what is evolving in parameters from other areas that may be relevant to the clinician's focus [F4a.2] . Likewise, throughout multiple assessments spanning time, the patient may be evaluated by professionals in the same clinical area who can also benefit from this notification.

*4.4.2 Direct Sharing [F4b].* Numerous participants emphasized that they frequently take notes on paper or exchange information via email with colleagues. This is time-consuming and adds to their workload [F4b.1] . Moreover, this approach scatters information across various channels and lacks systematization [F4b.2] . Consequently, the potential for data reuse is hindered, and the time required for retrieving past information and conducting comparisons is extended. To address this challenge, incorporating a chat or forum within the clinical interface holds promise for fostering improved communication among clinical teams.

*4.4.3 Indirect Sharing [F4c].* Indirect information exchange also occurs through platforms like PRIME, which holds patients' data, and DataPark. However, searching for specific information within these platforms can be time-consuming and challenging [F4c.1] . This delay hampers the ability to address potential uncertainties swiftly, even during patient evaluations, e.g., *"For us having access to the cognitive part and see something summarized, helps to understand if it's just the motor part that is affected"* - P3. Moreover, clinicians from the same area who require access to previous information for subsequent evaluations can benefit from a concise summary of prior assessments [F4c.2] . This eliminates the need to independently analyze data or consult colleagues, streamlining the decision-making process. This indirect sharing becomes even more relevant when considering patients undergoing evaluations in various healthcare facilities. Clinicians *"value access to patient's complete clinical histories, even if not previously documented in the same medical facility"* (NS3).

# 5 DISCUSSION

Clinicians use technology in their clinical practice, though its usage remains restricted, partly due to the challenges associated with interpreting the vast volume of collected data and effectively integrating it into their clinical workflows. These challenges arise from the substantial data volume and the imperative need for data sharing within the context of multidisciplinary care. We have illustrated with our findings 1) the current usage of technology in clinical practice [F1,F2a] , 2) potential future applications [F2b] , and 3) existing barriers [F2c] . Furthermore, we described 4) the contribution of dashboards to clinical practice [F3a] , 5) the visuals clinicians value [F3b] , and 6) the dynamics associated with data sharing [F3c, F4] . We extend previous work by characterizing the role of technology in a multidisciplinary approach to chronic disease monitoring, providing a deeper understanding of the role customizable dashboards can have in promoting awareness and information sharing.

Sensors and devices can generate vast amounts of data that can contribute to understanding patient health and disease management [41]. Nevertheless, the high volume of data poses a significant challenge regarding the interpretation and use in clinical practice [67]. Dashboards represent a vital bridge between the data available and its meaningful application in clinical practice [35]. In multidisciplinary teams, they are powerful tools for enhancing collaboration [F4a.2, F4c.2] , reducing the duplication of assessments [F4a.1] , and ultimately saving time (also for patients) and resources. Integrating a two-level dashboard [F3a.1] adds an extra layer of flexibility, empowering healthcare professionals to tailor their approach to each patient's needs fostering more personalized care and informed decision-making. In this section, we discuss these implications for the design of healthcare interfaces.

## 5.1 Supporting Multidisciplinary Teams Collaboration

Dashboards facilitate continuous monitoring of changes in patients' state [22, 39, 78], events and symptoms. They empower clinicians to delve into the collected data, extracting clinical insights through analysis or detecting outliers. Visuals within these dashboards make spotting changes from typical data patterns easier [F3b.9-12] . This detection is facilitated with the help of visuals that can highlight changes in the typical data patterns. In some chronic diseases, a multidisciplinary approach can benefit the patients [63, 83]. However, traditional dashboards are not inherently tailored for use by multidisciplinary teams [F4c] . Information sharing is essential in these scenarios where each area prioritizes distinct aspects while evaluating a patient [F4a.1, F4a.2, F4b.2] .

*Individual needs.* Multidisciplinary dashboards need to consider each clinical team's interests regarding the patient [F1c.1, F2c.2] . Moreover, clinicians might desire diverse perspectives within each team while examining the patient's data. This is valuable because, depending on the patient's difficulties and the assessments, it may be necessary to adapt the outcomes in which they are focused [F2b.1] . This adaptation could involve incorporating new outcome measures, adjusting levels of measurement, or varying the granularity of data analysis (ranging from daily to weekly or monthly) to align with the typical fluctuations experienced by patients [F3b.10] . Consequently, dashboards should include adaptable features and mechanisms that foster dynamic customization [F3a.3, F3a.6] . This strategy can empower clinicians with tools that enable them to tailor outcomes and visualizations to align with their specific requirements.

*Communication.* Clinical teams share information between them, a process that can be time-consuming for both those seeking and providing the information [F4b.1] . Nevertheless, this exchange is pivotal for a more comprehensive understanding of patients' disease progression. Furthermore, it also helps mitigate the necessity for repetitive assessments [F4a.1] , lessening patient inconvenience and enabling more personalized treatments based on shared knowledge across different domains. Dashboards should play a pivotal role in making information between clinical teams available [F4a.2] . They should facilitate the reuse of data from other domains [F4a.1] . Additionally, they should serve as a knowledge base for searching patients' clinical history. Thus, by promoting communication between clinical teams, dashboards are essential to expedite information sharing, promoting a more efficient treatment that benefits patients and clinicians.

## 5.2 Improve Decision-Making through Usable Visualizations and Stakeholder Involvement

To be effective and improve decision-making in healthcare, visualizations must be easily understandable and usable by users [35]. Similar to our findings, Gagnon [26] shows high cost [F2b.3] and high workload [F2b.2] as potential barriers to technology adoption.

Involving stakeholders when defining the outcomes and design applications (and visualizations) is a crucial step [14, 53, 57, 58, 84]. By combining best practices in visualization design with insights from stakeholders, we can create more effective and user-friendly visualizations for clinicians. We encourage designers and developers to follow established guidelines for creating visualizations and collaborate with stakeholders to ensure that their designs are well-suited for the intended context of use.

This approach creates a sense of commitment among stakeholders, who feel included in the design process and see their ideas reflected in the final product. Technology acceptance and usage in healthcare can be challenging, especially in clinical environments where time is limited [26]. When incorporating technology into clinical practice, it is essential to consider factors associated with the patient (such as motivation to use technology), the clinician (including considerations of risk and benefit), and the technology itself (including privacy and security concerns) [26]. Improving the expectations of the outcomes and reducing effort can increase the perceived value [91]. Therefore, by involving stakeholders in defining outcomes and designing interfaces, we enhance the benefits (as they can achieve their desired outcomes and shape the navigation workflow of interfaces) and, consequently, increase the perceived value associated with technology usage.

## 5.3 Enhancing Awareness through Customizable Dashboards

Technology usage in healthcare still has challenges that need to be overcome. Patients still have difficulties using technology [86], and concerns about data privacy [54]. Similar to our findings, Whitelaw et al. [86] points out clinicians felt an increased workload while using technology devices [F2b.2] . Personalized medicine has been proposed as a potential solution for addressing individual treatment needs in chronic diseases [63, 82]. Likewise, considering users' unique requirements has been demonstrated as a promising approach to improve the motivation for using technology by increasing the awareness of perceived benefits [3, 64, 69, 73]. Tailored technological strategies that consider users' personality [3], their preferences, and past experiences [64, 69], while also giving them the power to change outcomes[73], play a significant role in shaping the design of interfaces. These approaches can benefit healthcare by increasing data availabiliy, increasing patients' motivation to use technology, benefiting patients and clinicians, and leading to early disease detection, monitoring, and treatment [37].

### 5.3.1 *Adaptable interfaces.* 

Automatic adaption of interfaces facilitates data navigation [3, 90]. Interfaces that dynamically adjust based on data usage patterns hold the potential to enhance user awareness [25]. Nevertheless, as these adaptive approaches learn from the data provided, interface usage, and user choices, they can limit flexibility and introduce limitations. In clinical contexts, missing data can lead to systems and interfaces presenting inaccurate information. Lindgren [45] created a decision support system that provided recommendations for clinicians; however, when missing data happened, this led to poor recommendations. This can prolong the time required for assessment or even dissuade the use of such options, potentially impacting appointments. To mitigate these challenges, one effective strategy is to introduce an additional layer of customization, allowing clinicians to adapt their real-time data exploration during appointments [F3a.3, F3a.4, F3a.7] . The intelligent interfaces can provide suggestions that complement these customizations, offering a more tailored and reliable approach to decision support in clinical practice.

*5.3.2 Visuals.* The way outcomes are presented to clinicians can impact the recognition of patterns that aid symptom identification [F4b.9-12] . For instance, if clinicians are just provided with data that require extensive analysis to extract outcomes, this can result in additional time demands, potentially diverting their attention from patient care. Especially within the context of chronic diseases, where clinicians need to periodically evaluate disease progression, the time required to understand the most relevant challenges for patients holds significant weight. In some extreme cases, the complexity of data analysis may deter clinicians from utilizing this valuable information in their clinical practice [F2b.1] . Furthermore, clinical areas and even individual clinicians within the same specialties, often prioritize different aspects of patient evaluation [F1c.1] . Additionally, clinicians value the flexibility to customize visualizations based on their specific interests and patient assessments [F3a.3] . Factors such as time intervals (daily, weekly, monthly) [F3b.11] , levels of comparison (latest assessment vs. most recent, comparison with other patients) [F3b.10] , and establishing benchmarks for biomarker measurements [F3b.12] all play pivotal roles in tailoring these visualizations to their needs. Therefore, the organization and presentation of visualizations within dashboards can significantly impact their utility and effectiveness in clinical practice.

### 5.4 Supporting Clinician Collaboration with Patients, Family, and Caregivers

Patient-generated data usage has increased, contributing significantly to patient-centered care [18, 62, 66]. This enables healthcare providers to access more data, particularly concerning patients' daily lives, where information is typically scarce. Tools must be available for clinicians to capitalize on the collected data for clinical practice. Dashboards play a pivotal role in helping clinicians unveil patterns within the data [F3b.9] . These patterns facilitate communication between patients and healthcare providers and aid in identifying challenges and difficulties [48]. Moreover, tailoring dashboards to share with individual patients enhances this approach. With dashboards, the collaborative aspect of appointments is amplified, resulting in a more cooperative healthcare environment [58].

For the data collected to become useful, increasing the value tools may have for the patients [21, 47] is crucial. While clinicians can play a role in encouraging patients to engage with these applications, these tools need to be customized to cater to individual patient needs, thus adding meaningful value to their healthcare experience. One way of achieving this is by giving more agency to patients to define what, when, and how they are monitored. Moreover, empowering patients to define their desired outcomes and involving them in the design process of these tools and applications can substantially enhance the perceived value [40].

*Third-party data.* Family and caregivers have a dual role in patients' care, a role that is especially relevant within the context of chronic diseases [29, 52]. On one hand, they are intimately involved in the patient's daily routines. So, like clinicians, they can benefit from patient-generated data to provide more personalized and informed care. On the other hand, they can contribute more data to complement, enhancing clinicians' understanding of a patient's disease progression [F3c.3] . To increase the data available, they can use applications that allow them to take notes and link this complementary information to the data already collected by patients, either automatically or manually.

*Sharing Data and Privacy Issues.* Clinicians need access to all the available useful information to augment their understanding of a patient [F2c.1] . Dashboards can help by consolidating data and reducing the effort required for data processing by highlighting the more relevant aspects based on data patterns or pre-defined thresholds. Nevertheless, patients have raised privacy and security concerns, indicating a need for greater control over the data collected [18, 54]. On the one hand, clinicians consider that certain data could potentially pose risks to patients [88]. For instance, it can affect a patient's health perception, potentially resulting in severe hypochondria [88]. These variations might occasionally stem from unrelated factors to their medical condition, such as patients engaging in holidays. On the other hand, patients are the ones who generate the data and should be the owners of their data. Even with their healthcare providers, the data-sharing decision should fundamentally originate from the patients. By empowering patients to have more control over what and when they are monitored, we simultaneously decrease the volume of information available to populate the dashboard. For instance, if a patient restricts access to specific monitoring periods or only engages with devices during particular timeframes, it may become challenging for dashboards to depict data trends due to the potential difficulty in identifying consistent data patterns.

### 5.5 Dashboards as Trigger for Action

In addition to the rich visualizations that dashboards can provide, they can be used as a trigger for action. For that, they should be dynamic to stimulate user engagement. Dynamic dashboards play a pivotal role in aiding clinicians to notice data patterns that help them adjust patients' treatment plans [F3a.6] . They encourage data exploration, empowering clinicians to delve into data based on their specific areas of interest. Moreover, in the context of chronic diseases that require ongoing patient monitoring for disease progression and fluctuations, customizable dashboards prove helpful to aid clinicians in highlighting data patterns that may evolve over time within each patient. Furthermore, within multidisciplinary teams, these dashboards facilitate information sharing among clinical professionals [F4a.1] , promoting the potential discovery of new information [F4c.2] .

Through dashboard exploration, clinicians can identify missing data or potential data interests. Dashboards can be used to address gaps in data by leveraging alternate data sources. This functionality permits the usage of other data sources, such as requesting data from patients or families [F3c.3] , to complement the information or start a new data collection procedure. In such cases, automated notifications can be triggered, or new data entry points can be scheduled to commence via patients' or caregivers' smartphones or other relevant devices currently in use.

Clinicians can use the data collected and its corresponding visual representations as triggers to stimulate discussions with patients [F3c.1] . Dashboards have the potential to shift patient-provider collaboration [48, 58]. Moreover, patients can employ their personalized visualizations and data collected to initiate conversations with their healthcare providers [87]. The traditional approach to conducting appointments can change by integrating available dashboards. Nevertheless, the efficacy of this transformation heavily relies on the data collection within controlled clinical environments and uncontrolled environments, which are highly dependent on patients' willingness to use technological devices [F1c.2] .

### 5.6 Limitations

Our study focused on the perspectives of a multidisciplinary team of clinicians. These professionals have different backgrounds and experiences. Nevertheless, it is important to acknowledge the limitations of our study. Although we recruited clinicians from seven different areas with different backgrounds and technological experience, our outcomes portray the experiences of healthcare professionals from a specialized private clinic that may have different conditions from other hospitals or clinics. Nevertheless, the information displayed on dashboards can originate from diverse sources and it is not limited to a specific technology. This means that our findings can prove beneficial in diverse healthcare systems, despite budget constraints in hospitals or instances where clinicians and/or patients do not have access to the same applications mentioned in our studies. Our research underscores the usefulness of these findings within the context of dashboards designed for multidisciplinary teams of clinicians. Even so, further research is needed to explore and validate our findings across various settings and contexts. In particular, there is a need to delve into the practical implications of using these dashboards in clinical environments, namely how dashboards shift patient-provider collaboration.

## 6 CONCLUSION

Customizable dashboards can be pivotal in empowering clinicians to explore data patterns, enhance awareness, and foster more informed decision-making. In multidisciplinary care, sharing information between clinical teams is paramount for enriching patient treatment outcomes. Furthermore, dashboards can be valuable for facilitating communication between clinicians and patients, and improving collaboration. Future work should investigate the impact of customizable dashboards within clinical practice. One promising approach involves establishing a triad encompassing pre-defined templates, customization options, and automatic adaptation features. These templates should be designed for versatility, allowing different clinicians to reuse and adapt various components according to their needs. Striking a balance between automatic adaptations based on user usage patterns or other personal traits and the ability to create automatic templates and customize them can provide clinicians with a more diverse set of tools to enhance the clinical utility of data and visualizations. This multifaceted approach holds the potential to usher in a paradigm shift in integrating dashboards into healthcare settings, ultimately benefiting clinicians and patients.

One pivotal step in populating these dashboards is data availability. To achieve this, it becomes imperative to involve patients in the co-design process, for understanding and addressing the challenges and barriers they face. One approach involves empowering patients to define their own data collection mechanisms while affording them greater control over the outcomes generated. Embracing a personalized approach to data collection can enhance patient outcomes and benefit clinicians by providing them with more comprehensive data to understand their patient's healthcare needs. As patient-generated data continue to gain more relevance and contribute to patient-centered care, it becomes essential to explore how both patients and healthcare professionals can derive value from this data. Therefore, future research should delve into the dynamics of negotiating data collection procedures, pinpointing barriers and challenges faced by patients. This aims to offer patients more agency while upholding the clinical utility indispensable for healthcare professionals. This approach ensures that the data collected serves clinical purposes and holds personal significance for patients.

## ACKNOWLEDGMENTS

We thank all the clinicians that agreed to participate in these sessions. This work was supported by Fundação para a Ciência e a Tecnologia, through the LASIGE Research Unit [Ref. UIDB/00408/2020, UIDP/00408/2020], and scholarship SFRH/BD/144242/2019, Project 41, HfPT: Health from Portugal, funded by the Portuguese Plano de Recuperação e Resiliência, and IDEA-FAST project, which has received funding from the Innovative Medicines Initiative 2 Joint Undertaking under grant agreement No. 853981. This Joint Undertaking receives support from the European Union's Horizon 2020 research and innovation programme and EFPIA and associated partners.

## REFERENCES


[1] Chadia Abras, Diane Maloney-Krichmar, Jenny Preece, et al. 2004. User-centered design. *Bainbridge, W. Encyclopedia of Human-Computer Interaction. Thousand Oaks: Sage Publications* 37, 4 (2004), 445–456.

[2] Payal Agarwal, Dara Gordon, Janessa Griffith, Natasha Kithulegoda, Holly O Witteman, R Sacha Bhatia, Andre W Kushniruk, Elizabeth M Borycki, Lise Lamothe, Elena Springall, et al. 2021. Assessing the quality of mobile applications in chronic disease management: a scoping review. *NPJ digital medicine* 4, 1 (2021), 46.

[3] Ofer Arazy, Oded Nov, and Nanda Kumar. 2015. Personalityzation: UI personalization, theoretical grounding in HCI and design research. *AIS Transactions on Human-Computer Interaction* 7, 2 (2015), 43–69.

[4] Siddharth Arora, Vinayak Venkataraman, Andong Zhan, S Donohue, Kevin M Biglan, E Ray Dorsey, and Max A Little. 2015. Detecting and monitoring the symptoms of Parkinson's disease using smartphones: A pilot study. *Parkinsonism & related disorders* 21, 6 (2015), 650–653.

[5] Roozbeh Atri, Kevin Urban, Barbara Marebwa, Tanya Simuni, Caroline Tanner, Andrew Siderowf, Mark Frasier, Magali Haas, and Lee Lancashire. 2022. Deep

Learning for Daily Monitoring of Parkinson's Disease Outside the Clinic Using Wearable Sensors. *Sensors* 22, 18 (2022), 6831.
[6] Azumio. 2017. *Calorie mama instant food recognition, a smart camera app that uses deep learning to track nutrition from food images.* www.caloriemama.ai
[7] Joseph Barker, Karl Smith Byrne, Aiden Doherty, Charlie Foster, Kazem Rahimi, Rema Ramakrishnan, Mark Woodward, and Terence Dwyer. 2019. Physical activity of UK adults with chronic disease: cross-sectional analysis of accelerometer-measured physical activity in 96 706 UK Biobank participants. *International Journal of Epidemiology* 48, 4 (2019), 1167–1174.
[8] Gopi Battineni, Getu Gamo Sagaro, Nalini Chinatalapudi, and Francesco Amenta. 2020. Applications of machine learning predictive models in the chronic disease diagnosis. *Journal of personalized medicine* 10, 2 (2020), 21.
[9] Stephanie Bernell and Steven W Howard. 2016. Use your words carefully: what is a chronic disease? *Frontiers in public health* 4 (2016), 159.
[10] Owain Blackwood and Rahul Deb. 2020. Multidisciplinary team approach in breast cancer care: benefits and challenges. *Indian Journal of Pathology and Microbiology* 63, Suppl 1 (2020), S105–S112.
[11] Michelle A Borkin, Azalea A Vo, Zoya Bylinskii, Phillip Isola, Shashank Sunkavalli, Aude Oliva, and Hanspeter Pfister. 2013. What makes a visualization memorable? *IEEE transactions on visualization and computer graphics* 19, 12 (2013), 2306–2315.
[12] Aikaterini Bourazeri and Simone Stumpf. 2018. Co-designing smart home technology with people with dementia or Parkinson's disease. In *Proceedings of the 10th Nordic Conference on Human-Computer Interaction.* 609–621.
[13] Diogo Branco. 2019. *DataPark: A Data-Driven Platform for Parkinson's Disease Monitoring.* Ph. D. Dissertation. Universidade de Lisboa Portugal.
[14] Diogo Branco, Raquel Bouça, Joaquim Ferreira, and Tiago Guerreiro. 2019. Designing Free-Living Reports for Parkinson's Disease. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems.* 1–6.
[15] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77–101.
[16] Pascale Carayon and Peter Hoonakker. 2019. Human factors and usability for health information technology: old and new challenges. *Yearbook of medical informatics* 28, 01 (2019), 071–077.
[17] American Diabetes Association Professional Practice Committee and American Diabetes Association Professional Practice Committee:. 2022. 2. Classification and diagnosis of diabetes: Standards of Medical Care in Diabetes—2022. *Diabetes care* 45, Supplement_1 (2022), S17–S38.
[18] Mayara Costa Figueiredo, H Irene Su, and Yunan Chen. 2021. Using data to approach the unknown: Patients' and healthcare providers? Data practices in fertility challenges. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW3 (2021), 1–35.
[19] Silvia Del Din, Cameron Kirk, Alison J Yarnall, Lynn Rochester, and Jeffrey M Hausdorff. 2021. Body-worn sensors for remote monitoring of parkinson's disease motor symptoms: vision, state of the art, and challenges ahead. *Journal of Parkinson's disease* 11, s1 (2021), S35–S47.
[20] Milica Djurić-Jovičić, Igor Petrović, Milica Ječmenica-Lukić, Saša Radovanović, Nataša Dragašević-Mišković, Minja Belić, Vera Miler-Jerković, Mirjana B Popović, and Vladimir S Kostić. 2016. Finger tapping analysis in patients with Parkinson's disease and atypical parkinsonism. *Journal of Clinical Neuroscience* 30 (2016), 49–55.
[21] Orla Duffy, Jonathan Synnott, Roisin McNaney, Paola Brito Zambrano, W George Kernohan, et al. 2021. Attitudes toward the use of voice-assisted technologies among people with Parkinson disease: findings from a web-based survey. *JMIR rehabilitation and assistive technologies* 8, 1 (2021), e23006.
[22] Jordan J Elm, Margaret Daeschler, Lauren Bataille, Ruth Schneider, Amy Amara, Alberto J Espay, Michal Afek, Chen Admati, Abeba Teklehaimanot, and Tanya Simuni. 2019. Feasibility and utility of a clinician dashboard from wearable and mobile application Parkinson's disease data. *NPJ digital medicine* 2, 1 (2019), 95.
[23] JE Epping-Jordan, SD Pruitt, R Bengoa, and Edward H Wagner. 2004. Improving the quality of health care for chronic conditions. *BMJ Quality & Safety* 13, 4 (2004), 299–305.
[24] Alberto J Espay, Paolo Bonato, Fatta B Nahab, Walter Maetzler, John M Dean, Jochen Klucken, Bjoern M Eskofier, Aristide Merola, Fay Horak, Anthony E Lang, et al. 2016. Technology in Parkinson's disease: challenges and opportunities. *Movement Disorders* 31, 9 (2016), 1272–1282.
[25] Leah Findlater and Joanna McGrenere. 2010. Beyond performance: Feature awareness in personalized interfaces. *International Journal of Human-Computer Studies* 68, 3 (2010), 121–137.
[26] Marie-Pierre Gagnon, Patrice Ngangue, Julie Payne-Gagnon, and Marie Desmartis. 2016. m-Health adoption by healthcare professionals: a systematic review. *Journal of the American Medical Informatics Association* 23, 1 (2016), 212–220.
[27] Chao Gao, Jun Liu, Yuyan Tan, and Shengdi Chen. 2020. Freezing of gait in Parkinson's disease: pathophysiology, risk factors and treatments. *Translational neurodegeneration* 9 (2020), 1–22.
[28] Andrea Gentili, Giovanna Failla, Andriy Melnyk, Valeria Puleo, Gian Luca Di Tanna, Walter Ricciardi, and Fidelia Cascini. 2022. The cost-effectiveness of digital health interventions: A systematic review of the literature. *Frontiers in Public Health* 10 (2022), 787135.
[29] Muriel R Gillick. 2013. The critical role of caregivers in achieving patient-centered care. *Jama* 310, 6 (2013), 575–576.
[30] Christopher G Goetz, Barbara C Tilley, Stephanie R Shaftman, Glenn T Stebbins, Stanley Fahn, Pablo Martinez-Martin, Werner Poewe, Cristina Sampaio, Matthew B Stern, Richard Dodel, et al. 2008. Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): scale presentation and clinimetric testing results. *Movement disorders: official journal of the Movement Disorder Society* 23, 15 (2008), 2129–2170.
[31] David Gotz and David Borland. 2016. Data-driven healthcare: challenges and opportunities for interactive visualization. *IEEE computer graphics and applications* 36, 3 (2016), 90–96.
[32] Michael J Haller, Michael S Stalvey, and Janet H Silverstein. 2004. Predictors of control of diabetes: monitoring may be the key. *The Journal of pediatrics* 144, 5 (2004), 660–661.
[33] J Ignacio Hidalgo, Esther Maqueda, José L Risco-Martín, Alfredo Cuesta-Infante, J Manuel Colmenar, and Javier Nobel. 2014. glUCModel: A monitoring and modeling system for chronic diseases applied to diabetes. *Journal of biomedical informatics* 48 (2014), 183–192.
[34] Murtadha D Hssayeni, Joohi Jimenez-Shahed, Michelle A Burack, and Behnaz Ghoraani. 2021. Ensemble deep model for continuous estimation of Unified Parkinson's Disease Rating Scale III. *Biomedical engineering online* 20, 1 (2021), 1–20.
[35] Aleeha Iftikhar, Raymond Bond, Victoria McGilligan, Stephen J Leslie, Khaled Rjoob, Charles Knoery, and Aaron Peace. 2019. Role of dashboards in improving decision making in healthcare: Review of the literature. In *Proceedings of the 31st European Conference on Cognitive Ergonomics.* 215–219.
[36] Anna Janssen, Candice Donnelly, Judy Kay, Peter Thiem, Aldo Saavedra, Nirmala Pathmanathan, Elisabeth Elder, Phuong Dinh, Masrura Kabir, Kirsten Jackson, et al. 2020. Developing an intranet-based lymphedema dashboard for breast cancer multidisciplinary teams: design research study. *Journal of Medical Internet Research* 22, 4 (2020), e13188.
[37] Kevin B Johnson, Wei-Qi Wei, Dilhan Weeraratne, Mark E Frisse, Karl Misulis, Kyu Rhee, Juan Zhao, and Jane L Snowdon. 2021. Precision medicine, AI, and the future of personalized health care. *Clinical and translational science* 14, 1 (2021), 86–93.
[38] Aamir Khan, Hamid Mukhtar, Hafiz Farooq Ahmad, Muhammad Awais Gondal, and Qazi Mudassar Ilyas. 2017. Improving usability through enhanced visualization in healthcare. In *2017 IEEE 13th International Symposium on Autonomous Decentralized System (ISADS).* IEEE, 39–44.
[39] Yoojung Kim, Eunyoung Heo, Hyunjeong Lee, Sookyoung Ji, Jueun Choi, Jeong-Whun Kim, Joongseek Lee, and Sooyoung Yoo. 2017. Prescribing 10,000 steps like aspirin: designing a novel interface for data-driven medical consultations. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems.* 5787–5799.
[40] Nina Kongshaug, John-Arne Skolbekken, Arild Faxvaag, and Eva Hofsli. 2021. Cancer patients' perceived value of a smartphone app to enhance the safety of home-based chemotherapy: feasibility study. *JMIR Formative Research* 5, 1 (2021), e20636.
[41] Joseph C Kvedar, Alexander L Fogel, Eric Elenko, and Daphne Zohar. 2016. Digital medicine's march on chronic disease. *Nature biotechnology* 34, 3 (2016), 239–246.
[42] Chao-Han Lai, Kai-Wen Li, Fang-Wen Hu, Pei-Fang Su, I-Lin Hsu, Min-Hsin Huang, Yen-Ta Huang, Ping-Yen Liu, and Meng-Ru Shen. 2022. Integration of an intensive care unit visualization dashboard (i-Dashboard) as a platform to facilitate multidisciplinary rounds: cluster-randomized controlled trial. *Journal of medical Internet research* 24, 5 (2022), e35981.
[43] Anthony E Lang, Shirley Eberly, Christopher G Goetz, Glenn Stebbins, David Oakes, Ken Marek, Bernard Ravina, Caroline M Tanner, Ira Shoulson, and LABS-PD investigators. 2013. Movement disorder society unified Parkinson disease rating scale experiences in daily living: longitudinal changes and correlation with other assessments. *Movement Disorders* 28, 14 (2013), 1980–1986.
[44] JuHee Lee, Insun Yeom, Misook L Chung, Yielin Kim, Subin Yoo, Eunyoung Kim, et al. 2022. Use of Mobile Apps for Self-care in People With Parkinson Disease: Systematic Review. *JMIR mHealth and uHealth* 10, 1 (2022), e33944.
[45] Helena Lindgren. 2011. Towards personalized decision support in the dementia domain based on clinical practice guidelines. *User Modeling and User-Adapted Interaction* 21 (2011), 377–406.
[46] Vitor Lobo, Diogo Branco, Tiago Guerreiro, Raquel Bouça-Machado, and Joaquim Ferreira. 2021. Machine-learning models for MDS-UPDRS III Prediction: A comparative study of features, models, and data sources. (2021).
[47] Raquel Luis-Martínez, Mariana HG Monje, Angelo Antonini, Álvaro Sánchez-Ferro, and Tiago A Mestre. 2020. Technology-enabled care: integrating multidisciplinary care in Parkinson's disease through digital technology. *Frontiers in Neurology* 11 (2020), 575975.
[48] Yuhan Luo, Peiyi Liu, and Eun Kyoung Choe. 2019. Co-Designing food trackers with dietitians: Identifying design opportunities for food tracker customization. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems.* 1–13.

[49] Carlos J Madrid-Navarro, Francisco Escamilla-Sevilla, Adolfo Mínguez-Castellanos, Manuel Campos, Fernando Ruiz-Abellán, Juan A Madrid, and MA Rol. 2018. Multidimensional circadian monitoring by wearable biosensors in Parkinson's disease. *Frontiers in neurology* 9 (2018), 157.

[50] Walter Maetzler, Josefa Domingos, Karin Srulijes, Joaquim J Ferreira, and Bastiaan R Bloem. 2013. Quantitative wearable sensors for objective assessment of Parkinson's disease. *Movement Disorders* 28, 12 (2013), 1628–1637.

[51] Sara Marceglia, Elena Rossi, Manuela Rosa, Filippo Cogiamanian, Lorenzo Rossi, Laura Bertolasi, Alberto Vogrig, Francesco Pinciroli, Sergio Barbieri, Alberto Priori, et al. 2015. Web-based telemonitoring and delivery of caregiver support for patients with Parkinson disease after deep brain stimulation: protocol. *JMIR Research Protocols* 4, 1 (2015), e4044.

[52] Carmit K McMullen, Jennifer Schneider, Andrea Altschuler, Marcia Grant, Mark C Hornbrook, Petra Liljestrand, and Robert S Krouse. 2014. Caregivers as healthcare managers: health management activities, needs, and caregiving relationships for colorectal cancer survivors with ostomies. *Supportive Care in Cancer* 22 (2014), 2401–2408.

[53] Roisin McNaney, Catherine Morgan, Pranav Kulkarni, Julio Vega, Farnoosh Heidarivincheh, Ryan McConville, Alan Whone, Mickey Kim, Reuben Kirkham, and Ian Craddock. 2022. Exploring Perceptions of Cross-Sectoral Data Sharing with People with Parkinson's. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–14.

[54] Roisin McNaney, Emmanuel Tsekleves, and Jonathan Synnott. 2020. Future opportunities for IoT to support people with Parkinson's. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–15.

[55] Kalliopi Megari. 2013. Quality of life in chronic disease patients. *Health psychology research* 1, 3 (2013).

[56] Jie Mei, Christian Desrosiers, and Johannes Frasnelli. 2021. Machine learning for the diagnosis of Parkinson's disease: a review of literature. *Frontiers in aging neuroscience* 13 (2021), 633752.

[57] Mevludin Memedi, Gaki Tshering, Martin Fogelberg, Ilir Jusufi, Ella Kolkowska, and Gunnar Klein. 2018. An interface for IoT: feeding back health-related data to Parkinson's disease patients. *Journal of Sensor and Actuator Networks* 7, 1 (2018), 14.

[58] Helena M Mentis, Anita Komlodi, Katrina Schrader, Michael Phipps, Ann Gruber-Baldini, Karen Yarbrough, and Lisa Shulman. 2017. Crafting a view of self-tracking data in the clinical visit. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 5800–5812.

[59] Richard V Milani, Robert M Bober, and Carl J Lavie. 2016. The role of technology in chronic disease care. *Progress in cardiovascular diseases* 58, 6 (2016), 579–583.

[60] Sabuj Kanti Mistry, ARM Mehrab Ali, Uday Narayan Yadav, Saruna Ghimire, Md Belal Hossain, Suvasish Das Shuvo, Manika Saha, Sneha Sarwar, Md Mohibur Hossain Nirob, Varalakshmi Chandra Sekaran, et al. 2021. Older adults with non-communicable chronic conditions and their health care access amid COVID-19 pandemic in Bangladesh: Findings from a cross-sectional study. *PLoS One* 16, 7 (2021), e0255534.

[61] Chukwuma Nnaji and Ali A Karakhan. 2020. Technologies for safety and health management in construction: Current use, implementation benefits and limitations, and adoption barriers. *Journal of Building Engineering* 29 (2020), 101212.

[62] Chi Young Oh, Yuhan Luo, Beth St. Jean, and Eun Kyoung Choe. 2022. Patients Waiting for Cues: Information Asymmetries and Challenges in Sharing Patient-Generated Data in the Clinic. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW1 (2022), 1–23.

[63] Michael S Okun. 2017. Management of Parkinson disease in 2017: personalized approaches for patient-specific needs. *Jama* 318, 9 (2017), 791–792.

[64] Wilk Oliveira, Juho Hamari, Sivaldo Joaquim, Armando M Toda, Paula T Palomino, Julita Vassileva, and Seiji Isotani. 2022. The effects of personalized gamification on students' flow experience, motivation, and enjoyment. *Smart Learning Environments* 9, 1 (2022), 16.

[65] Truls Østbye, Kimberly SH Yarnall, Katrina M Krause, Kathryn I Pollak, Margaret Gradison, and J Lloyd Michener. 2005. Is there time for management of patients with chronic diseases in primary care? *The Annals of Family Medicine* 3, 3 (2005), 209–214.

[66] Adrienne Pichon, Kayla Schiffer, Emma Horan, Bria Massey, Suzanne Bakken, Lena Mamykina, and Noemie Elhadad. 2021. Divided we stand: the collaborative work of patients and providers in an enigmatic chronic disease. *Proceedings of the ACM on human-computer interaction* 4, CSCW3 (2021), 1–24.

[67] Ashley Polhemus, Laura Delgado Ortiz, Gavin Brittain, Nikolaos Chynkiamis, Francesca Salis, Heiko Gaßner, Michaela Gross, Cameron Kirk, Rachele Rossanigo, Kristin Taraldsen, et al. 2021. Walking on common ground: a cross-disciplinary scoping review on the clinical utility of digital mobility outcomes. *NPJ digital medicine* 4, 1 (2021), 149.

[68] Rana Zia Ur Rehman, Lynn Rochester, Alison J Yarnall, and Silvia Del Din. 2021. Predicting the Progression of Parkinson's Disease MDS-UPDRS-III Motor Severity Score from Gait Data using Deep Learning. In *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 249–252.

[69] Luiz Rodrigues, Paula T Palomino, Armando M Toda, Ana CT Klock, Wilk Oliveira, Anderson P Avila-Santos, Isabela Gasparini, and Seiji Isotani. 2021. Personalization improves gamification: Evidence from a mixed-methods study. *Proceedings of the ACM on Human-Computer Interaction* 5, CHI PLAY (2021), 1–25.

[70] Bahador Saket, Alex Endert, and John Stasko. 2016. Beyond usability and performance: A review of user experience-focused evaluations in visualization. In *Proceedings of the Sixth Workshop on Beyond Time and Errors on Novel Evaluation Methods for Visualization*. 133–142.

[71] Elizabeth B-N Sanders and Pieter Jan Stappers. 2008. Co-creation and the new landscapes of design. *Co-design* 4, 1 (2008), 5–18.

[72] Alper Sarikaya, Michael Correll, Lyn Bartram, Melanie Tory, and Danyel Fisher. 2018. What do we talk about when we talk about dashboards? *IEEE transactions on visualization and computer graphics* 25, 1 (2018), 682–692.

[73] Joe Saunders, Dag Sverre Syrdal, Kheng Lee Koay, Nathan Burke, and Kerstin Dautenhahn. 2015. "teach me–show me"—end-user personalization of a smart home and companion robot. *IEEE Transactions on Human-Machine Systems* 46, 1 (2015), 27–40.

[74] Johannes CM Schlachetzki, Jens Barth, Franz Marxreiter, Julia Gossler, Zacharias Kohl, Samuel Reinfelder, Heiko Gassner, Kamiar Aminian, Bjoern M Eskofier, Jürgen Winkler, et al. 2017. Wearable sensors objectively measure gait parameters in Parkinson's disease. *PloS one* 12, 10 (2017), e0183989.

[75] Matthew J Selleck, Maheswari Senthil, and Nathan R Wall. 2017. Making meaningful clinical use of biomarkers. *Biomarker insights* 12 (2017), 1177271917715236.

[76] Mark Sendak, Madeleine Clare Elish, Michael Gao, Joseph Futoma, William Ratliff, Marshall Nichols, Armando Bedoya, Suresh Balu, and Cara O'Brien. 2020. " The human body is a black box" supporting clinical decision-making with deep learning. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 99–109.

[77] Jirada Sringean, Poonpak Taechalertpaisarn, Chusak Thanawattano, and Roongroj Bhidayasiri. 2016. How well do Parkinson's disease patients turn in bed? Quantitative analysis of nocturnal hypokinesia using multisite wearable inertial sensors. *Parkinsonism & Related Disorders* 23 (2016), 10–16.

[78] Jennifer G Stadler, Kipp Donlon, Jordan D Siewert, Tessa Franken, and Nathaniel E Lewis. 2016. Improving the efficiency and ease of healthcare analysis through use of data visualization dashboards. *Big data* 4, 2 (2016), 129–135.

[79] Marc Steen, Menno Manschot, and Nicole De Koning. 2011. Benefits of co-design in service design projects. *International Journal of Design* 5, 2 (2011).

[80] Stefan Teipel, Deborah Gustafson, Rik Ossenkoppele, Oskar Hansson, Claudio Babiloni, Michael Wagner, Steffi G Riedel-Heller, Ingo Kilimann, and Yi Tang. 2022. Alzheimer Disease: Standard of Diagnosis, Treatment, Care, and Prevention. *Journal of Nuclear Medicine* 63, 7 (2022), 981–985.

[81] Hazhir Teymourian, Farshad Tehrani, Katherine Longardner, Kuldeep Mahato, Tatiana Podhajny, Jong-Min Moon, Yugender Goud Kotagiri, Juliane R Sempionatto, Irene Litvan, and Joseph Wang. 2022. Closing the loop for patients with Parkinson disease: where are we? *Nature Reviews Neurology* 18, 8 (2022), 497–507.

[82] Nataliya Titova and K Ray Chaudhuri. 2017. Personalized medicine in Parkinson's disease: time to be precise. *Movement Disorders* 32, 8 (2017), 1147.

[83] Anouk Tosserams, Nienke M de Vries, Bastiaan R Bloem, and Jorik Nonnekes. 2020. Multidisciplinary care to optimize functional mobility in Parkinson disease. *Clinics in Geriatric Medicine* 36, 1 (2020), 159–172.

[84] Carolina Wannheden and Åsa Revenäs. 2020. How people with Parkinson's disease and health care professionals wish to partner in care using eHealth: co-design study. *Journal of medical Internet research* 22, 9 (2020), e19195.

[85] Vivian L West, David Borland, and W Ed Hammond. 2015. Innovative information visualization of electronic health record data: a systematic review. *Journal of the American Medical Informatics Association* 22, 2 (2015), 330–339.

[86] Sera Whitelaw, Danielle M Pellegrini, Mamas A Mamas, Martin Cowie, and Harriette GC Van Spall. 2021. Barriers and facilitators of the uptake of digital health technology in cardiovascular care: a systematic scoping review. *European Heart Journal-Digital Health* 2, 1 (2021), 62–74.

[87] Robin L Whitney, Deborah H Ward, Maria T Marois, Christopher H Schmid, Ida Sim, and Richard L Kravitz. 2018. Patient perceptions of their own data in mHealth technology–enabled N-of-1 trials for chronic pain: Qualitative study. *JMIR mHealth and uHealth* 6, 10 (2018), e10291.

[88] Michał Wieczorek, Fiachra O'Brolchain, Yashar Saghai, and Bert Gordijn. 2023. The ethics of self-tracking. A comprehensive review of the literature. *Ethics & Behavior* 33, 4 (2023), 239–271.

[89] Mark L Wolraich, Eugenia Chan, Tanya Froehlich, Rachel L Lynch, Ami Bax, Susan T Redwine, Demvihin Ihyembe, and Joseph F Hagan. 2019. ADHD diagnosis and treatment guidelines: a historical perspective. *Pediatrics* 144, 4 (2019).

[90] Jason Wu, Titus Barik, Xiaoyi Zhang, Colin Lea, Jeffrey Nichols, and Jeffrey P Bigham. 2022. Reflow: Automatically Improving Touch Interactions in Mobile Applications through Pixel-based Refinements. *arXiv preprint arXiv:2207.07712* (2022).

[91] Jie Xiong and Meiyun Zuo. 2023. Factors influencing health care professionals' adoption of mobile platform of medical and senior care in China. *Information & Management* 60, 5 (2023), 103798.

[92] Dong Whi Yoo, Michael L Birnbaum, Anna R Van Meter, Asra F Ali, Elizabeth Arenare, Gregory D Abowd, and Munmun De Choudhury. 2020. Designing a clinician-facing tool for using insights from patients' social media activity: Iterative co-design approach. *JMIR Mental Health* 7, 8 (2020), e16969.

[93] Zhiyuan Zhang, Bing Wang, Faisal Ahmed, IV Ramakrishnan, Rong Zhao, Asa Viccellio, and Klaus Mueller. 2013. The five Ws for information visualization with application to healthcare informatics. *IEEE transactions on visualization and computer graphics* 19, 11 (2013), 1895–1910.