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A Dimensional Modeling Approach to Internet-Delivered Psychological Treatments

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Abstract

Mental health problems are becoming an increasingly significant public health concern on a global scale. While effective psychological treatments exist, they scale poorly to the number of people who require help, meaning many continue to suffer due to a lack of care. Internet-Delivered Psychological Treatments (IDPT) have emerged as an innovative alternative to traditional treatments that aims to be more scalable, cost-effective, and accessible. Although the use of IDPT has yielded promising results, it is also associated with a number of challenges. One challenge is preventing patient dropout, leading to an interest in adaptive IDPT that focuses on personalizing the treatment based on user needs. Furthermore, IDPT systems may generate large amounts of complex user data that must be structured sensibly in order to facilitate data analysis.

In this thesis, we demonstrate a dimensional modeling approach to organizing the components of IDPT. We focus on two use cases for this approach, namely (1) facilitating reuse of treatment materials and (2) adapting treatment to user needs. Using the design science methodology, we have developed a dimensional model for IDPT as our artifact. In addition, we discuss the implementation of the dimensional modeling approach in IDPT systems and related challenges. The artifact was primarily evaluated through a semi-structured interview with domain experts of psychology. Based on this, we found that the artifact represents a suitable starting point for future research within this topic.

Acknowledgments

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`Marianne Luengo Fuglestad`
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Chapter 1

Introduction

1.1 Motivation

Mental health problems are a growing public health concern that constitutes a significant contribution to the global burden of disease (Bucci et al. 2019). Poor mental health has a consequential impact on the world economy, largely due to indirect costs associated with reduced productivity (The Lancet Global Health 2020) (Trautmann et al. 2016). Furthermore, it is widely recognized that the current healthcare system lacks the capacity to offer accessible psychological treatments to all patients who need help (Bucci et al. 2019), as conventional treatments are costly with respect to time, resources, and availability of trained clinicians (Jacobson et al. 2019). The result is that patients often wait for months before receiving treatment (Wahle et al. 2016). This is unfortunate, as early diagnosis and treatment often lead to a better prognosis (Department of Health Human Services, State Government of Victoria, Australia 2021). Overall, traditional approaches to treating mental disorders are inadequate in multiple areas.

The utilization of ubiquitous digital technologies for alleviating mental distress shows promise in filling the described gaps in the healthcare system (Stroud et al. 2019). The application of these technologies has been explored in a variety of forms, such as online self-assessment applications (Weisel et al. 2019), mental health chatbot services (Vaidyam et al. 2019), symptom monitoring via passive collection of personal data (Trifan et al. 2019), and Internet-Delivered Psychological Treatments (IDPT) (Andersson 2016). One advantage with many of the digital technologies that facilitate these services (such as computers, smartphones and wearable devices) is that they are ubiquitous and frequently used (Mohr et al. 2017). In addition, they have the ability to collect data continuously in real time (Stroud et al. 2019). Recent research suggests that it is feasible to use data collected from these technologies to identify, predict, assess, monitor and treat mental health problems in ways that are more scalable, time-sensitive, and inexpensive than traditional methods (Jacobson et al. 2019) (Gutierrez et al. 2021).

However, challenges arise with the introduction of new technological solutions within the healthcare system. For instance, IDPT is associated with low user adherence, where insufficient tailoring of treatment to each individual user appears to be a significant contributor (Fernández-Álvarez et al. 2017). The use of IDPT also involves the acquisition, storage and analysis of health data, which are inherently high in complexity (Rabbi et al. 2020). Currently, there exist numerous software solutions for the collection of mental health data which tend to utilize entirely different data formats. The variety in formats decreases interoperability and makes data analysis significantly more challenging (Gutierrez et al. 2021). Furthermore, medical professionals involved in the care of a particular patient may be interested in different facets of that patient's medical background, such as certain details about appointments at specific clinics, the prevalence of specific symptoms or diseases, or previously conducted procedures or treatments (Rabbi et al. 2020). However, the aspects of a patient's medical background that are relevant to any one clinician may exist on different abstraction levels, which further complicates the data extraction. Thus, it may be beneficial to provide clinicians with data retrieval options that allow the selection of information from different abstraction levels. Ideally, this will yield a deeper understanding of each patient's mental health status, progress, goals, and preferences, which in turn may hold the potential to facilitate more personalized treatments and better clinical outcomes.

1.2 Problem Description

INTROducing Mental health through Adaptive Technology (INTROMAT) is a multidisciplinary research project whose vision is to utilize personalized digital health services to improve public mental health (INTROMAT 2021). One of INTROMAT's projects focuses on developing an Internet-based training program named MinADHD[1,2] (MyADHD in English) that addresses common struggles for adults with Attention Deficit Hyperactivity Disorder (ADHD), a condition characterized by concentration problems, agitation and impulsivity (National Health Service 2018). Users of MinADHD gain access to exercises and scenarios whose purposes are to improve functioning and quality of life, and to reduce stress and inattention.

A randomized controlled trial has been conducted in order to study the efficacy of MinADHD, as well as to investigate the relationship between adherence and individual adaptation of treatment (Nordby et al. 2021). However, analysis of the user-generated data was in some cases complicated by the data management approach used by MinADHD's underlying platform. It has been suggested that these issues may stem from the platform's flat data representation. That is, the platform does not differentiate sufficiently between abstraction levels in the data.

The concept of hierarchical data representations in healthcare settings has been explored further in an article by Rabbi et al. (2020), some of whom are associated with INTROMAT. In the paper, it is suggested to utilize hierarchical data representations and dimensional modeling, a technique for presenting analytic data in a way that is understandable by business users (Kimball & Ross 2013), to improve the analysis of complex healthcare data. Rabbi et al. (2020) argue that this technique facilitates grouping and filtering of related healthcare data in a way that provides meaningful information on a relevant abstraction level, thus making data analysis easier for clinicians. The ideas presented in this paper will be outlined further in Section 2.3.1.

[1] https://intromat.no/cases/cognitive-training-in-adhd/
[2] https://minadhdtrening.no/

In this thesis, we will explore the use of hierarchical data representations in the context of Internet-Delivered Psychological Treatments (IDPT). In particular, we aim to investigate the potential for this approach to improve the workflow of clinicians working with IDPT.

1.3 Research Questions

This thesis will explore research questions relating to two use cases for a dimensional modeling approach that structures and filters data in IDPT. The first use case concerns the facilitation of reuse of intervention contents in the design of new interventions, while the second use case is centered around adapting the treatment to each user based on their needs. Specifically, the following research questions will be explored throughout this thesis:

RQ1 How can a dimensional modeling approach be implemented to support reuse of treatment content in interventions for mental health?

RQ2 How can a dimensional modeling approach be implemented to support the adaptation of treatment to user needs within a specific intervention?

1.4 Research Methods

We have chosen design science as our research method for this thesis. This methodology is characterized by contributions to the knowledge base within a specific problem domain by the design and development of an artifact (Hevner et al. 2004). Design science will be outlined further in Section 3.1.

In this thesis, we developed the following artifact: A dimensional model representing the different components in IDPT. We intend for this model to be a research contribution to the domain of IDPT. Furthermore, we show how this model can be used to organize treatment content and user-generated data in innovative ways. The model is evaluated using qualitative methods.

1.5 Terminology

In this section, we present an overview of closely related terminology that will be used throughout this thesis, and how the different terms relate to each other.

Internet-Delivered Psychological Treatments (IDPT) IDPT refers to any form of psychological treatment that is administered using the Internet (Andersson 2016). We use the term *IDPT system* to denote a software system that facilitates IDPT. These terms are outlined further in Section 2.1.

Intervention We use the term *intervention* interchangeably with *mental health intervention*, a term that Benjenk & Chen (2018, p. 3) describe as involving "assessment of mental health symptoms, psychoeducation, therapy, or psychotropic medication management". A mental health intervention that is delivered via the Internet is an instance of IDPT.

Dimension The term *dimension* is used to conceptualize an aspect of IDPT at some abstraction level. A dimension may be a part of a hierarchy of dimensions, where each dimension may have parents or children. We will investigate dimensions further in Section 4.1.

Taxonomy In this thesis, *taxonomies* largely represent the same concept as dimensions. However, they are used in slightly different contexts. We use *dimension* as the general term, while the term taxonomy is used to represent a dimension in a specific implementation that will be presented in Section 4.3.3.

1.6 Thesis Overview

This section presents a brief structural overview of the thesis.

Chapter 1 gives an introduction to the thesis by describing the motivation for the thesis and the research problem we focus on. Additionally, research questions, research methods and terminology are outlined.

Chapter 2 provides relevant background materials for the thesis. This includes a presentation of IDPT, as well as related topics such as ontologies in healthcare and existing IDPT solutions.

Chapter 3 presents the research method followed in this thesis, in addition to an overview of the design process.

Chapter 4 outlines the development of the artifact and related work.

Chapter 5 presents the evaluation of the artifact. We also describe the role of domain experts in the evaluation process.

Chapter 6 includes a discussion on the findings presented throughout the thesis. This includes answers to the research questions, research contributions, reflections and a summary of the project limitations.

Chapter 7 concludes the thesis. Future work is also presented here.

Chapter 2

Background

In this chapter, the theoretical background of Internet-delivered psychological treatments is presented. We start by introducing IDPT systems and its adaptive variant, after which we describe the role of ontologies in healthcare software. Moreover, we present the adaptive IDPT system that we extend as part of our research, as well as existing IDPT solutions.

2.1 Internet-Delivered Psychological Treatment (IDPT) Systems

Coined in an article by Andersson (2016), the term Internet-delivered psychological treatments (IDPT) covers psychological treatments which are administered using the Internet. IDPT is one of many closely related terms that capture the essence of Internet-based treatment formats, such as "web-based treatment, online treatment, computerized psychotherapy, digital interventions, e-therapy, Internet-delivered cognitive-behavioral therapy (ICBT), and Internet interventions" (Andersson 2016, p. 158). Furthermore, there are two main variants of IDPT: Guided and unguided (Morgan et al. 2017). The former entails the support of a therapist who helps the patient complete a treatment program through asynchronous digital communication such as email or telephone (Andersson et al. 2017), while the latter lets the patient work through a self-help program without the direct help of a professional (Morgan et al. 2017).

In order for Internet-delivered psychological treatments to be available to patients, an appropriate treatment software platform is needed (Andersson et al. 2019). Such platforms must be able to perform a variety of tasks, such as presenting treatment materials to the patient, facilitating clinician-patient communication (in the case of clinician-guided treatment), and administering questionnaires at relevant intervals for symptom monitoring. Mukhiya et al. (2020b, p. 112222) refer to such systems as IDPT systems, and describe them as "any software applications that facilitate interaction with psychological therapy through the Internet", including "web-applications, mobile applications, augmented reality, and virtual reality applications".

IDPT has been proposed as a solution to problems arising in traditional face-to-face treatments for people with mental health issues. Among others, these treatments include Cognitive Behavioral Therapy (CBT), a frequently used psychotherapeutic treatment approach focusing on identifying, managing and modifying maladaptive patterns in an individual's thoughts and behaviors (Lichtenthal et al. 2011), and Goal Management Training (GMT), a rehabilitation program that is designed to improve executive functions through the use of "psychoeducation, narrative examples, mindfulness practice, and assignments" (Levine & Stamenova 2018, p. 1590). While traditional methods provide effective treatment for a variety of mental health issues, it also has shortcomings with respect to accessibility (Morgan et al. 2017). In particular, a large number of people experiencing mental health problems have difficulty accessing psychological treatments (Bucci et al. 2019), one reason being that the number of qualified therapists available does not scale to the number of patients who need help (Wahle et al. 2016). IDPT may improve upon these by offering both synchronous and asynchronous clinician-client communication (Andersson 2016) (Bucci et al. 2019). Additionally, IDPT offers a viable alternative to people who avoid traditional treatment methods due to economic cost (Mukhiya et al. 2020b), stigma or other practical matters (Fernández-Álvarez et al. 2017).

Although IDPT systems show promise in reducing the issues present in traditional face-to-face treatment methods, certain related challenges require further study. For instance, IDPT systems are associated with non-adherence problems (i.e. patient dropout), particularly the unguided variants. According to Fernández-Álvarez et al. (2017), a lack of personalization or tailoring of the treatment contents to the user appears to contribute to non-adherence in IDPT. Furthermore, Mukhiya et al. (2020b, p. 112220) state that "most current IDPT systems are tunnel-based, inflexible, and non-interoperable", arguing that implementing adaptability to patient needs in IDPT systems may improve user adherence and treatment outcomes. Adaptive IDPT systems will be described further in Section 2.2.

2.1.1 Central IDPT Components

Cases, modules and tasks have been identified as important components in IDPT (Mukhiya et al. 2020b) that will be referred to multiple times throughout this thesis. The relationships between them are hierarchical, where cases reside at the top with modules immediately below, and where tasks are below modules. The relationships between these components are illustrated in Figure 2.1, and a description of each component follows below.

- **Cases** are generally centered around specific mental health diagnoses such as depression or ADHD, or other mental health issues. A case may have multiple modules attached to it.
- **Modules** focus on specific aspects of the cases they are attached to. For instance, modules in an ADHD case may include modules on breathing or emotions. Additionally, modules may have dependencies, i.e. one module may require the user to have completed other modules before it can be started. Modules may have one or more tasks associated with them as child components.

  It is important to note that modules may belong to one or multiple cases, as some mental health issues (and thus cases) have some degree of overlap with one another. This means that we may reuse modules in multiple settings, depending on the users' needs.

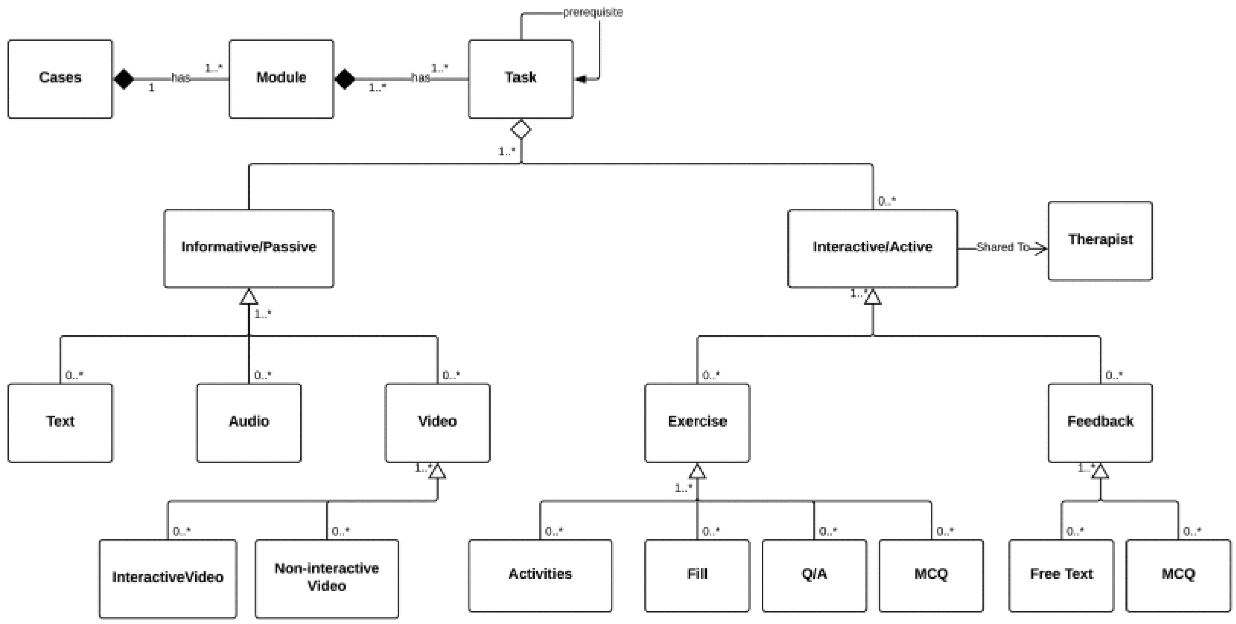


Figure 2.1: An overview of central IDPT components and relationships between them by Mukhiya et al. (2020b, p. 112223) in Figure 2.

- **Tasks** take the form of passive or interactive treatment materials whose primary purpose is to provide help in the form of illness management techniques, psychoeducation and connecting with others in similar situations. Passive tasks may include material in text, audio or video format for the user to consume, while active tasks may involve interactive activities such as physical workouts, digital multiple choice quizzes, questions and answers, and online diaries. Similarly to modules, tasks may have dependencies.
  An additional purpose of tasks in IDPT may be to facilitate collecting objective and active data from the user. This data may be used to adapt the application's content to the user, thus providing continually improving personalization.

2.2 Adaptive IDPT Systems

An adaptive approach to the development of IDPT systems may aid in finding a solution to the issues presented in the previous section by facilitating more flexibility and personalized content. In particular, Mukhiya et al. (2020b, p. 112221) describe the term *adaptive systems* as “a set of interacting or interdependent entities, real or abstract, forming an integrated system that changes its behavior in response to its environmental changes”. In the context of IDPT, this may entail presenting different learning materials or exercises to a user interacting with an IDPT system based on their current symptoms or their media preference. This concept is captured in the term *adaptive IDPT systems*, which is introduced and defined by Mukhiya et al. (2020b, p. 112222). A formal description is given in Definition 2.2.1, and the associated visualization of these components is shown in Figure 2.2.

Definition 2.2.1 (Adaptive IDPT systems). An adaptive IDPT system consists of

- E, a set of environments that provides context for IDPT to work in.
- I, a set of controlled inputs that are consumed by IDPT systems. The consumption of I alters the behavior of the IDPT process in some way.
- P, a performance measure of the IDPT process. This measure signifies the performance of the IDPT when consuming I as input in environment E.
- F, a feedback function. Using dynamic information about the IDPT process, F produces an adaptive strategy.
- S, a set of adaptive strategies. These strategies utilize the knowledge gained earlier in the system. S comprises the decision-making process of the adaptive IDPT system.
- A, a set of actors. Based on the adaptive strategies S, the actors A incite the adaptation within the system. These actors range from humans directly or indirectly involved in the care (e.g. patients, clinicians, IT admins) to the adaptive system itself.

2.2.1 Adaptive Dimensions

The ways by which an IDPT system changes its behavior to accommodate the user’s needs can depend on a variety of factors. In a systematic review inves-

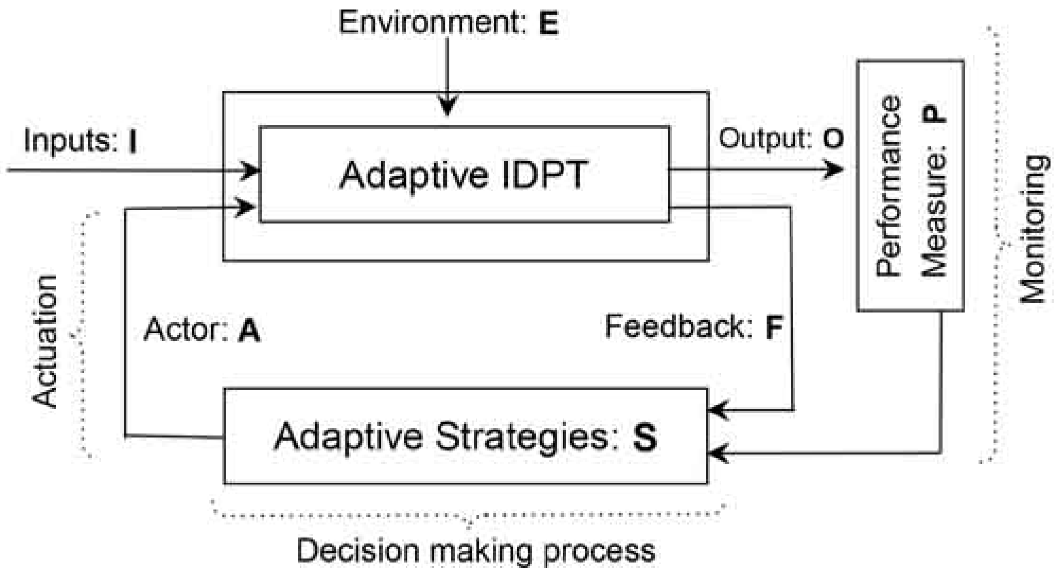


Figure 2.2: The adaptive IDPT system as depicted by Mukhiya et al. (2020b, p. 112222) in Figure 1.

tigating adaptive elements in IDPT systems by Mukhiya et al. (2020a), these factors are referred to as *adaptive dimensions*. The authors of the review found that dimensions more commonly utilized in the reviewed studies were user preferences (such as user context or location) and outcome measures (such as psychometric questionnaire scores or analysis of user interaction data in the IDPT system).

Mukhiya et al. (2020b) further propose to divide these factors of an IDPT system into the following five adaptive dimensions. These five dimensions and their associated subdimensions are visualized in Figure 2.3. In the figure, the lower-level subdimensions and dimensions not discussed in this thesis have been omitted for the sake of simplicity and readability.

User Preferences

Multiple existing adaptive IDPT systems were found to rely on the user's own preferences when delivering treatment (Mukhiya et al. 2020a). It is interesting to note that user preferences may be detected in both explicit or implicit ways. Explicit strategies involve the user directly, such as by asking them at certain times or by allowing them to express their preferences in the intervention's settings in their own time. Conversely, it is also possible to infer the user's preferences by analyzing the user's associated event logs in the system. Event logs are records of events that have occurred in a digital system that may be used to give an overview of user activities (Turkington et al. 2018).

Mukhiya et al. (2020b) further divide the user preferences dimensions into the following three subdimensions.

- **Temporal preferences** concern the time of the day a specific user tends to be active in the system. For example, some users may prefer doing exercises in the morning or in the evening.
- **Content presentation preferences** concern the type of content presentation mode the user favors. For example, some users may prefer video-based content over text-based exercises, or vice versa.
- **Lingual preferences** concern the user's chosen language in which they would like to consume treatment materials.

Goals of the Intervention

This dimension is based on the goals that the people involved in the intervention want to achieve. The goals differ somewhat between patients and therapists. For instance, patient goals are typically oriented around learning to manage one's illness, while therapist goals are more geared towards improving the quality of the treatment. Mukhiya et al. (2020b) characterize goals in IDPT with the following five attributes.

- **Evolution** It is possible to change the goal(s) of the intervention over time.
- **Flexibility** It is possible to express the goal(s) of the intervention in an unconstrained way.
- **Duration** It is possible to set some duration of the time a goal of the intervention remains valid. This means that a goal may last for the entirety of the intervention's duration or for a shorter period.

- **Multiplicity** It is possible for the intervention to have one or multiple associated goal(s).
- **Dependency** It is possible for goals of the intervention to depend on one another or be completely independent.

Measures

Outcome measures comprise another dimension that is commonly utilized in adaptive IDPT systems (Mukhiya et al. 2020a). Multiple data sources in an intervention can be used to indicate and measure user behavior.

In particular, many interventions make use of *psychometric questionnaires* or tests that assess the symptom severity in specific mental health disorders or issues. The questionnaires are typically filled out by the patients themselves, and result in a numeric score indicating a patient's current status pertaining to certain areas of their mental health. For example, the psychometric test Patient Health Questionnaire-9 (PHQ-9) may be used to assess whether a user is experiencing depressive symptoms, and the severity of these if present (Kroenke et al. 2001).

It is also common to utilize user interaction data as a measure to adapt the system by. By capturing certain interaction data, such as time spent on various exercises of different content types, the system can learn the user's behaviors and preferences and change thereafter. For example, a user who predominantly watches psychoeducation videos and skips other kinds of exercises may be offered more videos in the future. Analysis of user interaction data may also be used to measure the engagement levels of the users.

Other relevant data sources include recorded patient-therapist communication (written correspondence, audio files, or video files), patient diaries, responses to exercises, sensors, or logged user interactions (Mukhiya et al. 2020b).

Adaptation Actors

As shown in Definition 2.2.1 and Figure 2.2, an adaptive IDPT system has an associated set of (adaptation) actors. Some of the actors are responsible for triggering the adaptation in the system. In guided interventions, clinicians fall into this group. In unguided and guided interventions, the adaptive system itself is also considered an actor. Furthermore, there are actors that use the system without being directly involved in inciting the adaptation (patients), as well as actors who are responsible for maintenance of the system (IT administrators).

Adaptation Strategies

Definition 2.2.1 and Figure 2.2 also present adaptive strategies, which is the fifth and final adaptive dimension. These strategies comprise a collection of techniques that alters the functionality of the adaptive system in different ways.

2.2.2 User Profiling

The process of building a summary of information about a user in the context of a software application that helps provide the user with a personalized experience may be referred to as *user profiling*, or building a *user profile*. This information typically includes the interests, preferences and characteristics of a user, as well as their behaviors when interacting with the system (Eke et al. 2019). The application domain determines multiple factors about the user profiling process, such as what exactly constitutes relevant information, what the preferred method of information acquisition is, and the purpose of the user profiling itself (Schiaffino & Amandi 2009).

According to Schiaffino & Amandi (2009), the role of user profiles in adaptive systems is contributing to triggering useful adaptations. Thus, a user's

- Adaptive dimensions of IDPT systems
  - User preferences
    - Temporal preferences
    - Content presentation preferences
    - Lingual preferences
  - Intervention goals
    - Patient goals
    - Therapist goals
  - Measures
    - Psychometric questionnaire scores
    - User behavior analysis
  - Adaptation actors
    - Responsible for content adaptation
      - Clinicians
      - Adaptive IDPT system
    - System users
      - Patients
    - Responsible for maintenance
      - IT admins
  - Adaptation strategies

Figure 2.3: The adaptive dimensions of an IDPT system as described by Mukhiya et al. (2020b).

associated personal data such as demographic data and their inferred or explicitly stated preferences are taken into account when the system alters its behavior to match the needs of that user. In particular, user profiling based on patient behaviors is deemed essential in many digitized healthcare services (Eke et al. 2019). This perspective concurs with the concept of adaptive dimensions presented in Section 2.2.1, where user preferences and outcome measures based on user interaction data are central components in the adaptive IDPT system.

Eke et al. (2019) state that in addition to providing personalization, a major advantage of user profiling is that it may help reduce information overloading which is present in many software applications. High-quality user profiling can make it easier to present and manage information in the system that is relevant to the user.

2.3 Ontologies in Healthcare Software

An *ontology* can be described as "a semantic model that formally describes the concepts in a certain domain, their relationships and attributes" (Ongenae et al. 2013, p. 7631). In the context of software, ontologies are helpful for conceptualizing a domain in a way that is easily understandable by humans as well as readable by computers (Eke et al. 2019). Additionally, ontologies may be used to capture human situations in a hierarchical data structure (Kim & Chung 2014).

It is useful to utilize ontologies in the context of healthcare applications for a variety of reasons. Firstly, ontologies are already being used for standardization of medical terminology. It has been widely recognized that standardization of medical codes and terminology, as well as the structure of medical data itself, are central factors in achieving interoperability between different healthcare software (Hammond et al. 2014), and thus ontologies present a major advantage in the use of this software. For instance, International Statistical Classification of Diseases and Related Health Problems (ICD) is an ontology that is used to encode diseases, causes of mortality and other health data (World Health Organization 2021b). An excerpt of International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) is shown in Figure 2.4.

Furthermore, ontologies provide sensible ways to separate and relate various dimensions of domain knowledge such that they can be easily reused and integrated into different healthcare applications (Ongenae et al. 2013). Ontologies may also be used to determine a suitable scope for which healthcare data are currently deemed interesting based on specified criteria (Mans et al. 2013). These attributes suggest that ontological structures are highly useful in representing the different abstraction layers by which one may organize healthcare data in a way that decreases their complexity, thus making them easier to interpret and utilize from the perspective of a clinician (Rabbi et al. 2020). Moreover, the integration of ontologies that cover different areas of digitized healthcare (such as diseases, symptoms, or personalized treatment) further justifies the need for flexible ontological representations of healthcare information.

Puri et al. (2011) point out that while ontologies appear well suited for the integration of heterogeneous data sources in healthcare, no single ontology is adequate. Multiple ontologies must first be consolidated before the proper data integration can be fully realized. This is exemplified by looking at a typical patient's medical record, which presents multiple dimensions of that patient's health. These dimensions may include health conditions, prescriptions, treatment history, among others. Puri et al. (2011) refer to a number of ontologies which may be used to consolidate a patient's healthcare data. Examples of such ontologies include, but are not limited to:

Systematized Nomenclature of Medicine – Clinical Terms (SNOMED-CT), a comprehensive vocabulary of clinical healthcare terminology which captures information on health conditions, procedures and drugs (SNOMED International 2021),

ICD-10, which captures information on diseases and symptoms, and

RxNorm, a terminology for normalized named for clinical drugs available in the U.S.) (The National Library of Medicine 2021).

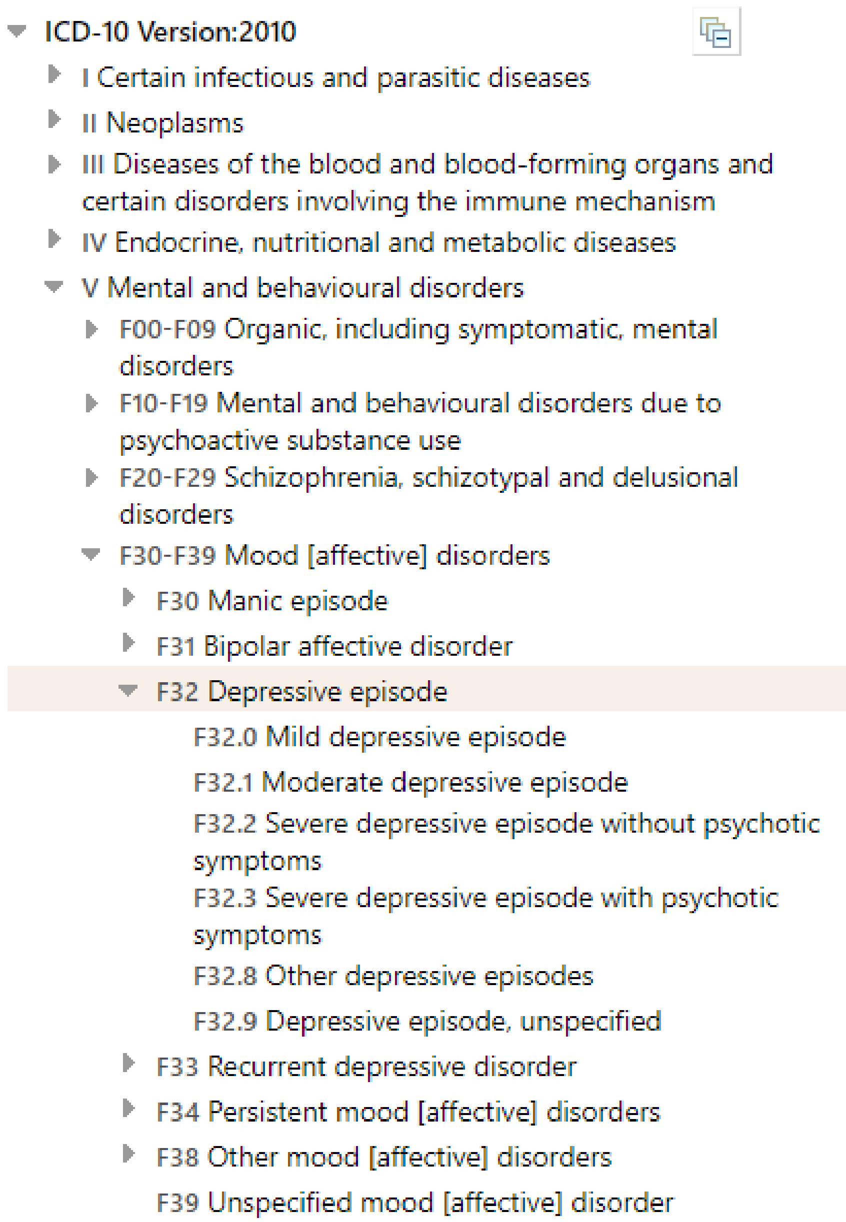


Figure 2.4: An excerpt from the ICD-10 ontology, showing the where depressive episodes are located in the hierarchy. The screenshot was taken of a website managed by the World Health Organization (2021a).

While attempts at combining multiple ontologies into one have occurred, a number of challenges arose during these attempts. These include difficulties in bridging the gaps between different syntax, as well as varying granularity in descriptions of events. Puri et al. (2011) state that the better solution to the integration problem is to aim for a way to create mappings between the different ontologies without changing them.

In Chapter 4, we will explore general representations for ontologies in the format of *dimensions* or *taxonomies*. Specifically, in Section 4.3.3, we describe an implementation of taxonomic structures that may be used to represent ontologies in a simple manner. This enables us to create separate ontologies that are linked through hierarchical relationships.

2.3.1 Ontological Hierarchies and Dimensional Modeling

As introduced in Section 1.2, Rabbi et al. (2020) discuss the role of process mining techniques in healthcare, and note how they can be applied more effectively to healthcare data by applying a preprocessing technique based on ontological hierarchies and dimensional modeling. Process mining techniques are characterized by their ability to "extract knowledge from event logs" (Aalst et al. 2012, p. 170), which prove useful in presenting an overview of healthcare processes and how they execute (Mans et al. 2013). In the paper by Rabbi et al. (2020), it is noted that while processing mining techniques are indeed powerful, they can be difficult to apply to healthcare data, which are typically highly complex.

The proposed solution to this issue involves taking advantage of the hierarchical structures that occur numerous places in the healthcare system. As previously mentioned, ontologies are an example of these hierarchical structures, though another example mentioned in the paper is the organizational structure of departments in hospitals. Furthermore, the approach described by Rabbi et al. (2020) involves the use of dimensional modeling. While primarily used to represent and display detailed domain information to business users in an intuitive way, Rabbi et al. (2020) present a new application area for dimensional models, namely supporting analysis of healthcare processes.

In this approach, ontologies are central in representing healthcare data on different levels of abstraction. Specifically, this entails using ontologies to form hierarchical representations of data for each of the dimensions of a dimensional model exemplifying some facet of the healthcare system. In dimensional modeling, dimensions provide entry points to the data from different angles (Kimball & Ross 2013). Rabbi et al. (2020) exemplify this by presenting a dimensional model for healthcare, along with an example case of an analyst who wants to investigate the care flow of patients with mental and behavioral disorders who have registered admissions in multiple hospital departments. The analyst is only interested in high-level admission details, and discards low-level details beyond the admissions themselves. It is demonstrated how the analyst is able to examine data gathered from two different main dimensions in the model. Specifically, they use the Clinical Finding dimension as an entry point by first grouping the event logs related to patients with mental and behavioral disorders. This selection is further used to group event logs from a different dimension (Episode of Care), where high-level admission-related event logs related to the selected patients are extracted. Figure 2.5 demonstrates this selection and its dimensional model.

Thus, ontologies play an important role in this preprocessing technique that may aid in organizing information by grouping patients who satisfy some specified criteria, as well as grouping other information for visualization purposes on a suitable level of abstraction. In this thesis, we aim to further examine the ideas presented in this paper, albeit on a smaller scale. We will present the process of developing dimensional models that represent aspects of IDPT in Section 4.1.

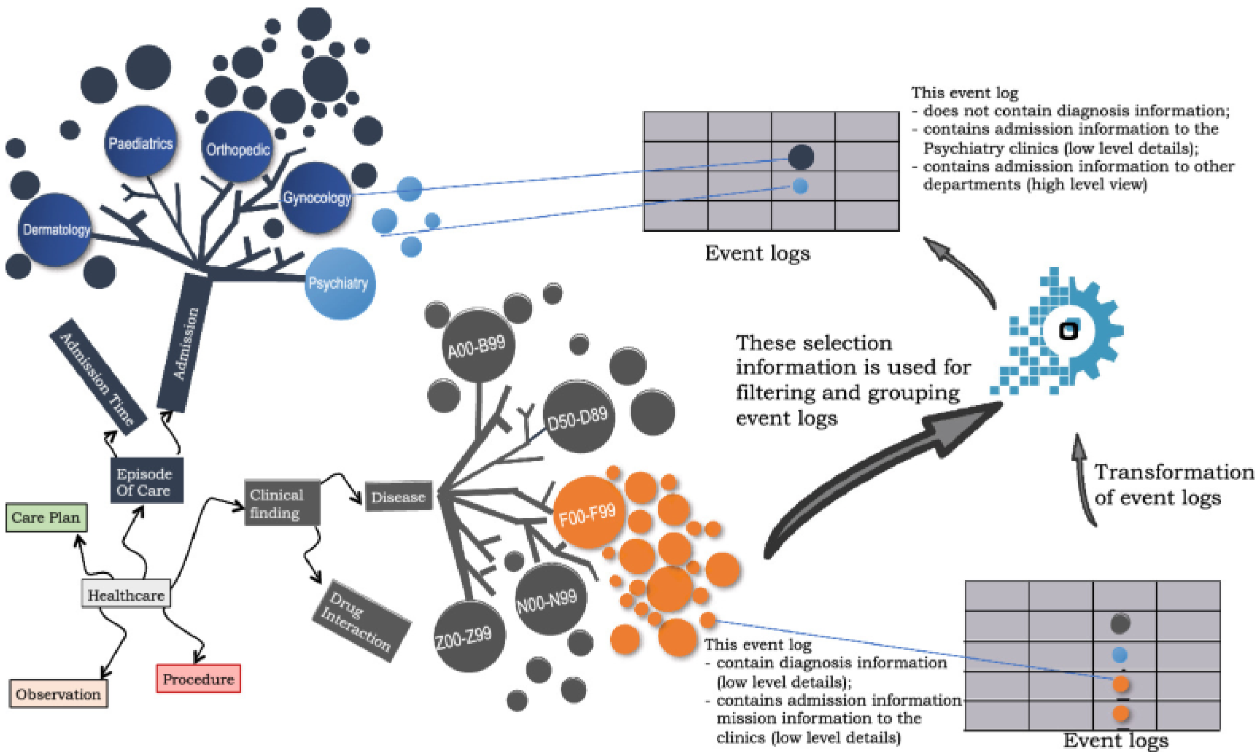


Figure 2.5: The dimensional model presented by Rabbi et al. (2020) in order to demonstrate how ontological hierarchies can be used to group event logs in preparation for process mining. F00-F99 are the ICD-10 codes that represent diagnoses belonging to the category of mental and behavioral disorders.

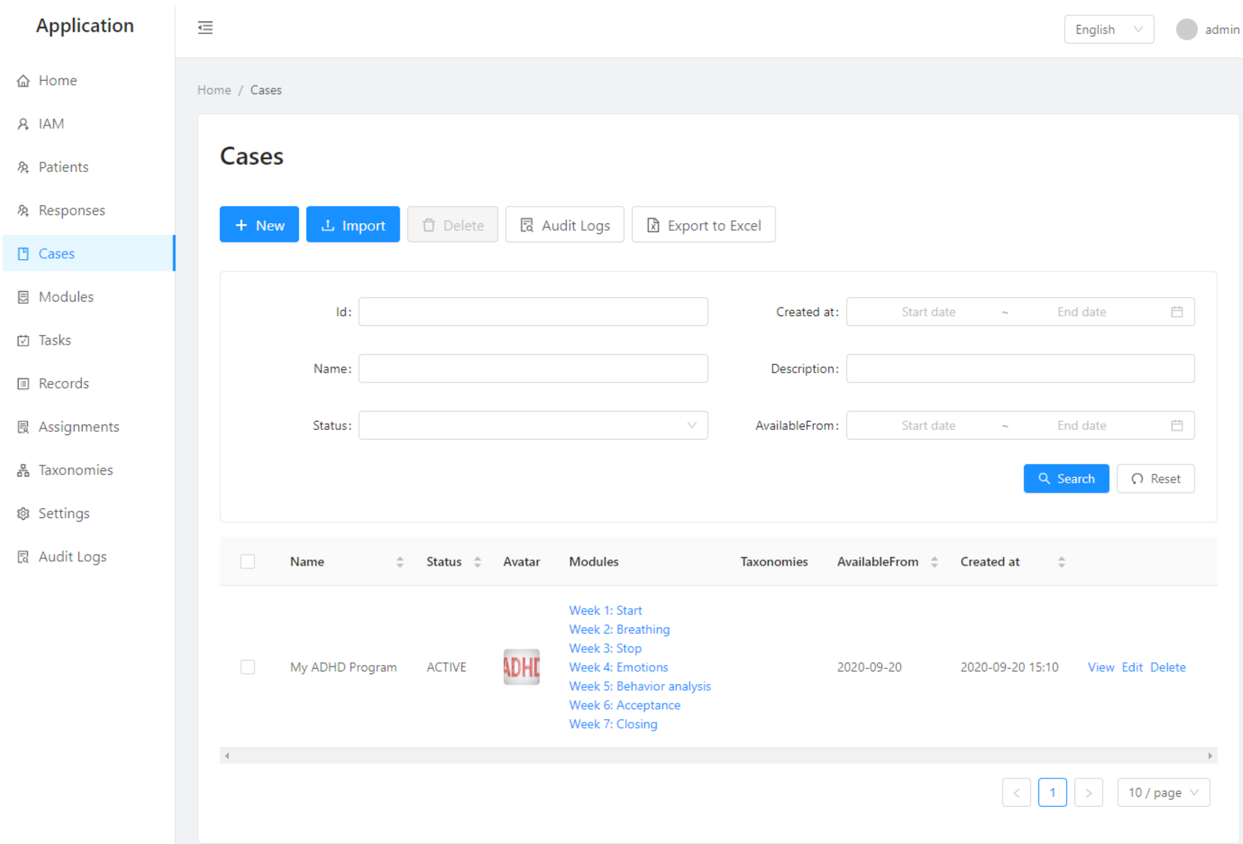


Figure 2.6: A screenshot of the Open-Source Adaptive IDPT System, showing an example case named "My ADHD Program" with seven associated modules.

2.4 An Open-Source Adaptive IDPT System

Building on the components outlined in Section 2.1.1 and Definition 2.2.1, an open-source[1] adaptive IDPT framework has been developed (Mukhiya 2021). While this system has primarily been built in the context of a PhD thesis by Mukhiya (2021), the development has taken a collaborative nature, allowing contributions from various interested parties. Among other features, the system currently supports the creation and manipulation of cases, modules, and tasks, meaning it is possible to create intervention treatment materials in the system. Figure 2.6 shows an example of this, along with the User Interface (UI) of the framework.

[1]The source code can be found at https://github.com/sureshHARDIYA/idpt

Part of our project entails extending this framework. Specifically, our contribution to the framework is adding support for *taxonomies*, which are currently used to annotate treatment materials with metadata in the form of hierarchical labels. The implementation of taxonomies and the implications thereof will be described further in Section 4.3.

2.5 Existing Solutions

We have reviewed available literature using Google Scholar and MEDLINE to gain insight into the nature of existing IDPT systems, and how they are described. In reviewing the literature, we noticed a trend: While numerous IDPT systems are described online, it appears to be uncommon to make the code base of these systems publicly available, or to comment on the systems' data management methods in detail. With the exception of MinADHD, where we were granted access at patient level for the purposes of this thesis, we did not have user access to the systems. Unfortunately, this poses a limitation on our work, as it becomes difficult to perform a thorough comparison between existing systems and our contributions with respect to inner data representations.

In this section, we will present a selection of IDPT systems. We have focused on platforms that host multiple programs or courses focusing on different topics within mental health that contain modules and tasks, or platforms that measure aspects of the user for the purpose of yielding the optimal clinical outcome. This is so that we can relate these solutions to our artifact either with respect to the structure or the user profiling aspect.

2.5.1 Youwell

Youwell is a digital health platform that allows clinicians to develop their own digital guided or unguided interventions (Youwell 2021). This means that clinicians may adapt the treatment to each individual patient at any time without requiring a particularly strong IT background (Youwell 2020). The platform offers a variety of features, such as clinician-patient communication, psychometric questionnaires, treatment material in the form of video, audio and text (Youwell 2020).

INTROMAT has used Youwell as the underlying platform in multiple interventions, including:

- **MinADHD**, which was described in Section 1.2,
- **RestDep**, an intervention for adults with lingering symptoms after depression (*RestDep — Behandling av restsymptomer etter depresjon* 2021),
- **Gynea**, which is aimed towards women who have experienced severe genital cancer (*Gynea — Velkommen* 2021), and
- **Co-mestring** (Co-coping in English), an intervention centered around reducing anxiety and worry arising from the COVID-19 pandemic (*Velkommen til Co-mestring! - Co-mestring* 2021).

Similarly to the hierarchical structure described in Section 2.4, the treatment materials in Youwell interventions are organized into programs (analogous to cases), modules, and tasks. In MinADHD, modules are comprised of tasks such as exercises, stories, questionnaires, videos, and user-filled logs, and offer some level of optionality (*Om MinADHD - MinADHD* 2021). Figure 2.7 shows an example of the treatment materials available in MinADHD.

According to clinicians at INTROMAT, the use of Youwell as the underlying platform for MinADHD has led to issues with data management. In particular, working with the format of the user interaction data captured by the platform has made analytics challenging. We will elaborate on this matter in Section 5.2.

2.5.2 Assistert Selvhjelp

Assistert Selvhjelp (2021) (Assisted Self-Help in English) offers Internet-based interventions for people with mental health issues. Specifically, the main user

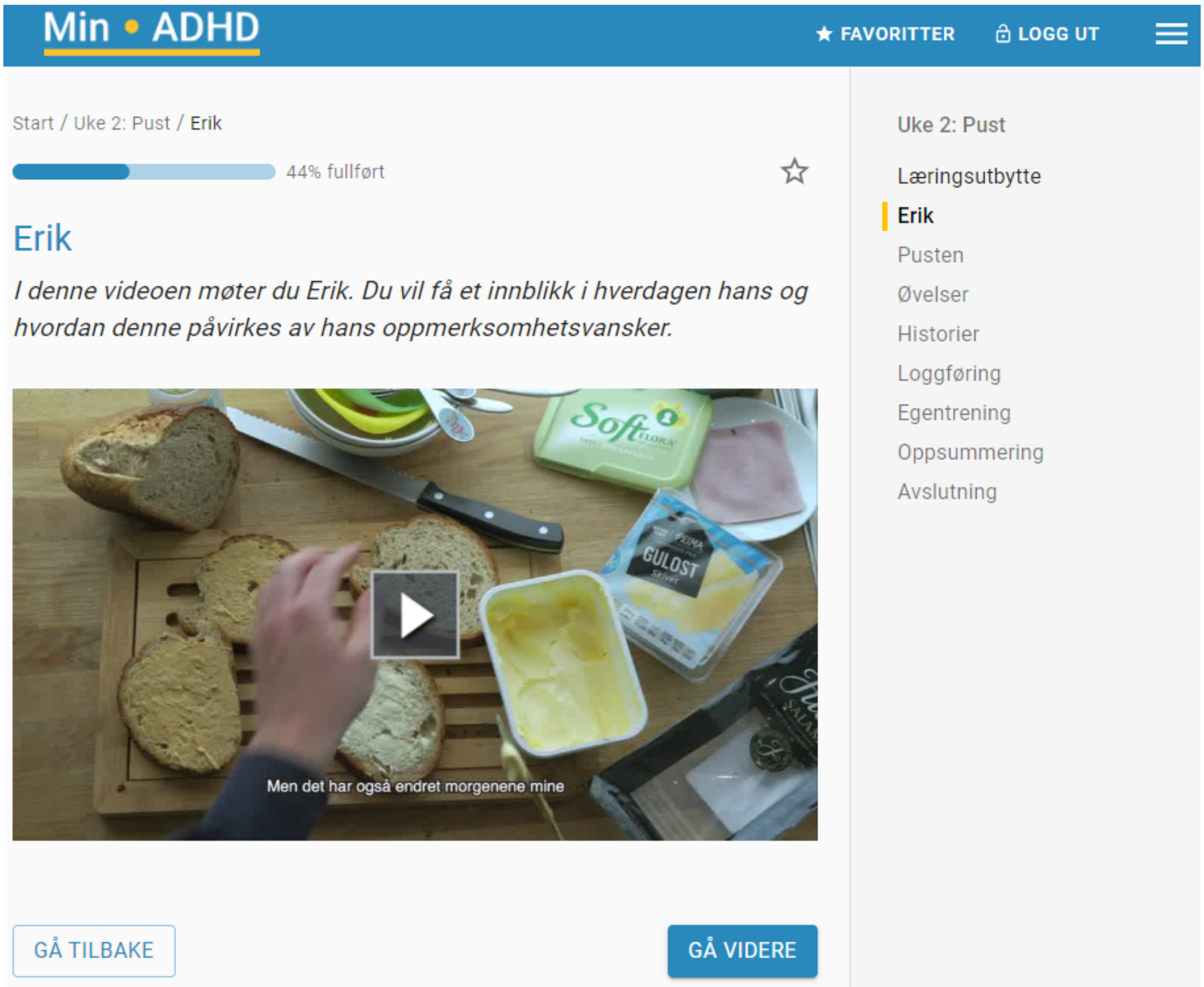


Figure 2.7: A screenshot of the Youwell-powered intervention MinADHD. In this image, the user has starting the program's second module, which is centered around breathing. Specifically, the user has clicked on a video that gives insight into the daily life of "Erik", who struggles with the ADHD symptom inattention. The module's full contents are listed on the right-hand side.

base consists of people with mild to moderate symptoms of common mental disorders (Assistert Selvhjelp 2019).

A variety of courses concentrating on relieving disorders or issues such as depression, anxiety, perfectionism, and low self-esteem is available. To gain access, a user must either have been given an access code by their healthcare providers or municipality, or have purchased access privately (Assistert Selvhjelp 2021). Although it is possible to complete these courses without the involvement of a clinician, it is recommended for patients to have access to structured guidance as well (Assistert Selvhjelp 2020). Each course consists of a series of modules that focus on an aspect of the course's main topic. The modules typically include exercises and information on the topic (psychoeducation), and end in a summary (Assistert Selvhjelp 2021).

Thus, the treatment materials in Assistert Selvhjelp constitute a structure similar to the IDPT component hierarchy described in Section 2.1.1.

2.5.3 The Innowell Platform

The Innowell Platform is a configurable digital platform that focuses on the delivery of personalized mental health care to young people (Iorfino et al. 2019). In particular, the platform has been described by the term *measurement-based care*, which is said to "[involve] the systematic and continued assessment of an individual's outcomes over the entire course of clinical care" (Iorfino et al. 2019, p. 2). The user's mental state is assessed and monitored by the platform for the purpose of reporting this information to clinicians, who receive guidance in determining the appropriate care options. The platform does not, however, offer "stand-alone medical or health advice, risk assessment, clinical diagnosis, or treatment" (Iorfino et al. 2019, p. 3).

The platform's assessment mechanism is multidimensional, meaning it considers the user in the context of multiple domains. These include demographic information (e.g. age or gender), clinical information (e.g. attitude

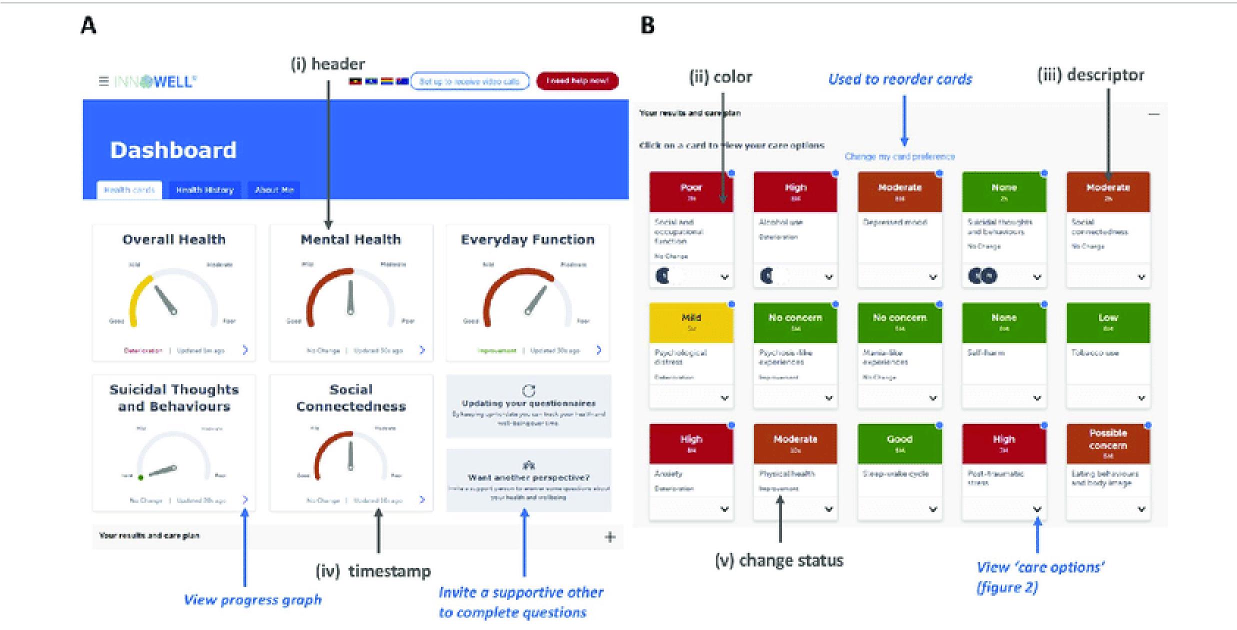


Figure 2.8: The Innowell Platform's clinical dashboard, as seen in Figure 1 in the paper by Iorfino et al. (2019)

towards self-harm or depression severity), and illness information (e.g symptoms or diagnoses). The exact set of domains that is considered in the assessment is configured in the mental health service that uses the platform as its underlying system. Additionally, the platform supports integrating information from external sources, such as clinicians not attached to the system or devices collecting physiological data. The results of the assessments are shown in a summary dashboard, which is shown in Figure 2.8.

This multidimensional approach to assessing users is similar to what we wish to capture in our artifact. In particular, expanding the adaptive dimensions described in Section 2.2.1 with contextual information used in this platform, such as the user's demographic or clinical background, is an idea that we explore further in this thesis. However, we also envision that it may be used in IDPT systems that provide treatment and coping tools in addition to decision-making support.

Chapter 3

Method and Design

In this chapter, we discuss the research method chosen for this project, as well as the iterative design process followed for developing a dimensional model representing IDPT.

3.1 Research Method

As mentioned in Section 1.4, the chosen research method for this project is design science. According to Hevner et al. (2004), design science is centered around the contribution to a problem domain in the form of an artifact. We judged this method to be well aligned with our goal of creating a preliminary dimensional model for representing IDPT in a new way. Thus, the design artifact presented in this thesis will be this dimensional model.

3.1.1 Applying the Design Science Guidelines

Hevner et al. (2004) present seven guidelines for utilizing the design science methodology in information systems research. A summary of the guidelines, in addition to a description of how they were followed in this project, follow below.

Guideline 1: Design as an Artifact

The first guideline is centered around the production of an artifact that is applicable to the problem domain. This artifact is the main result of design science research, and may take one of the following forms:

A construct that provides a vocabulary of symbols that may be used to communicate problems in the domain.

A model or abstraction that represents the problem domain. Such a model is typically built using constructs.

A method that captures processes in the problem domain, as well as guides the search for a solution. Algorithms are one way to do this.

An instantiation or system solution that demonstrates how constructs, models or methods may be implemented in practice.

The artifact that is presented in this thesis is a *model*, as it is an abstraction over the domain of IDPT. It represents the dimensions of IDPT, and the relationships between them. The process of developing this artifact is detailed in Section 4.1.

Guideline 2: Problem Relevance

The second guideline emphasizes that the chosen artifact should be developed in order to solve a problem that is *relevant* to the domain. Thus, the artifact should be *innovative*.

The context of the problems that our artifact aims to address was described in Section 1.2.

Guideline 3: Design Evaluation

Design science research requires a thorough evaluation of the resulting artifact. Evaluation is also a crucial part of the iterative design process, where feedback gives guidance as to how to improve the artifact further.

In this project, we have elected to use qualitative evaluation methods. The evaluation process will be discussed further in Chapter 5.

Guideline 4: Research Contributions

The fourth guideline presented by Hevner et al. (2004) conveys how design science research should yield valuable contributions to the problem domain. Specifically, these contributions take at least one of the following forms:

The design artifact In design science research, it is common that the main contribution to the knowledge base is the artifact itself.

Foundations Another form of contribution to the knowledge base is a construct, model, method or instantation that further extends the foundations of the knowledge base. This contribution must be evaluated with a suitable method.

Methodologies Evaluation methods themselves can also be valuable contributions. This may include metrics by which something in the problem domain is evaluated.

Section 6.2 will summarize the research contributions of this project. Our main contribution is the artifact itself. However, the artifact also takes the form of a model that extends the foundations of the knowledge base.

Guideline 5: Research Rigor

Research rigor in the context of design science entails employing rigorous methods in order to develop and evaluate the design artifact. Furthermore, "rigor is derived from the effective use of the knowledge base" (Hevner et al. 2004, p. 88).

A crucial part of this project has been the involvement of experts on the domain of psychology with experience with IDPT. We consider this to be an effective use of the knowledge base, as the experts have been able to provide relevant theoretical foundations as well as practical experiences in order to guide the development and evaluation of our artifact. The process of developing the artifact is described in Sections 3.2 and 4.1, while methods used to evaluate it are described in Chapter 5.

Guideline 6: Design as a Search Process

The penultimate guideline is centered around the search for an effective design artifact that provides an adequate solution to a domain problem. This is described as a cyclical process where new ideas are tested against the constraints in the domain. Hevner et al. (2004) also mention that in design research, it is common to decompose the main problem into smaller subproblems. While providing solutions to these subproblems is unlikely to leave a substantial impact on the domain's practices, this may instead serve as a starting point for future research on a larger scale.

The artifact presented in this thesis is an instance of such a decomposition of problems. As discussed in Section 2.3.1, there is potential for dimensional modeling to be an innovative approach to analyzing multiple kinds of health data on different abstraction levels and in different contexts. However, this is a highly complex problem that goes beyond the scope of this thesis. Instead, we focus on the application of this approach to IDPT, thus decomposing the larger problem with the purpose of providing a starting point for further research.

The iterative design process of this project is described in Section 3.2.

Guideline 7: Communication of Research

Finally, design science research must be communicated in a way that is understandable for both technology-oriented and management-oriented audiences. This must include technical descriptions of the artifact that are detailed enough to facilitate further implementation and usage. Additionally, management-oriented audiences require adequate information on how to apply the artifact in practice.

The results of our research are communicated throughout this thesis. In particular, the results are discussed in Chapter 6, and future work is outlined in Section 7.2.

3.2 Design Process

In this section, the project's iterative design process is described. Over the course of the project, we had multiple meetings with different domain experts of psychology associated with INTROMAT. New ideas for the design of the artifact often originated from these meetings. In two of the meetings, domain experts provided feedback for the artifact, thus providing qualitative evaluations of it at different stages in the process.

The project was comprised of four primary iterations, which are described below.

Iteration 1: Early in the process, we decided to create a simple, general implementation of taxonomies in the adaptive IDPT framework described in Section 2.4. We consider this to be the first iteration of the project, where initial experiments with the structure were made. At this point, we had not yet determined the exact scope of the project, although we were considering the possibility of utilizing secondary data collected as part of an INTROMAT study to guide our direction.

Iteration 2: The second iteration was centered around initializing the development of a dimensional model with input from the domain experts. This included a brainstorming session with the experts, in addition to multiple meetings related to an intervention content library that is a collaboration between INTROMAT and Helse Vest IKT[1], a company that provides ICT services for public and private health services in Western Norway. A brief description of the library is given in Section 3.2.1. Based on these meetings, it was decided that we would base parts of our work on INTROMAT's ADHD case, and in particular, the MinADHD intervention, to which we were granted patient access. We planned to look at how the user-generated data captured in MinADHD was structured. In addition, we decided to create example use cases for the dimensional model that was aimed towards clinicians working with ADHD interventions.

Iteration 3: In the third iteration, we continued developing the dimensional model with a particular focus on reuse of treatment content. Example use cases for this were generated and presented to domain experts as well as a developer from Helse Vest IKT. In this meeting, the domain experts gave feedback regarding how the dimensional model may be improved to promote reuse of treatment materials, as well as how this approach may potentially support the content library.

During this iteration, we were also given access to the MinADHD data, which was used to guide the design of the artifact.

Iteration 4: The final iteration focused on designing the dimensional model to fit the use case of adapting treatment in a specific intervention based on user needs. A semi-structured interview with domain experts from INTROMAT was held in order to acquire a qualitative evaluation of the artifact's potential. This is described further in Section 5.2.

More details about the process will follow in Section 4.1.

[1]https://helse-vest-ikt.no/

3.2.1 The Content Library

In collaboration with INTROMAT, Helse Vest IKT has developed an Application Programming Interface (API)[2] for reusing treatment materials from existing interventions (Mukhiya 2021). Specifically, the intended purpose of the API is to facilitate the extraction of treatment materials so that they become accessible from different user interfaces, such as web applications or mobile applications. In terms of the IDPT components described in Section 2.1.1, the API represents a library of intervention contents, allowing fetching cases (referred to as programs), modules, and tasks associated with a selection of interventions (including MinADHD).

In Chapter 4, we utilize the content library as a possible area of application for our dimensional modeling approach when presenting some of the example cases.

[2]https://dev-content-intromat-apim.developer.azure-api.net/api-details#api=intromat-content-api

Chapter 4

Implementation

In this chapter, we detail the process of developing the artifact, and investigate how it may be implemented in IDPT systems.

We begin by describing the initial model and the related example cases showing the intended use of the dimensional modeling approach, with a particular focus on reuse. After discussing feedback on the model given by domain experts, we continue the development of the dimensional model, focusing more on individualization. The final version of the dimensional model is then presented. In the following sections, we experiment with developing a general data structure representing dimensional models for IDPT. Finally, a simplified implementation of the data structure in the open-source adaptive IDPT system introduced in Section 2.4 is discussed.

4.1 Developing Dimensional Models for IDPT

In order to develop the dimensional model, we experimented with a set of example cases centered around interventions for people with ADHD. This way, we could look to MinADHD and the experts on ADHD to gain insights into which components are central in IDPT, and to the MinADHD interaction data to learn more about what types of data clinicians may use for analysis.

4.1.1 Formulating the Preliminary Example Cases

The purpose of the example cases was to demonstrate some potential use cases for ontological hierarchies in the context of mental health interventions.

The ideas behind the example cases were drawn from a number of sources. Firstly, the dimensional model for healthcare described in Section 2.3.1 served as a starting point for how to model the various dimensions and abstraction levels of event logs in IDPT. Furthermore, the adaptive dimensions of adaptive IDPT applications described in Section 2.2.1 and visualized in Figure 2.3 provided a general example of how to separate and structure the various dimensions in an intervention. Another source of inspiration was the user data collected in MinADHD, as mentioned in Section 3.2.

Higher-Level Hierarchical Models for Healthcare

The structure presented in Figure 2.5 was followed when designing new example cases. While this model follows the star-like structure often used in dimensional modeling (Kimball & Ross 2013), we decided to reorganize it to emphasize its hierarchical nature. This hierarchical structure was then followed in the dimensional models developed during this project. The new version of the model is shown in Figure 4.1.

We based our initial models on the content library described in Section 3.2.1. The library consists of multiple existing interventions, which typically contain at least one case focused on a specific disorder or mental health issue. The cases contain at least one module, often focusing on a specific symptom or theme. The modules contain exercises centered around this theme. Additionally, some of the interventions collect user data, in addition to prompting the users to answer psychometric questionnaires.

Based on these attributes, a dimensional model for IDPT was proposed in Figure 4.2. This model could then be used as a starting point for visualizing the process of querying the content library from different perspectives. Its

```
Healthcare dimensions
├── Care plan
├── Observation
├── Procedure
├── Clinical finding
│   ├── Admission time
│   └── Admission department
│       ├── Psychiatry
│       ├── Gynecology
│       └── ...
└── Episode of care
    ├── Drug interaction
    └── Disease
        └── F00-F99 (mental disorders)
```

Figure 4.1: A minimalistic hierarchical model for the various healthcare dimensions. It is based on Figure 2.5.

purpose is not to capture all possible subdimensions and all possible variants of data collected, but merely to give an overview of what sort of data belongs where in the hierarchical structure. In general, there is a focus on the capture of patient-generated event logs, as these are central in monitoring patient status, as well as measuring the usefulness of the interventions by looking at engagement levels and symptom improvement.

The model declares three primary dimensions of user profiling in the library interventions. Firstly, the *user dimension* encompasses all data and event logs that are related to the users themselves. Note that while the user dimension is meant to capture data for multiple user roles, not all subdimensions and associated event logs are generated by all users. For instance, the user personalia subdimension is primarily relevant for patient users, as they may be asked to provide demographic and personal information such as age, gender, occupation, medication status or treatment history. While clinicians, researchers and intervention designers may not generate these data themselves, they may still use these event logs to group patients based on demographic information, e.g. grouping patients within a certain age interval. User preferences, on the other hand, may pertain to different user roles - for example, any user benefits from the ability to choose their preferred locale (and thus the language

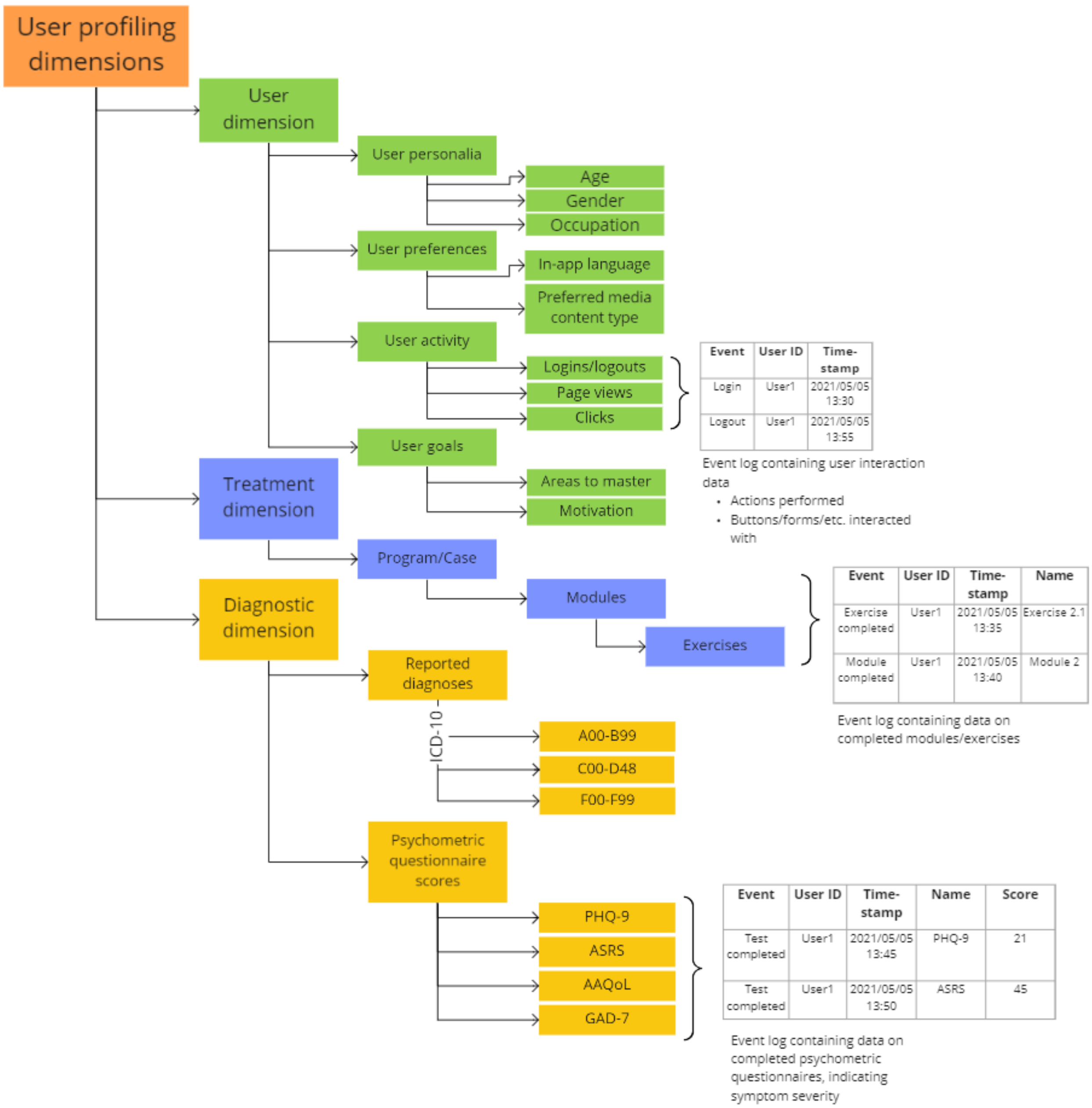


Figure 4.2: A dimensional model illustrating the suggested dimensions of an IDPT system. Examples of related event logs are shown as tables.

used in the intervention), if available. User activity refers to the user's interactions with the systems, such as logins and logouts, page views (being active on the intervention page) and page blurs (having the intervention open in a non-active tab), and clicks on specific HTML elements on the page. Simplifies event logs capturing interaction events, the associated user ID and the timestamp can be seen in this portion of the figure. Moreover, the user dimension also includes user goals, as this was found to be an adaptive dimension of IDPT in Section 2.2.1.

The second high-level dimension in the model is the *treatment dimension*. This closely follows the structure of the treatment materials, i.e. the components of IDPT introduced in Section 2.1.1. As shown in the figure, event logs collected in the treatment dimension will likely revolve around the completion of cases, modules and tasks. One central idea presented alongside this model is the ability to annotate each of the programs, modules and exercises with searchable metadata. These metadata may be derived from the other two top-level dimensions. For instance, as MinADHD is a treatment program that is suited for adults with ADHD, the case node in the hierarchy could be annotated with "Age group: Adult" and "Diagnosis: ADHD". The former annotation is demographic metadata retrieved from the user dimension, while the latter is information on the patients' diagnoses retrieved from the diagnostic dimension (which will be described shortly). In practice, this means that a tagging system must be in place to facilitate these annotations. An example of an annotated treatment hierarchy is shown in Figure 4.3.

The final top-level dimension is the *diagnostic dimension*. This dimension captures diagnostic information, in addition to psychometric questionnaire scores and symptoms. The subdimension for reported diagnoses provides an excellent opportunity to take advantage of standardized ontologies, such as ICD-10. In the model, a subset of this ontology is visualized with three nodes representing chapters I (Certain infectious and parasitic diseases), II (Neoplasms), and V (Mental and behavioral disorders) of ICD-10, respectively (World Health Organization 2019). The diagnosis may be explicitly expressed by the user, e.g. in the case of MinADHD, patients are expected to have a prior ADHD diagnosis to gain access to the intervention (*Hvem passer*

MinADHD for? - MinADHD 2021). Psychometric questionnaire scores are also represented as a subdimension, with a subset of tests on the next level in the hierarchy. The figure exemplifies an excerpt of relevant event logs containing information on a completed test of some kind, the associated user, the timestamp, and the questionnaire score.

The patients' symptoms and their severity levels also belong to the diagnostic dimension, and thus need to be represented. One way to do this is to let the most recent symptoms be determined by the most recent questionnaire scores. For instance, Adult ADHD Self Report Scale (ASRS) is a scale consisting of 18 questions, which are divided into two parts. The first part is concentrated on inattention, while the second focuses on hyperactivity-impulsivity (Kessler et al. 2005), both of which are central symptoms of ADHD (World Health Organization 2019). Thus, the annotations "Symptom: Inattention" and "Symptom: Hyperactivity-Impulsivity" may be attached to the ASRS node. An alternative is to attach these symptoms to a relevant ontology. If the ICD-10 hierarchy is used, the relevant symptoms belong under "Mental and behavioral disorders" (codes F00-F99), "Behavioral and emotional disorders with onset usually occurring in childhood and adolescence" '(codes F90-98), "Hyperkinetic disorders" (codes F90.x), under which there exist four subgroups of ADHD ("F90.0 Disturbance of activity and attention", "F90.1 Hyperkinetic conduct disorder", "F90.8 Other hyperkinetic disorders" and "F90.9 Hyperkinetic disorder, unspecified") (World Health Organization 2019).

Regardless, it is natural to measure the severity levels of the symptoms by analyzing the nuances of the questionnaire scores. For example, the two parts of ASRS generate one score each, meaning these values can be used to determine the current impact of inattention and hyperactivity-impulsivity, respectively. It is also possible to utilize the questionnaire scores to measure the fluctuations in symptom severity over time. Within a specific intervention, this can be used to adapt the treatment to every patient, for instance by suggesting exercises that have been annotated with the patients' symptoms that have shown a trend of deterioration.

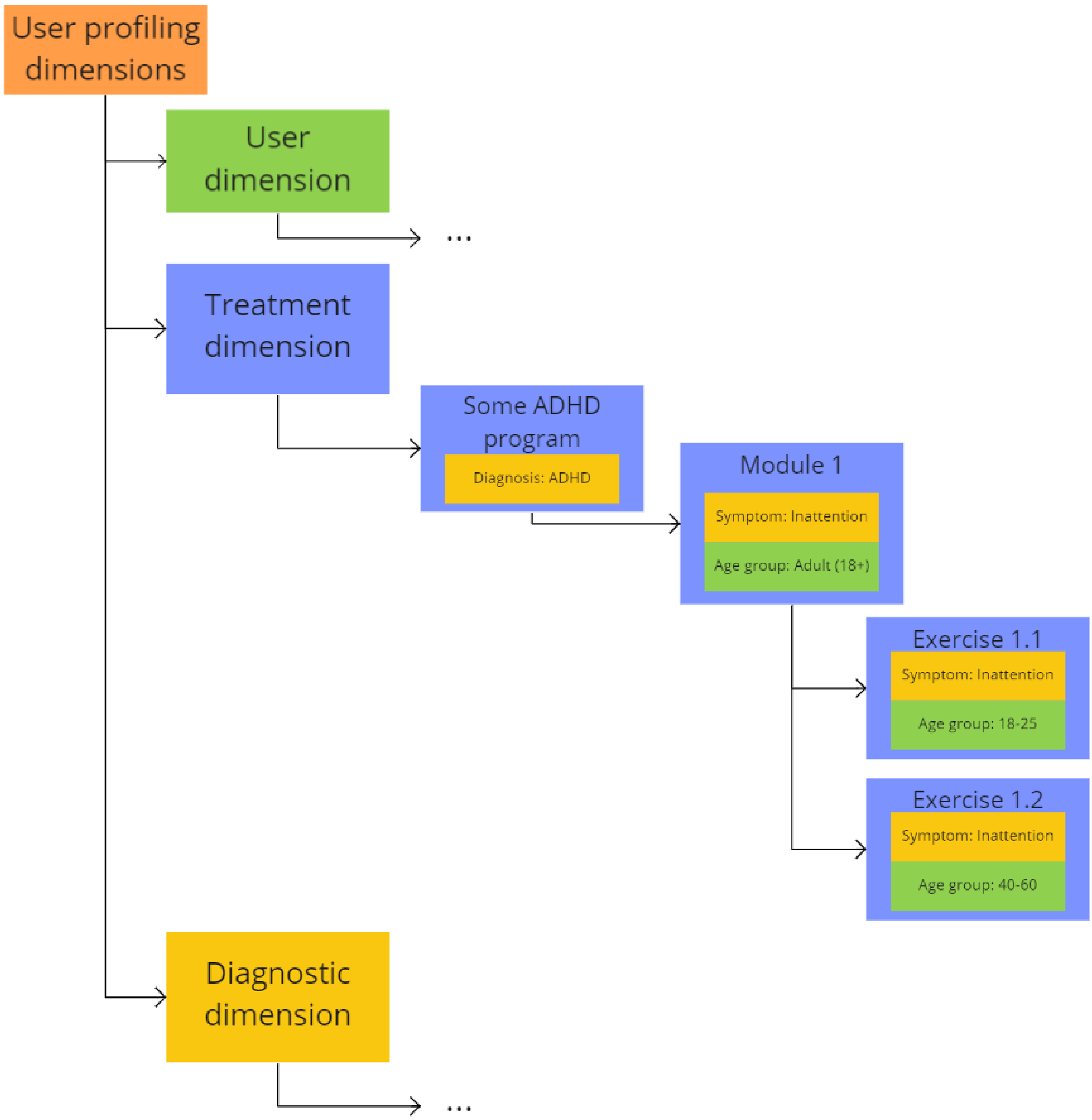


Figure 4.3: An example of how a treatment hierarchy of an intervention may be annotated. Note that the metadata is borrowed from the two other primary dimensions: The user dimension (demographic information, green labels) and the diagnostic dimension (symptoms and diagnoses, yellow labels).

Changing Abstraction Levels with Dimensions

Using the new dimensional model, we also aimed to demonstrate how the dimensions could be used to select relevant abstraction levels. In particular, we consider other dimensions from the perspective of one dimension, and show how this can be used to group event logs such that the users gain access to relevant data without information overload. The role of the user in the following two example cases is assumed to be a clinician or researcher analyzing the effect of an intervention for adults with ADHD, or alternatively a designer of a future intervention that wants to gain insight into the strengths of existing treatment programs.

In the first example query presented to the experts, we investigate a potential connection between patients with ADHD-related symptom improvements and the number of modules and exercises completed. This process is visualized in Figure 4.4. Firstly, we select the patients whose ADHD symptoms have improved over time. For this, we would need some mechanism to determine exactly what improvement entails. Additionally, since we are specifically interested in examining ADHD symptoms, we only group the event logs in the diagnostic dimension that represent the results of ASRS and Adult ADHD Quality of Life Questionnaire (AAQoL), as they are centered around ADHD. Since the initial step groups patients based on their psychometric questionnaire scores, we have chosen to envision this filtering process to use the diagnostic dimension as a starting point. Based on this selection, the next step is to group all event logs of modules and exercises that these patients have completed. This secondary selection may aid in allowing the user insight into whether there is a correlation between patients who have a certain symptom pattern and patients who have completed a set of modules and exercises, perhaps in a specific order. Now that the pre-processing step of organizing relevant event logs has been completed, we facilitate the reduction of the associated process model, which in theory helps simplify further analysis of the data (Rabbi et al. 2020).

The second example case presents a scenario where the relationship between low engagement rates and psychometric questionnaire scores is exam-

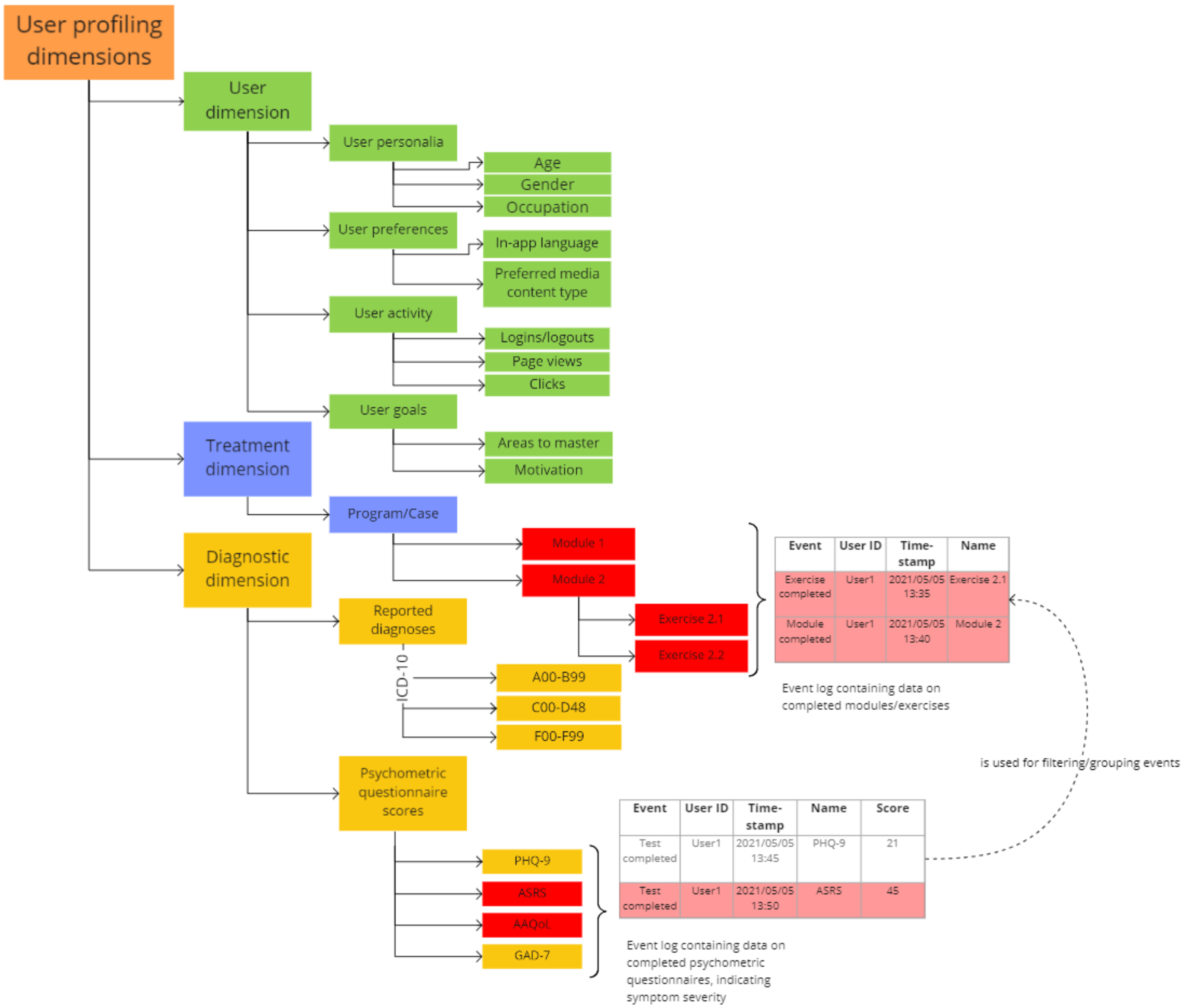


Figure 4.4: The first example case. This selection process may serve as a precursor for examining the relationship between symptom improvement and typically completed modules and exercises.

ined. As Figure 4.5 shows, we consider the diagnostic dimension (questionnaire results) from the perspective of the user dimension (user activity). The first step entails the selection of patients who rarely interact with the system. As in the first example step, we need some mechanism to define what *rarely* means in this context, perhaps even allowing the therapist to define their own thresholds for various degrees of engagement. Here, we group logs for events such as logins, logouts, clicks, and page navigation, and filter these so that event logs associated with patients with low interaction rates remain. These event logs are then used to query these patients' questionnaire scores. In this scenario, we are interested in all test results and subsequently all associated symptoms, and thus do not discard some questionnaires as in the first example case.

4.1.2 Feedback from Domain Experts

The resulting dimension model and the example cases were then presented to domain experts of psychology affiliated with INTROMAT. A developer from Helse Vest IKT working with the content library was also present. The presentation was given in the context of a meeting centered around the content library, and was used as an opportunity to obtain useful feedback and evaluations of the dimensional model at this point in time. In this section, we present an overview of the concrete feedback given by the domain experts and the Helse Vest IKT developer. The evaluation aspect of the meeting will be discussed further in Section 5.1.

Firstly, it was requested by the experts that we use "Education level" instead of "Occupation" under "User personalia", and to add "Reading comprehension" in the same subdimension. These are metrics that have been used in several of the INTROMAT research projects. It was mentioned that it is easier to group patients by their highest attained level of education than their occupation. One reason for this may be that education levels are more standardized and recognizable than occupations, which can vary to a far greater degree. Moreover, the experts recalled the reactions of previous intervention

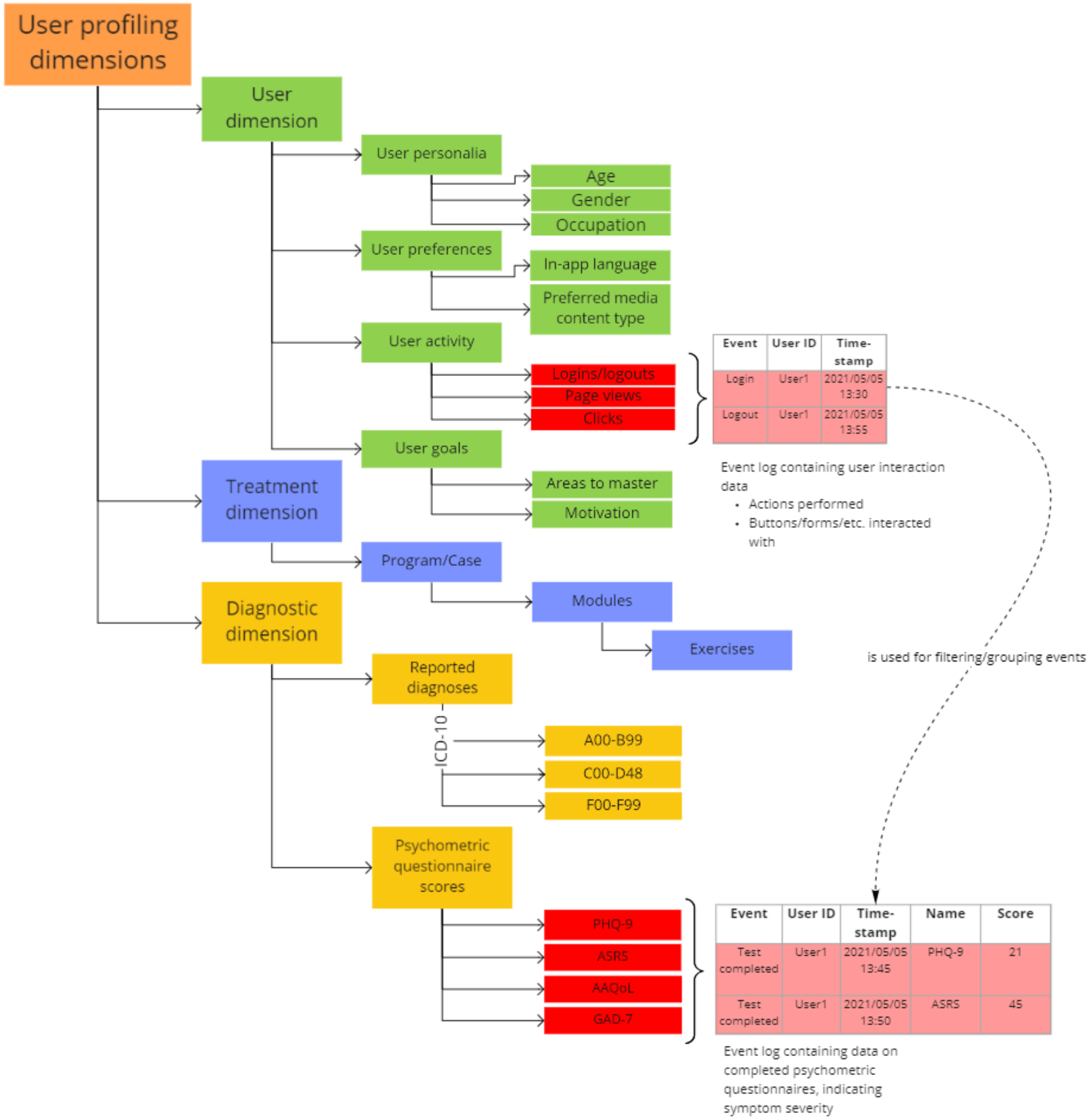


Figure 4.5: The second example case. In this example, we visualize the process of examining a possible relationship between user activity and psychometric questionnaire scores.

study participants who had negative reactions to tasks that were presented in an unnecessarily simple manner. It was requested that reading comprehension be included as a metric by which intervention contents may be measured in order to avoid these negative reactions. However, more research into exactly how to measure this would be needed.

Another proposition entailed expanding the treatment dimension to explicitly capture more than the treatment content hierarchy. For instance, it was suggested to add a subdimension for treatment techniques. This way, it would be possible to label programs, modules and exercises according to the treatment techniques they employ, such as mindfulness, cognitive training or physical activity. This subdimension was added to the new version of the dimensional model, along with a subdimension representing content format (e.g. video, text, or audio), to give further options for filtering treatment content.

The feedback also included a discussion on psychoeducation and its place in the treatment dimension. In some of the previous INTROMAT interventions, psychoeducation has taken the form of stories detailing common scenarios that patients in the target group may relate to. For example, MinADHD contains stories in video format, showing situations that adults with ADHD typically find difficult. These videos are not necessarily meant to be exercises, but instead have the goal of normalizing ADHD-adjacent experiences to the user, as well as helping the user connect the displayed scenarios to their own experiences. MinADHD also contains informative content in text format describing various aspects of ADHD (e.g. hyperfocus, inattention) that also serve as learning materials. In this intervention, interactive exercises and educational materials both belong to specific modules. To reflect this approach, the treatment program hierarchy was altered so that exercises and learning material were represented as different instances of *tasks*, which exist directly below modules.

Additionally, the domain experts introduced the concept of *common factors* of psychological treatments, and suggested its inclusion in the model. Common factors of psychotherapy are based around an idea originally introduced in 1936 that claims all therapies produce comparable outcomes, and thus also have certain core factors in common (Cuijpers et al. 2019). Multiple models describing and defining these common factors have since emerged. One popular model is the contextual model which presents three pathways for patients in psychotherapy: A connection between therapist and patient, the patients' expectations, and specific ingredients of therapies (Wampold 2015). During the meeting, the domain experts pointed to a set of slightly different common factors that they have found to be relevant in their work with digital interventions, namely normalization, hope, motivation, and credibility. Firstly, the psychoeducation present in interventions such as MinADHD aims to normalize the patients' experiences related to their diagnosis. Furthermore, another goal behind the intervention contents is to motivate users and instill them with hope. Designing interventions that meet the patients' expectations in regards to credibility has also been central. As a result, the dimensional model was expanded to reflect these common factors of digital interventions.

The presentation also prompted a discussion headed by the Helse Vest IKT developer regarding how taxonomic annotations would best be implemented and managed in a content library. One option would be to let clinicians using the content library define their own taxonomies on the fly. The perceived advantage of this approach is that is easy for clinicians to define the taxonomies they need to annotate their treatment materials. However, since any taxonomy could be added at any time, this would likely come at the cost of duplication, noise, and loss of standardization. Another approach that was theorized to combat these issues entails creating have predefined, rigid taxonomies for the clinicians to use. The cost of this approach is that it is more difficult to expand the set of available taxonomies.

The result of accommodating the suggested changes to the dimensional model is shown in Figure 4.6. This figure constitutes the design artifact of this thesis.

4.1.3 Introducing Measurements to the Dimensions

Moving forward, we also decided to put a greater emphasis on assigning measurements to the dimensions. The motivation for this is that we want to improve the structures in interventions through systematic annotation of mental

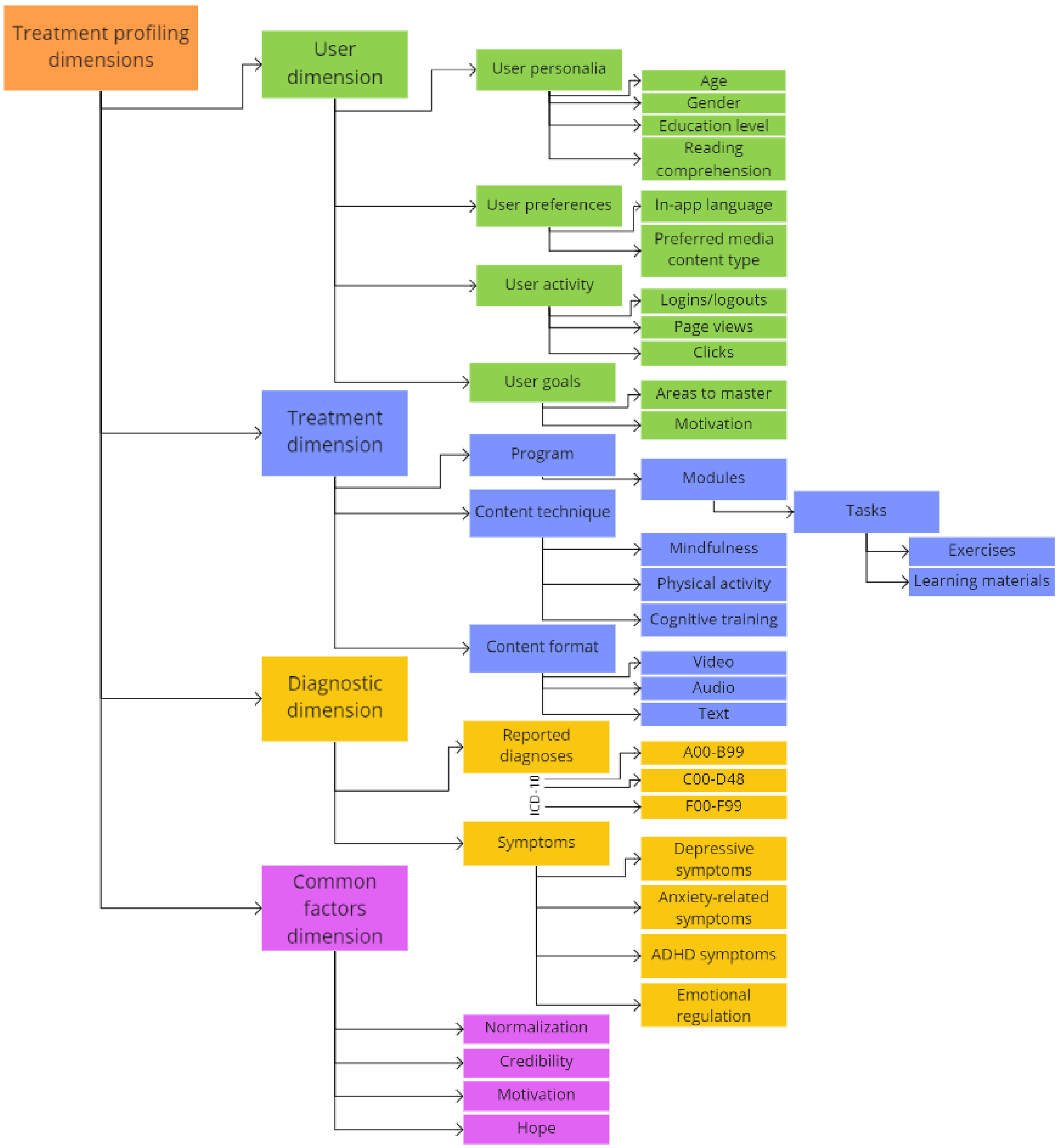


Figure 4.6: The dimensional model for IDPT, altered based on domain expert feedback.

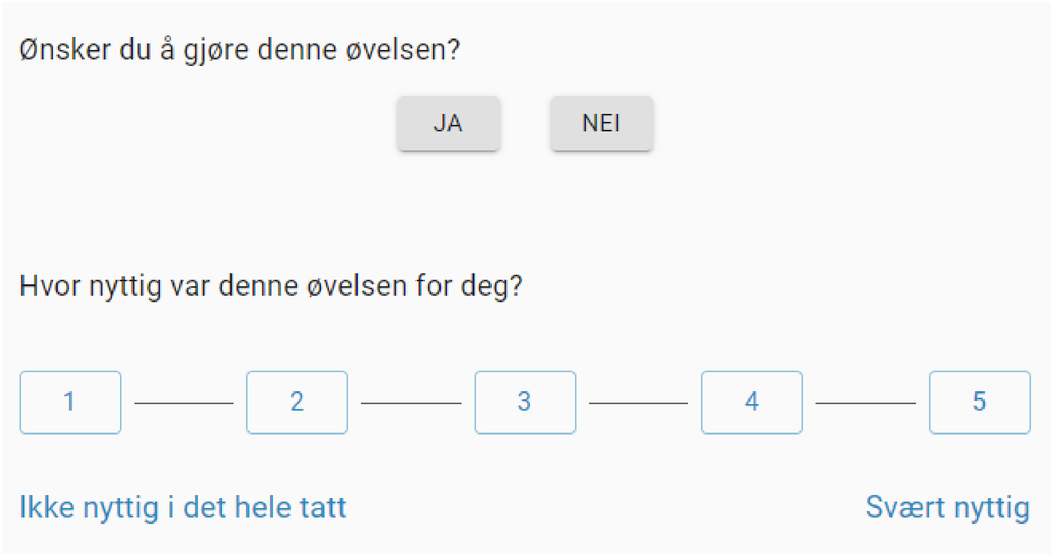


Figure 4.7: A screenshot of an exercise evaluation in MinADHD.

health information. Such annotations may boost the querying of information from different information sources (Hadzic et al. 2008). We envision that these measurements may be used to support the adaptive assignment of treatment materials to patients based on their unique user profile.

As discussed in Section 2.2.1, there are multiple forms of measurements already in use in interventions. For instance, it is common to use psychometric questionnaire scores to assess patient status, and this is generally considered to be a method that works well (Andersson & Titov 2014). Another form of measurement is used in MinADHD, where patients are sometimes asked whether they want to do a specific exercise, and to evaluate the usefulness of that exercise from one (not at all useful) to five (very useful). This is shown in Figure 4.7, and is an example of how the usability of exercises may be measured.

4.2 Generalizing Hierarchical Dimensions

In this section, we discuss how the dimensions of IDPT may be represented in a data structure. We treat the data structure as a theoretical conceptualization, not as a feature in a specific implementation of an intervention. An implemented version of the representation will be discussed in Section 4.3.

4.2.1 A General Data Structure

The initial idea involved creating a general representation for the dimensions seen in Figure 4.6.

Firstly, it is natural to assign a unique ID and name to each dimension. The name will be the main label by which dimensions are identified by human users. Basing this representation on the dimensional model shown in Figure 4.6, examples of names would be “Age”, “Depressive symptoms” or “Preferred media content type”.

Furthermore, there is a need for some mechanism for establishing a hierarchy of the various dimensions. For this, it was decided that each dimension would keep a list of its parents. This enables us to create trees (i.e. each dimension has at most one parent), while also leaving room for modeling hierarchies as graphs (i.e. each dimension may have zero, one or multiple parents). We chose to represent ancestry as a list instead of a single parent because we were uncertain whether dimensions would always have only one parent, and thus we opted for the more general representation.

Additionally, as discussed in Section 4.1.3, we aimed to assign one or more measurements to each dimension to improve querying of the data structure. In practice, this would mean grouping data based on their labels, which have values associated with them. For example, one may want to group a set of exercises based on what age group they target, or a set of patients based on the severity of a specific symptom. In both of these cases, selection could be done by specifying some numeric interval as a filter.

An early draft showing how hierarchical dimensions may be represented is expressed in pseudocode in Listing 1. Here, we have a data structure `Dimension` with four fields with associated types: (1) `id`, represented by some arbitrary type that is suited for representing unique identifiers, (2) `name` in the form of a string, (3) `parents`, a recursive list of dimensions that are directly above this dimension in the hierarchy, and (4) `measurements`, a function which given some measurement unit will return the corresponding value if

```
Dimension {
  id: ID,
  name: String,
  parents: [Dimension],
  measurements: Unit -> Measurement
}
```

Listing 1: An early pseudocode representation of hierarchical dimensions.

available. For the purposes of this simple representation, the types `Unit` and `Measurement` are not defined explicitly, but merely communicate the concept of a mapping between different modes of measurements (for example the psychometric questionnaire PHQ-9, or "Content format" directly below the "Treatment dimension", a parent node to the specific format types intervention content may take) to values (such as the numeric score resulting from a patient completing PHQ-9, or the categories of "Content format", namely "Video", "Audio" and "Text").

One aspect to consider is the concept of multidimensional measurements. With regards to psychometric questionnaires, we may be interested in deriving information about specific symptoms, and not just the total score. This accumulated score gives an indication of the overall symptom severity for some aspect of the patient's mental health, such as a specific diagnosis. However, the total score gives little information about exactly which symptoms need the most attention at a given time, and thus we want to include the option of partitioning the total score into subscores indicating the severity of each main symptom. The hierarchical structure of dimensions can enable this by letting the children of a dimension with some accumulated measurement represent these submeasurements.

An example of this can be seen in Listing 2, where we have created three dimensions centered around ADHD symptoms. In `adhd_symptoms`, the uppermost dimension in the hierarchy, we use the psychometric test ASRS as a measurement of ADHD symptom severity. Its `measurements` mapping keeps track of the accumulated ASRS score, but does not give further information about intensity at symptom level. As mentioned in Section 4.1.1, the questions in ASRS are arranged into two parts A and B that focus on the ADHD symptoms inattention and hyperactivity-impulsivity, respectively. Thus, we can model this multidimensional measurement by letting the two subdimensions of `adhd_symptoms` keep track of any subscores that operate at symptom level.

4.2.2 Developing the Data Structure Further

Based on this initial draft, we experimented with the data structure by attempting to map multiple of the different nodes in Figure 4.6 to this new representation. What was quickly discovered to be problematic was the attempt to assign measurements to the various dimensions. As these dimensions are quite heterogeneous, trying to make them adhere to the same general mapping representing measurements shed light on multiple challenges with this data structure.

Firstly, not all measurements are strictly numeric the way age intervals or psychometric questionnaire scores are. Instead, some dimensions belong to different subgroups. For instance, the aforementioned "Content format" dimension acts as a category type, and thus is measured, or more accurately grouped or categorized, by its children. Similarly, "Content technique" is not measurable on its own, though its properties may be expressed by using its children as a form of categorization.

Furthermore, the `measurements` mapping does not leave room for the presence of multiple values per unit for a given measurement, dimension, and a given user. For example, an intervention may prompt a user to answer the same psychometric questionnaire multiple times in order to monitor the development of their mental health status over a prolonged time period. The data structure must therefore take into account that there may be multiple readings available. There are multiple ways to solve this – for instance, it is possible to retrieve all measurements, the most recent measurement, or some sort of a manipulated measurement, such as an average reading. Exactly how

```
let adhd_symptoms = Dimension {
  id: 0,
  name: "ADHD Symptoms",
  parents: [],
  measurements: { ASRS: 40 }
}

let adhd_symptom_inattention = Dimension {
  id: 1,
  name: "ADHD Symptom: Inattention"
  parents: [ adhd_symptoms ],
  measurements: { ASRS_Part_A: 23 }
}

let adhd_symptom_hyperactivity_impulsivity = Dimension {
  id: 2,
  name: "ADHD Symptom: Hyperactivity-Impulsivity"
  parents: [ adhd_symptoms ],
  measurements: { ASRS_Part_B: 17 }
}
```

Listing 2: An example hierarchy of dimensions modeling multi-dimensional measurements of ADHD symptoms. Note that the first dimension is the parent of the other two, and that the first dimension's measurement is the sum of the two submeasurements.

```
Dimension {
  id: ID,
  name: String,
  parents: [Dimension],
  measurements: (UserID, Unit) -> Nullable [Measurement],
}
```

Listing 3: Another pseudocode representation of hierarchical dimensions.

this is done in practice is an implementation detail, though it is important to be able to take historical data into account where relevant.

Some of these observations challenge the data structure proposed in Listing 1. We extend this representation in Listing 3, which addresses some of the issues with the first version. For instance, the possibility of multiple measurements is addressed by letting the `measurements` mapping return a list of measurements instead of a single measurement. This list is wrapped in a `Nullable` pseudocode type, which we envision to work similarly to Haskell's `Maybe`[1] or Rust's `Option`[2] in that, based on the input, the mapping returns the requested value(s) if available, and some empty value if not. In cases where at least one measurement is available for a given dimension, user and unit, it will be returned, while cases where there are no relevant measurements signalize this with an empty value. The latter could be dimensions that do not have directly associated measurements.

Another change made between the Listings 1 and 3 is the inclusion of the `UserID` as an explicit input to the `measurements` mapping. This was done to emphasize that each measurement is tied to a user in some way, e.g. the user's engagement level, symptom severity, or enjoyment of a certain exercise type. We envision that these measurements can support user profiling in the future. Specifically, we are interested in using user-centered measurements of various aspects of an intervention to improve the adaptation of treatment to each user. However, the exact details of how this would be implemented are beyond the scope of this thesis, and will instead be summarized as future work in Section 7.2.

4.3 Extending the IDPT Framework

In this section, we present an implementation of the hierarchical dimensions as an extension of the adaptive IDPT framework described in Section 2.4. We begin by giving a brief overview of the technical details, including the main technologies used and the architecture. A description of the extension follows.

[1]https://hackage.haskell.org/package/base-4.15.0.0/docs/Data-Maybe.html
[2]https://doc.rust-lang.org/std/option/

4.3.1 Technologies

This section gives an overview of the main technologies used during development. As the implementation is a contribution to an existing development project, the relevant technologies had already been chosen before this project commenced, and thus the overview is brief. The application's codebase is largely based around JavaScript frameworks.

MongoDB The application uses *MongoDB* (2020) as its NoSQL database.

Mongoose *Mongoose* (2021) provides a schema-based method for modeling data in the database.

NodeJS *Node.js* (2020) is a JavaScript runtime environment that is used to handle the bulk of the logic in the application's backend.

GraphQL The application uses *GraphQL* (2020) for creating and dispatching dynamic queries between the frontend and the backend.

ReactJS The application's UI is built in *React* (2020), a component-based JavaScript library that facilitates the creation of declarative views.

Ant Design *Ant Design* (2020) is a React-compatible UI design language used for styling.

4.3.2 Architecture

In this section, we present the architecture of the IDPT application. Similarly to the application's technologies, the architecture was determined and implemented outside of the context of this project, and thus we only give a brief overview of it. The main components and the code flow are visualized in Figure 4.8.

In the backend, we have four main components, namely the MongoDB database, repositories, services and API endpoints. In general, there are similar pathways for each of the main entities in the application (e.g. users, cases, modules, tasks, taxonomies). This means that each of the entities has a corresponding database schema, repository, service and API endpoint. The role

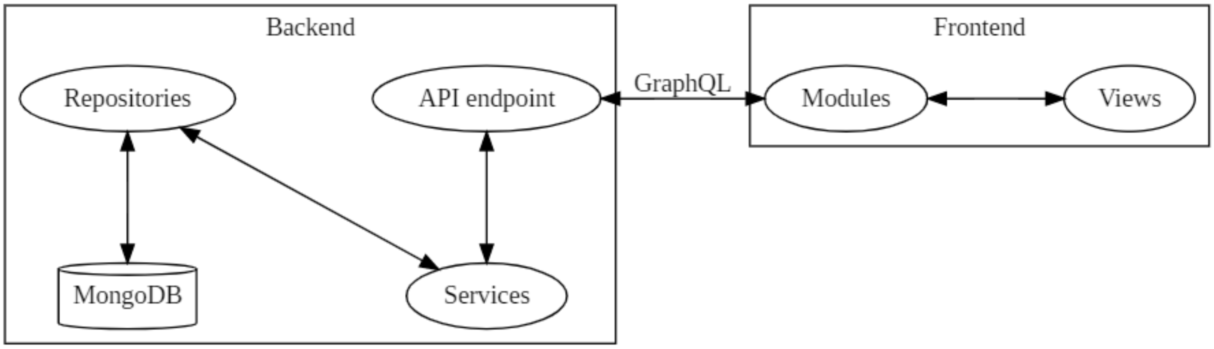


Figure 4.8: The architecture of the IDPT framework.

of a repository is to manage database operations (e.g. Create, Read, Update, and Delete (CRUD) operations and related actions) for a specific entity. On the other hand, services also handle entity-specific operations, but do not interact with the database directly. These operations are called from the backend's API endpoint, where GraphQL queries and mutations (i.e. queries that may modify data) are received from external actors (such as the application's frontend). Users of the API are required to adhere to a set of custom-made GraphQL types for each of the entities that they wish to interact with.

The frontend follows a similar approach to the backend, where each of the entities has an associated service responsible for performing entity operations. However, for each operation, the corresponding GraphQL mutation or query is formulated and dispatched to the backend's API endpoint. This service, along with associated operations and models representing the entities are grouped as *modules* in the codebase (not to be confused with treatment modules in an intervention that have an associated set of tasks for the patient users to complete).

Furthermore, each entity has a number of React components associated with them that comprise a view, which presents the user interface. From this user interface, users with the appropriate privileges are able to view and interact with existing entities.

4.3.3 Implementing Taxonomies

A simplified version of the general representation introduced in Section 4.2 has been implemented in the IDPT framework. We use the term “taxonomy” instead of “dimension”, as the initial experiments in the IDPT framework predate the development of the dimensional models. In this section, we present an overview of the taxonomy support added to the framework, and the implications of this work.

Representing Taxonomies

Each taxonomy entity has an ID, a name, and a list of parents, where each parent is another taxonomy. Initially, the implementation followed the parent references pattern described in the MongoDB documentation (*Model Tree Structures with Parent References* 2021). In this pattern, child nodes in a tree keep references to their parent nodes. Taxonomies were later altered so that the parent attribute was represented as a list — thus, they may have zero, one or multiple parents. Representing parents as a list of taxonomies rather than one singular taxonomy enables the user to view relationships between different components as graphs, rather than limiting the visualization to trees.

Due to time constraints, and because user profiling was not available in the IDPT framework while we added taxonomy support, we opted to not add measurements to the taxonomies. Instead, adding measurements to taxonomies will be left as future work in Section 7.2.

The representation of taxonomies in the database is shown in Listing 4, which is the application’s Mongoose schema for taxonomies. This means that all taxonomies in the database conform to this structure. It is required for all taxonomies to have a name, however, the list of parents may be empty. The `id` is generated automatically, and thus is not explicitly included in the schema. An example of how specific taxonomies appear in MongoDB is shown in Figure 4.9.

```
_id: ObjectId("60eeb6ada563f65450aa8429")
⌄ parent: Array
name: "ADHD symptoms"
__v: 0

_id: ObjectId("60f00977ed42d90f9887748c")
⌄ parent: Array
    0: ObjectId("60eeb6ada563f65450aa8429")
name: "ADHD symptom: Inattention"
__v: 0

_id: ObjectId("60f0098bed42d90f9887748e")
⌄ parent: Array
    0: ObjectId("60eeb6ada563f65450aa8429")
name: "ADHD symptom: Hyperactivity-Impulsivity"
__v: 0
```

Figure 4.9: Specific taxonomies as represented in the database.

```
const TaxonomySchema = new Schema(
  {
    name: {
      type: String,
      required: true,
    },
    parent: [
      {
        type: Schema.Types.ObjectId,
        ref: 'taxonomy',
      },
    ],
  }
);
```

Listing 4: The database schema for taxonomies.

Furthermore, there are multiple GraphQL types related to taxonomies implemented in the system. These are defined in the GraphQL schema language, and ensure that API calls to the backend related to taxonomies provide appropriate data. For example, we have defined an input type `TaxonomyInput` (as seen in Listing 5) that imposes restrictions on how new taxonomy data introduced to the system (such as in a create or update operation) is structured. In particular, each taxonomy is required to have a name. Additionally, if the taxonomy has at least one parent, the parents must not be null. This is enforced by the `!` symbol, which signalizes that the entity of the preceding type is non-nullable (*Schemas and Types* 2021).

Currently, there are no restrictions on the taxonomies' ancestry. For instance, there is no cycle prevention, meaning any one taxonomy can be a parent of any taxonomy, including itself. Whether this should be prevented, and whether the maximum number of parents should be reduced to one to reduce the complexity of the data structure, are matters that should be considered in future implementations.

```
const schema = `
  input TaxonomyInput {
    name: String!
    parent: [String!]
  }
`;
```

Listing 5: The GraphQL input type that represents taxonomies.

Interacting with Taxonomies in the User Interface

Currently, the application's UI allows the user to view and manipulate taxonomies from a dedicated page, as shown in Figure 4.10. The interactions available include CRUD operations, free text searching for taxonomies based on name and/or parents, importing and exporting taxonomies as Microsoft Excel (.xlsx) files, and viewing relevant audit logs. The user may alter the contents of the parent list when updating a taxonomy, meaning it is possible to restructure the hierarchy this way (e.g. by removing, adding or replacing parents).

During the implementation of taxonomies in the IDPT application, we initially discussed implementing an interactive visualization of the taxonomies. This would provide the users with an intuitive overview of the taxonomies and their relationships aimed at users with direct access to taxonomies (such as clinicians who create treatment courses). One way to do this would be to implement a tree view closely resembling a directory hierarchy where the user could navigate up and down in the tree, where subtrees could be collapsed or hidden. As this approach is based on trees, we would then require each taxonomy to have at most one parent. However, this was not implemented during this project due to time constraints, and is instead described as future work in Section 7.2.

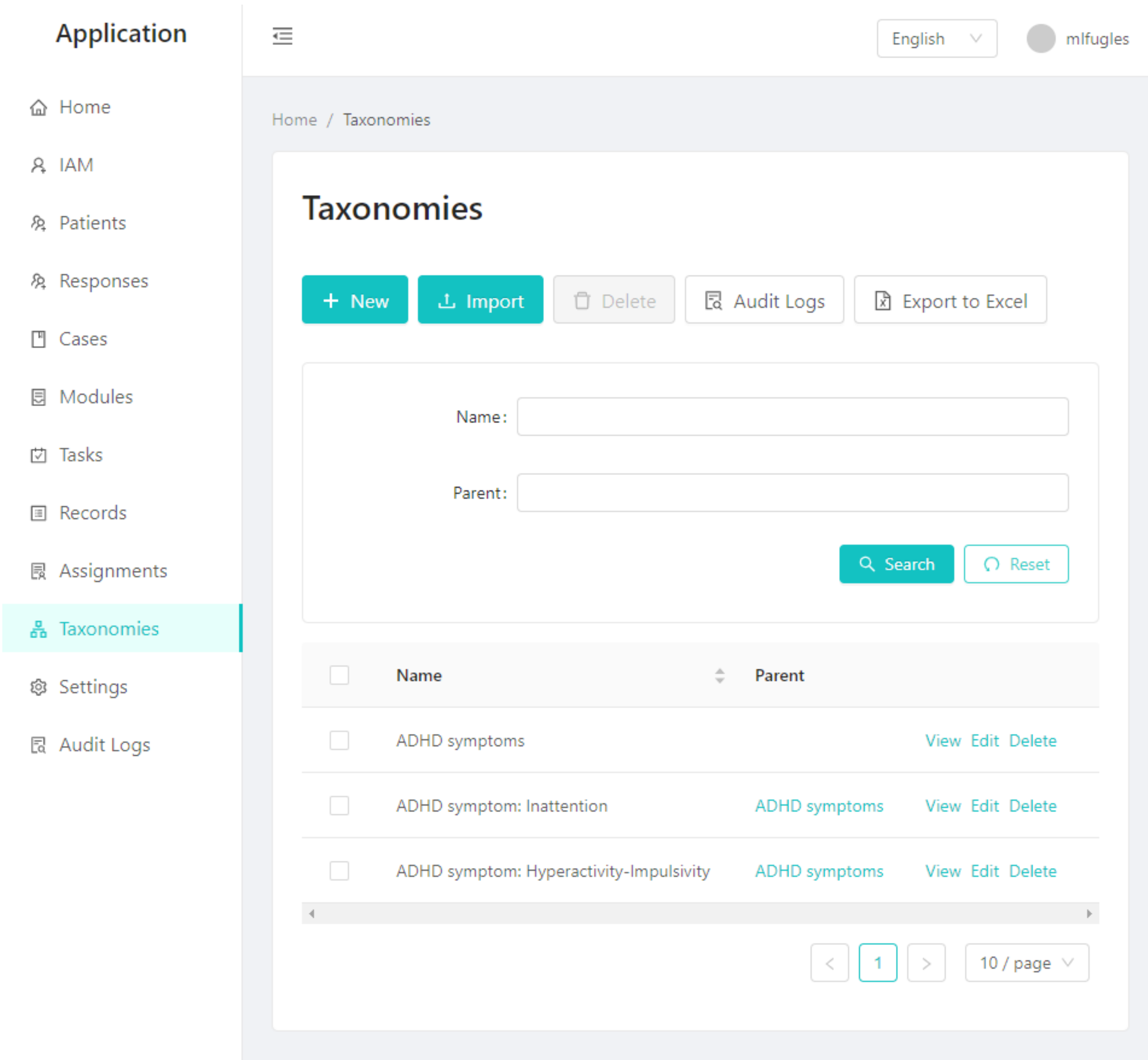


Figure 4.10: The list of taxonomies displayed in the UI of the IDPT framework.

```
Taxonomy:  "ADHD Intervention Example"
├── Diagnosis:  ADHD
│   └── ADHD symptoms
│       ├── ADHD symptom:  Inattention
│       └── ADHD symptom:  Hyperactivity-Impulsivity
└── Age group:  Adult
    ├── Age group:  18-25
    └── Age group:  40-60
```

Figure 4.11: An example taxonomic hierarchy that may be used to annotate the treatment content in an intervention for adults with ADHD.

Assigning Taxonomies to Cases, Modules, and Tasks

As explained in Section 2.4, the hierarchy of treatment components consisting of cases, modules and tasks is a central part of IDPT. In this project, we have extended the implementation of these components in the IDPT framework so that it is possible to assign a list of taxonomies to any case, module or task. This enables the designation of hierarchical labels or annotations which may be used to filter treatment materials in the future.

In practice, this means that we have realized the concept conveyed in Figure 4.3 in our implementation. We will now demonstrate how we can recreate this specific example in the IDPT framework using cases, modules, tasks and taxonomies. Firstly, we recreate the case, module and the two tasks used in this hierarchy (Figure 4.12), in addition to a taxonomy corresponding to the hierarchy shown in Figure 4.11. Relevant taxonomies can then be used to annotate the treatment content by assigning them to the suitable case, module or task in order to to obtain the annotated hierarchy visualized in Figure 4.13. This recreation in the IDPT framework may be viewed in Figure 4.14.

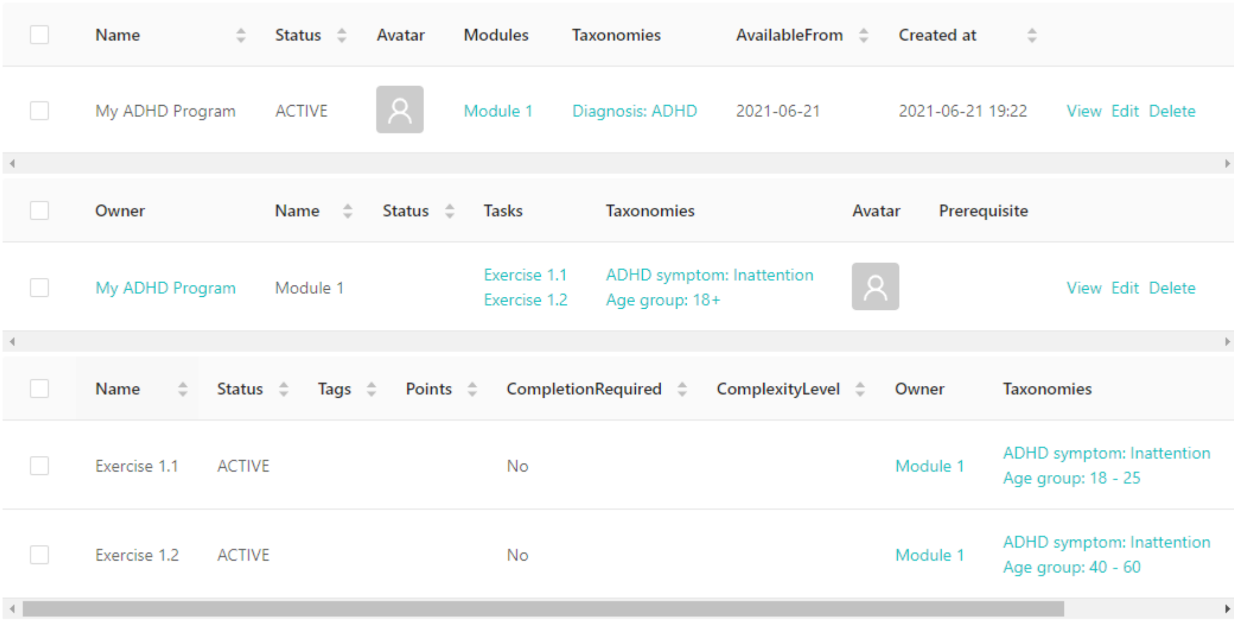
In our example, we utilized two small, custom-made ontologies representing some aspects of ADHD and some age groups within the adult category, respectively. However, as discussed in Section 2.3, it is beneficial to adhere to standardized, well-established health terminologies where possible to improve interoperability. For example, instead of using the annotation "Diagnosis: ADHD", we may use the corresponding codes in terminologies such as

```
Case:  "My ADHD program"
  modules:
    Module 1
      tasks:
        Exercise 1.1
        Exercise 1.2
```

Figure 4.12: A simplified representation of the treatment component hierarchy shown in Figure 4.3.

```
Case:  "My ADHD program"
  taxonomies:
    Diagnosis:  ADHD
  modules:
    Module 1:
      taxonomies:
        ADHD symptom:  Inattention
        Age group:  Adult
      tasks:
        Exercise 1.1:
          taxonomies:
            Age group:  18-25
            ADHD symptom:  Inattention
        Exercise 1.2:
          taxonomies:
            Age group:  40-60
            ADHD symptom:  Inattention
```

Figure 4.13: The same hierarchy as in Figure 4.12 annotated with taxonomies from Figure 4.11.



	Name	Status	Avatar	Modules	Taxonomies	AvailableFrom	Created at	
	My ADHD Program	ACTIVE		Module 1	Diagnosis: ADHD	2021-06-21	2021-06-21 19:22	View Edit Delete

	Owner	Name	Status	Tasks	Taxonomies	Avatar	Prerequisite	
	My ADHD Program	Module 1		Exercise 1.1 Exercise 1.2	ADHD symptom: Inattention Age group: 18+			View Edit Delete

	Name	Status	Tags	Points	CompletionRequired	ComplexityLevel	Owner	Taxonomies
	Exercise 1.1	ACTIVE			No		Module 1	ADHD symptom: Inattention Age group: 18 - 25
	Exercise 1.2	ACTIVE			No		Module 1	ADHD symptom: Inattention Age group: 40 - 60

Figure 4.14: The annotated hierarchy of treatment components realized in the IDPT application. The first table lists the case “My ADHD Program”, the second lists the module “Module 1”, while the third lists the two tasks “Exercise 1.1” and “Exercise 1.2”.

```
Case:  "My ADHD Program"
├── taxonomies:
│   ├── ICD-10:  F90.9
│   └── SNOMED-CT: 31177006
└── modules:
    └── ...
```

Figure 4.15: In this example, we use the well-established health terminologies ICD-10 and SNOMED-CT to annotate our case with codes representing the diagnosis ADHD (*2021 ICD-10-CM Diagnosis Code F90.9* 2021) (*31177006 : Attention Deficit Hyperactivity Disorder, Combined Type (Disorder)* 2021)

ICD-10 and/or SNOMED-CT. Since we allow the treatment components to keep a list of taxonomies, it is possible to assign multiple of these terminologies with an equal level of importance. An example of what a case annotated with standard terminology codes could look like is shown in Figure 4.15.

The taxonomy referred to in each case, module and task presents information on some abstraction level (such as diagnosis level). If that taxonomy has descendants, it may be further expanded to present the subtrees, which offer additional details (such as specific symptoms of a diagnosis). This way, we lay the groundwork for offering the user a method for selecting the preferred level of abstraction or detail.

Chapter 5

Research Evaluation

In this chapter, we describe how we evaluated the artifact with the aid of domain experts of psychology. Two meetings were held in which we presented the artifact and received feedback from the experts. The first meeting resembled an unstructured interview, while the second was specifically conducted as a semi-structured interview.

5.1 An Unstructured Midway Evaluation

As described in Section 4.1.2, a meeting with two domain experts from INTROMAT and a developer from Helse Vest IKT was held in order to discuss the future of the content library project. During this meeting, we presented the state of the dimensional model at the time to the domain experts. The purpose was to gauge the experts' interest in utilizing the dimensional modeling approach to support reuse of treatment materials, particularly in the context of the content library, and to elicit suggestions for improvement.

Due to time constraints, and because the meeting was not wholly dedicated to the presentation of our artifact, we did not have the opportunity to conduct a comprehensive interview with some degree of structure. Instead, the format of the meeting resembled an unstructured interview, which according to

Seaman (1999) is characterized by a lack of or few predefined questions, and where the interviewer's objective is to obtain as much information as possible on a broad topic. During and after the presentation, we allowed the experts to give concrete feedback and suggestions for future iterations of the model. The concrete suggestions were detailed in Section 4.1.2.

In addition, the meeting was used as an opportunity for the experts to give a midway evaluation of the dimensional modeling approach with respect to the reuse aspect. The feedback from the domain experts was predominantly positive — they expressed that the use of taxonomic annotations was promising for supporting reusing treatment materials in new interventions. Overall, they judged the chosen dimensions and their organization to be a sensible starting point for the dimensional modeling approach for IDPT.

In hindsight, the unstructured nature of the evaluation did not elicit a particularly detailed evaluation, and a more structured interview likely would have been more valuable for our project. Thus, in future research on this topic, we recommend performing a more thorough and structured evaluation of using dimensional modeling in IDPT with respect to reuse.

5.2 A Semi-Structured Interview with Domain Experts

In order to evaluate the dimensional modeling approach presented in this thesis, a semi-structured interview with two domain experts of psychology was conducted. While the previous meeting with other domain experts described in Section 4.1.2 focused on reusing treatment content from multiple interventions, the topic of this interview concerned adapting treatment to user needs within a specific intervention. Both of the domain experts interviewed are psychologists with prior experience with the use of IDPT systems for people with ADHD.

According to Hove & Anda (2005), it is common to utilize qualitative research methods to fulfill research goals in software engineering research that are qualitative in nature. Thus, we chose the semi-structured interviewing method because of its capability to provide relevant qualitative data using both predefined questions about a topic in addition to unforeseen observations and impressions (Seaman 1999). Performing semi-structured interviews tends to be costly (Hove & Anda 2005), however, the cost of performing this interview was low due to only interviewing two domain experts once.

The interviewing process was comprised of two stages.

1. In the first stage, the updated version of the dimensional model (Figure 4.6) was presented to the domain experts. The presentation also included two example cases for usage, in addition to a simple non-interactive prototype and a verbal description of how we envision this to be used in future interventions.
2. After the presentation, we moved on to the second stage of the interview. The experts were then asked to verbally answer thirteen predefined questions (and one spontaneous follow-up question) about their experiences with IDPT and their opinions on the presented dimensional model.

The format of the meeting allowed for general questions and feedback from the experts at any point in both stages.

The questions presented in the second stage, the corresponding answers, and related reflections are detailed in Appendix A. For the sake of brevity, the answers (which were transcribed during the interview) have been paraphrased and compiled into bullet points. In addition, the feedback and answers to the questions were originally given in Norwegian, and thus they have been translated into English. As the interview occurred as a conversation with both experts simultaneously where they would often build their answers off each others' contributions, we do not distinguish between their answers to the questions. The exception to this is the first question, as it concerns the experts' professional backgrounds and experience with IDPT.

5.2.1 Interview Results

The experts' reactions to the presentation of the dimensional model were primarily positive. However, aspects of the model were also met with some skepticism.

On the one hand, they expressed that the model was neatly organized, and that it was a good representation of the dimensions of IDPT. Domain expert 2 (as described under Q1 in Appendix A) was particularly interested in the idea of using the model in the context of Sequential Multiple Assignment Randomized Trials (SMART) designs, which are used to obtain high-quality data for building adaptive interventions (Lei et al. 2012). In general, both experts interpreted the model as an adequate starting point for future research.

However, they also suggested moving some of the subdimensions to another place in the hierarchy, as their current placements seemed inaccurate. For instance, one proposal was moving the "Emotional regulation" subdimension out of the "Symptoms" subhierarchy, as emotional regulation is not a symptom, but rather a measurable mental process.

The presentation of the model also prompted a discussion about the relationship between diagnoses and symptoms, and how this could be reflected in the model's hierarchy. The experts commented on the separation of the "Reported diagnoses" and "Symptoms" hierarchies; expressing that the relationship between the two as reflected in the hierarchy may differ based on the premise of each individual intervention. For example, in an intervention that is intended for users with a specific diagnosis already established, the "Reported diagnosis" dimension may be suited as an ancestor of the "Symptoms" hierarchy, as the diagnosis is a precedent for measuring the user's symptoms in the intervention. In the case of an intervention that assesses the users' symptoms for the purpose of diagnosing them, however, the symptoms would come before the diagnosis in the process. Here, it may be better to reflect this process by letting "Symptoms" be an ancestor to "Diagnoses".

Furthermore, domain expert 1 noted the *transdiagnostic* nature of the model. According to Fusar-Poli et al. (2019, p. 192), “a transdiagnostic approach in psychiatry is expected to cut across existing categorical diagnoses and go beyond them, to produce a better classification system, compared to the existing gold standard”. As domain expert 1 remarked, a diagnosis is merely a set of symptoms of which one must have a certain subset in order to get that diagnosis. Moreover, overlap in symptoms between different diagnoses is common. Based on this, domain expert 1 noted that the model may hold the potential to be particularly useful for representing interventions made for users with a wide variety of symptoms, regardless of diagnosis.

When asked about their experiences with data representation in intervention applications, the main problem discussed was proper management of interaction data. While their experiences with extracting, organizing and analyzing psychometric questionnaire results have been positive, interaction data had typically been poorly represented in a way that inhibited their clinical workflow. Thus, structuring interaction data in a sensible manner requires attention in the development of future IDPT systems. The experts suggested that in order for this to improve, the communication between clinicians and developers of IDPT must improve as well.

In addition, the experts had an optimistic view of the introduction of measurements to the dimensions and their involvement in user profiling. They suggested that primarily using psychometric questionnaire scores to measure the user gives does not provide a sufficiently nuanced snapshot of the user’s mental health status. The experts expressed an interest in supplementing the user profile with measurements such as answers to open-ended questions, physiological data, or speech recognition. However, they also noted that this would require further research into each of these measurements and how effective they are when used in IDPT.

Results from this evaluation and the feedback from the meeting discussed in Section 4.1.2 provide valuable insight into how this model may be useful for designing and improving IDPT systems. In general, the experts’ impression of the model was that it is an interesting avenue to explore in future interventions. However, thorough empirical testing of its contents is required to fully understand its potential. Further testing and improvement of the model will be left described as future work in Section 7.2, as this reaches beyond the scope and time constraints of this thesis.

Chapter 6

Discussion

In this chapter, we discuss the results of this thesis. This entails a presentation of the findings derived from the design process, the development of dimensional models and the related data structures, and the research evaluation. We will provide answers to the research questions defined in Section 1.3, reflect on this thesis' contributions to the knowledge base, and discuss the limitations that affected the project.

6.1 Answering the Research Questions

This section presents answers to the research questions introduced in Section 1.3.

RQ1: How can a dimensional modeling approach be implemented to support reuse of treatment content in interventions for mental health?

The first research question was primarily answered in Chapter 4 and Section 5.1. We used the intervention content library described in Section 3.2.1 as a starting point for this work. In particular, through the experiments with the dimensional modeling approach described in Sections 4.1.1, and with the feedback and evaluations given by the first set of domain experts presented in Section 4.1.2 and Section 5.1, we gained insights into how we can annotate the treatment content in IDPT in a way that may help support reuse in future interventions. These insights were used to propose a format for these taxonomic annotations in Section 4.2. We then discussed the implementation of a simplified version of the data structure in Section 4.3.3.

As discussed in Section 4.1.2, choosing between allowing free creation of new taxonomies at any time and utilizing rigid, predefined taxonomies is a central problem that must be considered in future implementations. Based on the discussion we had with the domain experts and the representative for the content library, choosing predefined taxonomies appears to be the safer option, as it enables us to avoid noise in the content library. However, this means that we likely need a mechanism that allows adding new taxonomies in a controlled manner, to avoid situations where clinicians are unable to annotate their intervention because no relevant taxonomies are available. Exactly what this entails goes beyond the scope of this thesis, and requires further development and testing in the future.

Thus, in order for the dimensional modeling approach to support reuse of treatment materials, we envision the further development of a useful taxonomic data structure for annotating the interventions with hierarchical metadata. The data structure presented in this thesis needs further testing before we can ascertain whether it is useful, and which aspects of it must be altered. In addition, it is necessary to examine the issue of standardizing the annotations within a specific content library, and to identify to what degree of restricting free taxonomy creation leads to the best user experience for clinicians using the library.

RQ2: How can a dimensional modeling approach be implemented to support the adaptation of treatment to user needs within a specific intervention?

The second research question was addressed in Chapter 4, Section 5.2, and Appendix A. In Chapter 4, we described the development of the dimensional model and a preliminary implementation of it in the IDPT framework, and in Chapter 5 and Appendix A, domain experts evaluated its potential to support personalization in IDPT. As mentioned in Section 3.2, we adjusted the artifact to fit this use case in the fourth iteration of the design process.

By conducting the semi-structured interview, we found that implementing the dimensional modeling approach in IDPT for the purpose of supporting adaptive treatment is worth further investigation. With some exceptions, the feedback indicated that the overall organization of the dimensions was sensible, and that surveying the user with respect to different dimensions appears to be a promising approach. In particular, the experts noted that relying solely on psychometric test scores to assess the user does not provide sufficiently nuanced data. Thus, they expressed their interest in assessing the user with respect to other measurements, including answers to open questions, speech recognition, and physiological data such as heart rate. However, further research into identifying effective measurements for the various dimensions must be conducted.

Moreover, the experts stressed the importance of good multidisciplinary communication when developing IDPT systems, and that implementing the dimensional modeling approach would be no exception. In previous experiences with IDPT in studies, there had been miscommunication between clinicians and developers where poor labeling of user data led to difficulties in data analysis. With clearer communication across the disciplines, this may have been avoided. Building on this, the experts emphasized that ensuring satisfactory data management in IDPT systems will likely be essential for implementing the dimensional modeling approach successfully.

In conclusion, in order to implement the dimensional modeling approach to support adaptive personalization, we must identify appropriate measurements for the dimensions and test them, in addition to promoting strong multidisciplinary communication and proper data management.

6.2 Research Contributions

Following the fourth guideline of design science by Hevner et al. (2004) (as described in Section 3.1.1), our research should yield valuable contributions to the area of the design artifact, namely IDPT. A summary of the contributions yielded by the project follows.

Our goal was to create a dimensional model for IDPT that serves as a foundation for making reuse of treatment material and adaptation of IDPT content easier to implement in future interventions. In particular, we endeavored to lay the groundwork for a solution that addresses the difficulties previously encountered by clinicians of INTROMAT when dealing with unstructured intervention data. By involving domain experts with experience with IDPT in the design and evaluation processes, we conclude that the artifact demonstrates the application of dimensional modeling in a new area, thus applying existing methods in new ways. It also represents a hypothesis that remains to be tested empirically in future work. Thus, the artifact itself constitutes our main research contribution to the knowledge base. Additionally, we contribute the data structure presented in Section 4.2 and implementation described in Section 4.3.3 as examples of how the concept presented in the artifact may be transferred to IDPT systems in practice.

Some of the aspects of the model that were hypothesized to be specifically useful in comparison to other solutions were uncovered during the semi-structured interview with the domain experts. For instance, the experts pointed to its capability to communicate the concept of hierarchical structures to clinicians in a clear manner. They had been exposed to the concept presented in this thesis in previous meetings, but had trouble understanding its potential before the interview. Moreover, they cited difficulties with multidisciplinary communication as a pain point in previous projects, and suggested that the ideas communicated in the model may aid in improving this in future projects.

Furthermore, the structure of the model was theorized to be useful for examining the components of an intervention on different abstraction levels.

According to the experts, it is common to declare an intervention either as effective or not effective, without identifying the exact source of the effectiveness. The separation of different components of IDPT in the model appears to hold the potential for identifying exactly which aspects of an intervention are effective. The experts stated that this may aid in making replication of results easier in future studies on the subject.

The experts described the dimensional modeling approach to IDPT as transdiagnostic. They suggested that this property implicates that the model may be particularly suited for assessing heterogeneous patient groups, e.g. patient groups who may experience a wide range of symptoms. People with ADHD is one such group that is characterized by great diversity in clinical profiles and symptom manifestation (Luo et al. 2019). Since the dimensional modeling approach allows for annotation of content material with a variety of symptoms and other personal characteristics, it may make it easier to create personalized interventions aimed at heterogeneous patient groups, which is known to be challenging (Nordby et al. 2021).

When asked about what user characteristics the experts judged to be especially important for tailoring IDPT content to users, this combination of personal difficulties and strengths was brought up, along with adherence, content type preference and enjoyment of tasks. They also suggested that another advantage with the structure of the model is that it not only leaves room for conceptualizing a person's difficulties (such as symptoms), but also personal strengths — for instance, ADHD is associated with creativity (Boot et al. 2017). Thus, the ideas presented in the artifact may lay the groundwork for the development of better user profiling in IDPT in the future.

6.3 Reflections

6.3.1 Choosing Design Science and Qualitative Methods

We found design science to be a suitable research method for our project. It provided a straightforward framework for conducting our research, in addition to helpful guidelines for how to design, develop and evaluate an artifact that represents our contributions to the problem domain.

In terms of the evaluation, we also found interviewing domain experts of psychology was an appropriate method for evaluating the artifact, as our project was centered around improving the workflow of clinicians working with IDPT. The interviews yielded useful information, both as answers to specific questions and other astute insights. However, it likely would have been beneficial to evaluate our work using other methods as well, such as evaluating the usability of our implemented work.

In retrospect, it would also have been advantageous to perform a more structured interview with the first set of domain experts. With more structure, we may have gotten more concrete feedback for the use case focused on reuse of treatment materials. Fortunately, we used this lesson to prepare a semi-structured interview for the second set of domain experts, which yielded a more concentrated evaluation of the dimensional modeling approach.

6.3.2 Revisiting the Design Process

The design process of this project was affected by a number of delays. For instance, establishing contact with the domain experts in the initial stages of the project to the extent that the ADHD case could be chosen took longer than necessary. Additionally, a considerable amount of time passed between requesting access to the MinADHD interaction data and receiving it. Unfortunately, this led to loss of time that could have been utilized to improve the artifact and the IDPT framework extension. Aside from the suboptimal time utilization, the iterative format of the design process aligned well with the project.

As with the final evaluation, having access to input from domain experts at multiple points throughout the project was valuable for guiding the development process.

6.3.3 Reflecting on the IDPT Framework Extension

As mentioned in Section 2.5, we were unable to review the data management methods in existing solutions, as the solutions we encountered were not open-source. Our experience with contributing to an open-source framework was therefore positive, as we envision that making implementation details publicly available facilitates research further into this field. Additionally, the open-source nature of the IDPT framework facilitates reuse of our work in future implementations.

Over the course of the project, we did not encounter any cases of taxonomies that could not be modeled as a tree. Thus, following MongoDB's parent references pattern instead of keeping a list of parents would likely have reduced the complexity of the feature slightly. This means that we also could have implemented cycle prevention. However, we do not wish to rule out the possibility that future testing may uncover examples of taxonomies that can be modeled as a graph or a cycle.

For the purposes of readability, we have used intuitive names and measurements in our taxonomy examples. However, in future implementations, we propose using existing ontologies where applicable, such as ICD-10 and SNOMED-CT for representing diagnoses in order to promote interoperability and standardization.

Largely due to the delays mentioned in Section 6.3.2, we were unable to implement all of the features we envisioned in the IDPT framework. These features are mentioned in Section 6.4.

6.4 Project Limitations

The execution of this project was limited by multiple factors.

Firstly, after reviewing literature on IDPT applications, we found that it was very uncommon for these systems to have an overview of their architecture or source code publicly available. This meant that it was difficult for us to perform a thorough comparison of our work to existing solutions. Our main source of information on how certain solutions operated under the surface was the domain experts we interviewed. Ideally, we would have liked to gain direct access to the architecture of multiple existing systems in order to learn about their solutions, their strengths and their shortcomings, which in turn could have been put to good use when developing our own solution in the IDPT framework.

Furthermore, time constraints limited the scope of our implementation work in the IDPT framework. This resulted in fewer features implemented than what we had planned initially. In particular, we would have preferred to extend our taxonomy implementation to include measurements as expressed in our general representation in Section 4.2.1, to experiment with the data structure, and to have this version evaluated by domain experts. Additionally, we would have liked to implement the visualization of taxonomies, and to have this feature evaluated as well.

Finally, only a small number of domain experts were available to be interviewed during the project. In order to get an in-depth idea of how to best adapt the hierarchical structures to help the clinicians, it would be beneficial to interview a larger number of potential users in the future.

Chapter 7

Conclusion

Through this thesis, we have investigated the application of dimensional modeling in the domain of IDPT. Our work represents a starting point for future research into how this approach may be applied further to interventions for mental health.

7.1 Summary

Using design science as our chosen research method, we have developed a dimensional model representing the various components of IDPT as our primary artifact. The development of this model was guided by feedback given by multiple domain experts of psychology. We have focused on two particular use cases, namely (1) reuse of treatment content and (2) adapting treatment to user needs. In addition to the model, we have experimented with the development of a data structure that can represent this model's structure, and implemented this partially in an existing web framework for IDPT.

Through an iterative design and development process, and qualitative evaluations of our work, we conclude that it represents an adequate starting point for future research within the area of IDPT.

In retrospect, aspects of the project would have benefited from doing things differently. For instance, it would have been advantageous to the project to perform a more thorough evaluation. With fewer time constraints, we would have preferred to perform semi-structured interviews with more domain experts in order to obtain more data, particularly about the use case centered around reuse. Additionally, the project likely would have benefited from having more time dedicated to adding measurements to the taxonomies in the IDPT framework.

7.2 Future Work

Further research remains to be conducted to fully investigate the potential of this dimensional modeling approach in the context of IDPT.

One issue that needs further examination is measurements. Firstly, in order to assign measurements to the various dimensions in our model for user profiling purposes, we need to identify which measurements are suitable for each of the dimensions. In particular, for the purpose of improving user adherence, we are interested in identifying a mechanism for measuring the user's engagement and motivation, so that we can optimize the treatment content based on these metrics. Furthermore, we suggest adding measurements to the taxonomies in the IDPT framework, and taking these into account when performing user profiling in the future. This implementation could be used in further research to study whether these measurements have a positive effect on user adherence.

Another feature that we suggest adding to the IDPT framework in the future is a tree- or graph-based visualization for taxonomies. The intention behind this idea is to create an intuitive mechanism for navigating the hierarchy of taxonomies visually instead of relying on information about each taxonomy's parents to infer the structure of the hierarchy.

Finally, in our semi-structured interview, the domain experts expressed that while the dimensional modeling approach is promising, it remains a hypothesis at this stage. Extensive empirical testing is needed before we can fully conclude regarding its usefulness.

List of Acronyms and Abbreviations

AAQoL	Adult ADHD Quality of Life Questionnaire.
ADHD	Attention Deficit Hyperactivity Disorder.
API	Application Programming Interface.
ASRS	Adult ADHD Self Report Scale.
CBT	Cognitive Behavioral Therapy.
CRUD	Create, Read, Update, and Delete.
GMT	Goal Management Training.
ICD	International Statistical Classification of Diseases and Related Health Problems.
ICD-10	International Statistical Classification of Diseases and Related Health Problems 10th Revision.
IDPT	Internet-Delivered Psychological Treatments.
INTROMAT	INTROducing Mental health through Adaptive Technology.
MINI	Mini-International Neuropsychiatric Interview.
PHQ-9	Patient Health Questionnaire-9.
SMART	Sequential Multiple Assignment Randomized Trials.
SNOMED-CT	Systematized Nomenclature of Medicine – Clinical Terms.
SUS	System Usability Scale.
UI	User Interface.

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Appendix A

Answers to the Semi-Structured Interview

Below follow the answers to questions asked to domain experts in the semi-structured interview described in Section 5.2.

Q1: What are your experiences with Internet-delivered psychological treatments?

Domain expert 1

- Clinical neuropsychologist with experience with the investigation of different patient groups.
- Domain expert for INTROMAT's ADHD case.
- Experience with GMT studies for ADHD.

Domain expert 2

- Psychologist with experience with intervention studies with INTROMAT, including GMT studies for ADHD.
- Most of the prior experience has been with Internet-based interventions.

Q2: What types of measurement methods have you typically utilized when assessing the users in an intervention?

- The primary measurement method is assessing symptoms using psychometric questionnaires.
- Online self-reporting of self-compassion, cognitive difficulties (e.g. emotional regulation).
- One disadvantage with self-reports is that they can be biased.
- In studies with physical meetings with participants, cognitive tests have been used. These are difficult to use in fully Internet-based studies.
- Simplified diagnostic assessments of study participants have been conducted by telephone. A diagnostic test called Mini-International Neuropsychiatric Interview (MINI) has been used to assess whether a potential participant had to be excluded from the study due to psychological problems beyond the scope of the study. This data was not used in the study beyond checking exclusion criteria.

Q3: What types of measurement methods have you typically utilized when assessing aspects of the intervention itself?

- Self-reported user evaluation of the intervention's usability using System Usability Scale (SUS).
- Post-study interviews with users who were asked what they liked or did not like about the intervention.
- Qualitative feedback in focus groups.
- Qualitative usability testing of the interventions.
- The participants answer open questions about the intervention in writing, such as what they liked about the intervention, what can be improved, and what aspects of the intervention were the most or the least useful for them.

Q4: If you were to make adjustments to an intervention to improve the treatment it offers, which parameters would you ideally consider?

- Testing the intervention and consulting with people with ADHD. Designing an intervention is a long process, and many changes are made along the way. Changes to the interventions are made based on the feedback.
- A previous small study on adaptive assignment of exercises has been conducted. However, no significant effect was observed. Adaptive assignment of exercises is still an interesting avenue that should be explored more in the future.

Q5: Are there any measurements that would be particularly useful for clinicians who want to improve the effectiveness of an intervention that are not usually available?

- More types of measurements are needed so that the data gathered on the users is nuanced.
- Only using psychometric tests such as ASRS do not provide enough sufficiently nuanced information about the users.
- Some measurements that may add more nuance are answers to open questions, speech recognition, and physiological data (e.g. heart rate).
- However, more types of data increase the complexity of the analysis process.
- Substudies must be conducted for each of the measurement types, especially the physiological measurements, in order to understand their effect on interventions.

Q6: Have you experienced limitations due to the way data is presented to clinicians in the intervention application? If so, how has this affected the analysis work?

- Proper representation and management of intervention data is very important for the analysis process.

- In previous projects, data management has not been good enough.
  - The psychometric questionnaire data has been fairly easy to handle, as this generally is well labeled, and the numeric values are easy to interpret.
  - Interaction data has not been managed in a good way. They have not been labeled in a good way, which makes searching, sorting and organizing the data very difficult.
  - For example, treatment modules were labeled by week number. This was not reflected in the interaction data related to the modules, which made organizing the interaction data by module challenging. As different users completed tasks in the same time periods, the overlap between the timestamps in data made analysis unnecessarily difficult.
  - It has also been difficult to get an overview of the interaction data because there are so many entries. For instance, each user login was registered, meaning there were a large number of login data entries. The same could be said for whether or not a user had been sent a reminder to use the intervention.
  - In some cases, the format of the interaction data makes it untrustworthy. For example, the system would mark a module as finished by a user if they had clicked through every element. However, this says little about whether the users have actually internalized the contents.
- Ensuring proper data management would be a central issue when using the dimensional modeling approach.

Q7 (follow-up question to Q6): What does good data management entail for interventions?

- The data should be aggregated in one platform and organized into tables. Searching these tables should be easy. Manual organization and grouping of data should be minimized.

- Clear communication between clinicians and the designers of the platforms is important to achieve this.

Q8: Is there anything in the data that you as clinicians would like to be able to search for in intervention data that may be difficult in the applications you have used?

- Searching by labels should be easier, especially for data entries that include timestamps.
- In general, searching by timestamp should be easier.

Q9: What are your thoughts on the dimensional modeling approach to grouping intervention data, with respect to how useful it may be for clinicians in your positions?

- The model is organized tidily, and may be particularly useful when using SMART designs.
- It appears to be important, although we are unaccustomed to organizing complex, heterogeneous data into boxes and arrows.
- It appears to be a good starting point, though the contents will ultimately determine its usefulness.
- The examples cases were good.

Q10: Is there anything you would like to change about the dimensional model?

- Emotional regulation should be removed from symptoms.

Q11: How do you think this dimensional modeling approach would augment clinicians' workflow, if at all?

- Clinicians would get more accustomed to this way of thinking if they were exposed to it.
- Multidisciplinary work related to interventions would be improved.
- Normally, an intervention as a whole is identified as effective or not effective. Models such as this may be helpful for identifying which parts of an intervention are effective. It is possible that this division of intervention components would make replication of study results easier.

Q12: What are your thoughts on whether this dimensional modeling approach would be helpful in understanding patterns in how different patients interact with the intervention contents?

- The model is a good starting point, but it is a hypothesis that must be tested empirically. Testing small parts of the model at a time could be useful. This would be a long empirical process, however.

Q13: Do you see any use cases where this approach would be particularly helpful for clinicians?

- It appears to be especially useful for heterogeneous users groups, such as people with ADHD. They often differ greatly from day to day, meaning observing patterns over greater time periods is important.
- The model may be useful for assessing users' positive traits. For example, people with ADHD tend to have certain personal strengths, such as creativity or high energy.
- The approach may be less useful for less heterogeneous groups, such as people with anxiety.
- The model appears to be transdiagnostic.

Q14: What parts of a user profile are the most relevant for adaptively suggesting content to a user, in your opinion?

- A combination of difficulties (e.g. symptoms) and resources (e.g. personal strengths).
- Adherence. It is important to know whether some users tend to finish modules quickly, or not at all.
- Which types of tasks the users prefer.
- The degree to which users enjoy certain tasks.