A Visual Analytics Dashboard to support iCBT Therapists

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Abstract
This research lifts Internet-based Cognitive Behavioural Therapy (iCBT) further by introducing visual analytics dashboard techniques to facilitate iCBT therapists in organising and carrying out their work in a potential more efficient way. Following a design science methodology we developed a web-app and dashboard that processes standardized mental health screening questionnaires and visualizes the result at both individual patient and group levels. The dashboard was evaluated through user testing and semi-structured interviews by two experts (one psychiatrist and one psychologist), who responded with great interest and enthusiasm, and gave suggestions for further development. Finally, scalability issues using HL7 FHIR are addressed.

Keywords
Mental Health, iCBT, Dashboard, Visual Analytics, Visualization, Decision Support, FHIR, Interoperability.

1 INTRODUCTION

Mental health disorders constitute the single largest source of health-related economic burden worldwide [1]. According to a recent Lancet Commission report, mental disorders are recognized as a continuously growing problem worldwide, and are expected to reach an US$16 trillion impact by 2030 [2]. The majority of these costs are indirect, such as social security and welfare, costs related to law and order, and loss of productivity. The minor direct costs relate to healthcare, medicine, and other therapies.

In 2018 an OECD report calculated the economic impact of mental illness to average more than 4% of GDP in the EU countries, with Norway placing 5th at 4,97% [3]. Furthermore, the WHO considers mental illness to be the leading cause of disability worldwide [4].

Cognitive Behavioural Therapy (CBT) is a well-documented therapy used to treat patients with a variety of mental disorders with good results [5]. CBT treats mental problems through challenging and actively changing dysfunctional emotions, behaviours, and thoughts, while promoting well-being. In a therapist-patient, one-to-one setting, the therapist's role is to assist the patient in finding and practicing effective strategies to address identified goals and decrease symptoms of the disorder. Despite CBT being acknowledged as a long-term cost-effective therapy when compared to the use of drugs, or in combination with drugs [6], it has been widely accepted over the last two decades that the healthcare system does not have the capacity to deal with the growing numbers in need for treatment through traditional CBT. This has been one of the main motivations for Internet-based Cognitive Behavioral Therapy (iCBT) [7], which makes CBT more accessible and efficient. Therapist guided iCBT has shown the same efficacy as regular CBT for some patient groups [8], while reducing the time required per patient for the therapist.

We propose that introducing visual analytics dashboards to guided iCBT is one area that has great potential for improving the cost-benefit ratio of CBT. Dashboards will provide the therapist with much needed visual decision support functionalities for dealing with individual patients, as well as supporting a better and more efficient organisation of their workflow.

2 BACKGROUND

2.1 Important variations in CBT and iCBT

iCBT can take the form of guided or unguided self-help programs [7] [9]. In guided iCBT, a therapist guides the patient through the treatment program using electronic asynchronous communication such as email or messages, typically through a patient portal. Systematic reviews of literature reporting on outcomes from the two types of iCBT conclude that unguided self-help, also referred to as "stand-alone" programs, are known to have poorer outcomes and higher dropout rates than guided programs [7] [9]. In another systematic review of iCBT for depression, it was found that the difference in the numbers completing iCBT was dependent on who provided the guidance, favouring therapists-guidance (72%) over administrative support (65,2%), although both had much better results than unguided iCBT (26%) [10].

Cost wise, unguided iCBT has the lowest cost per patient, while traditional face-to-face CBT is by far the most expensive therapy. With qualified psychologists and psychiatrists being a scarce resource and with traditional CBT having a high cost, iCBT and other Internet therapies will play an even more significant role in a future with a growing number of people suffering from mental disorders.

In recent meta-analyses on iCBT it is argued that unguided iCBT might be the most efficient way to scale up iCBT, also when looking at cost-effectiveness [11] [12]. We feel that there is an important aspect missing in these discussions. As guided iCBT is more effective, but more costly due to the involvement of a therapist – can we find innovative ways to improve and scale-up guided iCBT with respect to the quality of therapy, the adherence/dropout rate, and therapist capacity? These are important challenges that should be addressed in an attempt to improve guided iCBT and make it more cost-effective.

2.2 Looking at eMeistring for improving iCBT

eMeistring is a guided iCBT program addressing panic disorder, depression, and social anxiety through different modules, that has been in successful routine clinical use in Bergen since 2013 [13]. The program has shown the same outcome as regular CBT for some patient groups, while reducing the time required per patient for the therapist. Therapists working with eMeistring can help 10-12 patients per day, while therapists providing traditional face-to-face CBT had 3-4 consultations per day [14]. Due to its proven success, eMeistring is now in regular use in other regions of Norway as well.

Brainstorming ways to improve eMeistring, together with a psychiatrist with long experience as a therapist using the platform, revealed a weakness that could be improved. eMeistring does not provide therapists with an overview of their patient's current status, nor their activities and progress over time. This is in part due to eMeistring being built on a platform that relies on data being stored in pdf-forms, a data format that is not well suiting to handing and analysing patient data. This is a data representation that is basically an electronic paper format, with all the limitations of having data stored as typed letters and numbers on pieces of paper. If a therapist wants to see a patient's progress over time, this requires opening a corresponding *set of .pdf files* and processing the content on their own. A better data representation would open for new possibilities in making more efficient and better quality use of the data for the therapists. Some of these challenges are also described by Folker et al. [15] in their analysis of iCBT treatments in Europe. Looking for a suitable data representation also has to comply with general requirements of interoperability standards for health data [16].

2.3 Visual Analytics Dashboard functionalities in iCBT, can it make a difference?

The nature of the asynchronous patient-therapist communication in iCBT opens up for new therapist workflow options. Visual analytics dashboard techniques have the potential to enable therapists to choose their workflow based on decision support made available through suitable and well-presented information, as opposed to having a strictly synchronous workflow. Determining workflow based on prioritization, rather than a predetermined sequence, has successfully been applied in other medical domains [17]. In CBT, therapists use a range of qualitative and quantitative data to provide guidance for their patients. In this paper, we limit ourselves to quantitative numerical data (e.g., sleep duration) and standardized mental health screening questionnaires that provide an overview of the patient's mental health at any given time. An eMeistring patient produces over 20 filled-in questionnaires during the course of treatment. Thus, as each therapist has multiple patients (generally 15-20), the amount of data available for each therapist is too large to make optimal use of in its current raw format.

Better presentations of the data can improve therapist workflow by removing the need to manually consider each data point. Providing automatic processing of complex data sets can further optimize therapist performance. By being given an overview of a patient's state through the available data, the therapist can tailor the treatment towards each single patient. Therapists will also be better equipped to prioritize within their group of patients. Combined, this can lead to both higher efficiency and efficacy of guided iCBT.

Data visualization and Clinical Decision Support (CDS) tools can contribute to providing insight both within the context of a single patient, and for a group of patients. Therapists can more easily identify trends in the data for a single patient, which can provide opportunities to customize the treatment to the patient. For a group of patients, a fast overview based on the visualised data can provide faster help for those in special need, as well as freeing more of the therapist's time for patients needing it the most. This resembles the medical technique of triage, where treatment providers assign each patient degrees of urgency depending on their need for care [18], although on a different time scale. A better overview of a group of patients with summary or status variables presented to express the need of each individual patient might also contribute to help the therapist organize her workday in a better way.

2.4 Dashboards and Visual Analytics

Thomas and Cook [19] define visual analytics as the science of analytical reasoning supported by interactive visual interfaces. While visual analytics includes visualization, it also considers the disciplines of decision-making, human factors, and data analysis [20].

By leveraging multiple disciplines, visual analytics aims to reduce the effect of information overload, and achieve higher utilization of large data sets. Procedures to automatically process data can be implemented, and when further automatic analysis are intractable, the result can be integrated with visualization and interaction techniques [20]. The techniques of visual analytics can be combined with dashboard techniques to create tools for continuous data processing and visualization. Such techniques have proven valuable within other health domains. Dashboard applications can be categorised into administrative or clinical dashboards. Common places to see clinical dashboards in healthcare are within Intensive Care Units. Clinical dashboards contribute to increasing efficiency, quality, safety, and clinician satisfaction in some situations [21]. In this paper we address the development of a clinical dashboard for iCBT.

2.5 Fast Healthcare Interoperability Resources

The HL7 FHIR standard [22] provides a common data format for health data. This is achieved by dividing data into logical resources where each resource represents a concept. The intention of the standard is to provide interoperability between health IT systems. For dashboards gathering data from various external sources, this is important. The clinical dashboard developed in this research makes extensive use of the FHIR Questionnaire, QuestionnaireResponse, and Observation resources.

3 METHOD AND DESIGN

In a Masters thesis by the first author, a design science approach was used to design and develop a clinical dashboard [23] as a web-app comprising two primary views: Master View and Detail View. The purpose of the dashboard is to display the overview and status of both a single patient (Detail View) and a group of patients (Master

View). The web-app uses FHIR to interface to the data source, and as such has the potential to support a wide range of iCBT treatments.

To our knowledge, and supported by extensive searches of the scientific literature databases Google Scholar and MEDLINE, this is the first implementation of a clinical dashboard within the domain of mental healthcare.

3.1 Master View

The Master View, see figure 1, is the landing page of the web-app. In this view, a therapist is presented with an overview of her group of patients. The view is designed to comply with Shneiderman's mantra [24], giving first an overview with possibilities to filter, and then details on demand. Status variables are presented to describe each patient. For particularly urgent patients, a warning string is presented. Each patient will have a progression string and numerical urgency score (if the data is present), with optional flags and warning strings.

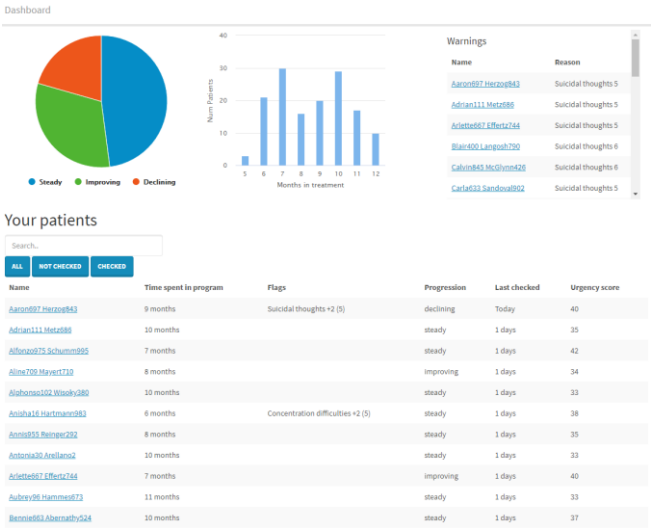

Figure 1 Master View

3.2 Detail View

The visualizations available in the Detail View, see figure 2, are dependent on the data available from the resource server. All QuestionnaireResponse and Observation resources for the patient are pulled from the FHIR server. QuestionnaireResponse resources are, by default, visualised as a line chart over the sum of its answers. The therapist can then select which of the available Observation resources should be shown. The Observation resources are visualised as regular line charts.

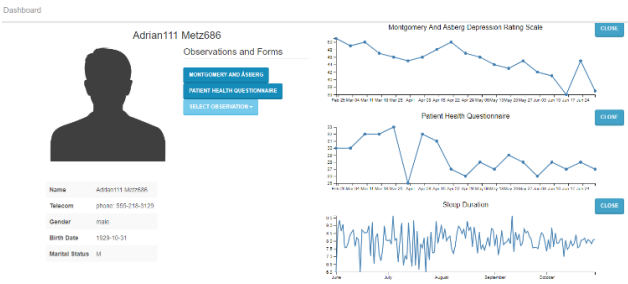

Figure 2 Detail View

Visualization of the QuestionnaireResponse resources requires a multidimensional approach. The method used in the artefact is an interactive combination of a spider chart and a line chart, as shown in figure 3.

3.3 Psychometric screening data as time series

There is a wide range of unique questionnaires suitable for iCBT. Based on the questionnaires used in eMeistring, we determined the following patterns applied to all questionnaires:

- Each question has a numerical answer, or an ordinal answer that can be converted to a numerical value.
- The number of answer choices is the same for all questions in the questionnaire.
- The set of answers can be aggregated to an overall result by, for example, summarizing all the answers in the questionnaire. This aggregated result can be compared to threshold values in order to determine a diagnosis.

By utilizing these patterns, series of questionnaires over time for a patient can be represented as an unevenly spaced multidimensional time series, as shown in table 1. We have not seen these patterns for psychometric screening questionnaires mentioned elsewhere. The basis for determining these patterns was the MADRS questionnaires used in eMeistring.

	t_0	t_1	t_2	t_3
1. Reported sadness	4	6	4	4
2. Inner tension	4	2	4	6
3. Reduced sleep	5	2	3	4
4. Reduced Appetite	4	2	2	0
5. Concentration difficulties	2	5	2	0
6. Lassitude	4	2	3	4
7. Inability to feel	1	2	4	2
8. Pessimistic thought	4	0	3	4
9. Suicidal thoughts	0	2	3	0

Table 1 Multidimensional time series example for the MADRS questionnaire

3.4 Visualizing multidimensional time series

With the goal of visualizing data from the format shown in table 1, we built a custom visualization, shown in figure 3. As a high degree of customizability was required, we chose the D3.js library for this task. A spider chart was chosen to represent a set of answers at one point in time. As the dimensionality of the intended data is mid-range, spider charts are a suitable option for visualizing the questionnaire data. For mid-range, we consider roughly between four and 20 dimensions. Three dimensions or less could be visualised in a line or bar chart. More than 20 dimensions requires more complex techniques.

The spider chart comprises two traces, one representing the most recent QuestionnaireResponse and the other representing an earlier QuestionnaireResponse selected by the user. Using the data representation in table 1, the blue trace represents column t_{n-1} where n is the number of data points. Similarly, the orange trace represents any column in t_0 to t_{n-2}. Two traces were chosen to easier display changes in patient state, where blue being lower than orange indicates improvement along an axis.

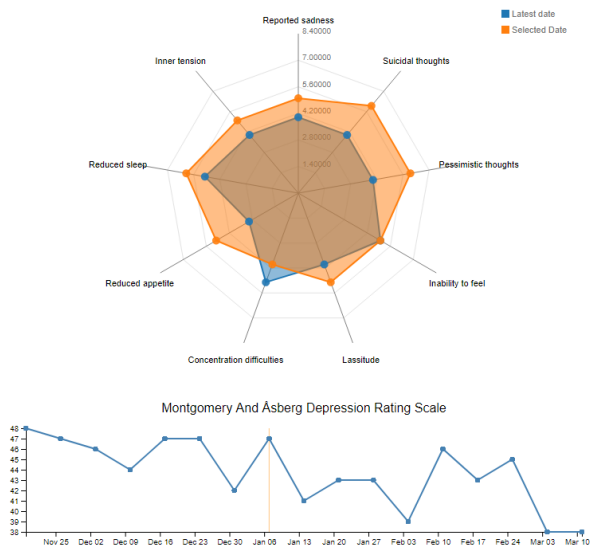

Figure 3 Interactive Spider Chart

When the therapist hovers over this line chart, the orange trace of the spider chart updates to the date closest to the cursor. The orange vertical line in figure 3 represents the selected date. This approach allows the therapist to quickly compare patient progress along each axis in the spider chart. Furthermore, each axis can be clicked on to display a line chart over the time series in the selected category (see under spider chart in figure 3), enabling the therapist to customize which visualizations to display for each patient. The visualization in figure 3 is designed for any series of QuestionnaireResponse resources, given the constraints previously described and at least two data points.

3.5 Calculating status variables

By using the FHIR format and the constraints described in section 3.3, we processed all QuestionnaireResponses for each patient in order to calculate their status variables. The status variables are displayed in the Master View. The algorithms used to process the resources (i.e., the QuestionnaireResponses) are isolated in the artefact through a strategy pattern and are subjected to simple interfaces. Due to this, it will be easy to replace/tune the logic for calculating the variables and tailor the artefact to any specific treatment.

4 IMPLEMENTATION

4.1 System Architecture

The architecture of the web-app is based on the Model View Controller (MVC) pattern [25]. The FHIR server, see figure 4, is an implementation of the HAPI JPA server [26]. This server is replaceable by any resource server implementation conforming to FHIR version DSTU3.

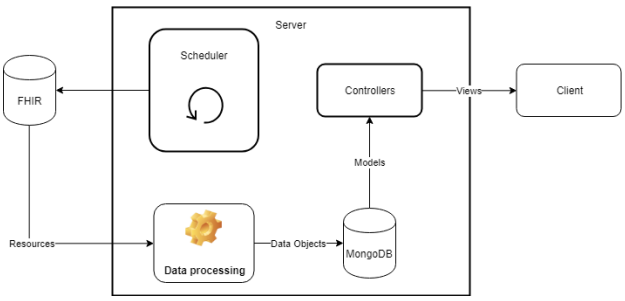

Figure 4 Architecture model

Due to the performance considerations discussed in section 4.2, interactions with the FHIR server run in a scheduled background process on the server. The scheduled update process runs independently of user interactions. When the client requests a view, the data is already available. This enables the artefact to scale well with respect to the amount of therapists using the application. A drawback with this approach can be that the data is not freshly updated when displayed.

4.2 Scalability

Throughout the development process, as more features were added, performance problems became more apparent. The main performance bottleneck was identified as the interaction with the FHIR server, where retrieving the resources for one patient could take multiple seconds. To mitigate this issue, we separated the logic for processing the bulk of the resources from the logic called on requests. The process handling the resources could then be scheduled to run at fixed intervals, resulting in pre-calculated data being available for the views.

5 EVALUATION

The evaluation of the web-app with dashboard is threefold. We performed a usability inspection and evaluated the dashboard against the clinical dashboard guidelines presented by Khairat et. al. [21]. Here we found our dashboard fulfilled eight of the ten guidelines. Then, we performed a user test of the dashboard and carried out semi-structured interviews with two experts in psychiatry and psychology. The psychiatrist was the same psychiatrist that participated in the initial phase of this project, and the psychologist is a colleague who is a CBT expert. Lastly, we measured empirical performance for the runtime of several of the procedures in the web-app.

5.1 User evaluation

The user test and interviews were structured as follows:

- A short presentation with a brief explanation of the dashboard features.
- A think aloud procedure was used while the expert tested dashboard (audio was transcribed and analysed).
- After testing the dashboard, the expert participated in a semi-structured interview (audio was transcribed and analysed).

Overall, the two experts expressed positive opinions about the dashboard functionality, and many of the implemented features (e.g. progression variables, warnings and spider charts) were found to be very useful, some of which they had never experienced before (e.g. interactive spider charts). In addition, the experts could see many new opportunities and suggested several new features (e.g. patient reported events and options for manipulating the line charts displayed for each patient). Furthermore, potential benefits of the displayed functionality were highlighted. These benefits are discussed in section 6.2.

5.2 Scalability measurements for evaluating system performance

In order to gain a detailed overview of how the web-app scales with respect to the number of data points, C# methods in the web-app were timed during the update. The empirical measurements show that interaction with the

resource server is responsible for most of the latency. The experiment was run twice with the same resources to observe the effect of resource server paging. For the experiment, the HAPI JPA reference implementation cloned in November 2018 was used. For the experiment, we used 147 generated patients with their corresponding data, giving in total approximately 22 thousand resources.

	μ time	σ time	μ RC	σ RC
Observations	0.90s	2.48s	95.4	163.3
Questionnaire Responses	0.34s	0.1s	52.4	23.9
Questionnaires	0.41s	0.04s	2.0	0.0
Total patient	3.05s	3.21s	149.8	166.7

Table 2 Single patient measurements, RC = resource count

The total runtime across all patients was 541 seconds, or about nine minutes. In the second experiment, with server paging of 10 resources enabled, we observed an increased runtime of about 56%. Table 2 shows measured time required to fetch a set of resources for one patient. There are multiple ways to mitigate this latency. We described one method for achieving this in section 4.2. As the scalability of HL7 FHIR was not the main concern of this paper, the results here only display that scalability problems can occur when using the HAPI JPA implementation. The reason for these problems and more robust solutions for handling large amounts of FHIR resources are topics for further research.

6 DISCUSSION AND FINDINGS

This research has followed a design science methodology [28]. Consequently, the findings are presented as contributions to the knowledge base of health informatics and to the domain of iCBT.

6.1 Contributions to the knowledge base

The main findings (see [23] for more detail):

- Psychometric screening questionnaires over time, can be represented as a multidimensional time series.
- The multidimensional time series from the questionnaires can be visualised through a novel interactive version of spider charts, for an arbitrary number of questionnaires per patient.
- Status variables can be calculated from a series of questionnaires to determine a patient's state and progression.
- The HAPI JPA reference server of HL7 FHIR STU3 does not scale well with respect to the number of requested resources.

6.2 Contributions to the domain

The development of the web-app and dashboard was motivated by a challenge to design and implement new functionality that can have the potential to make guided iCBT more cost-effective. Expert evaluation identified the novel functionality of the artefact as useful for both current iCBT, as well as potentially regular CBT. The main findings are:

- Status variables for a group of patients were identified to be useful for gaining an overview of a group of patients in iCBT.
- Visualizing quantitative measurements for patients enables therapists to faster gain an overview of their patients, their progress, and current status.
- Various additional tools for comparing patient sub-groups could be beneficial.

7 CONCLUSION

Through a design science methodology we designed, implemented, and evaluated a web-app and dashboard developed to address and improve relevant problems regarding a therapist's overview of patient data in iCBT [23]. Specifically, the web-app takes standardized mental health screening questionnaires and presents these as a numerical time series. We have introduced and proposed novel methods for providing therapists with overviews of both single patients and of groups of patients.

We identified patterns commonly occurring in psychometric screening questionnaires and used these to represent the data as time series, a novel approach we have not seen elsewhere. Similarly, the visual representation we built based on this representation, in the form of an interactive spider chart, is also a novel approach in iCBT. Both the representation of the data (described in 3.3) and the visualization (described in 3.4) are linked with the clinical domain. We visualize the most important information available for current clinical use in iCBT. The data representation also enables the use of other approaches of data analytics. Furthermore, we identified scalability problems with the HAPI JPA server reference implementation of the HL7 FHIR standard.

As this research was carried out in the scope of a Masters thesis, we were limited in both time and resources to do a more solid evaluation study that included more therapists We consider this to be a weakness of this study.

Research on iCBT is still in its infancy. iCBT has, however, already proven to be a game-changer within a field in desperate need of solutions to address the global epidemic of mental diseases. We believe that optimizing iCBT with respect to the quality and cost-effectiveness of the provided therapy will be among the future targets of the field – and that further research on the design and use of dashboards within guided iCBT will play an important role. Although we cannot yet make any strong empirical claims, this research represents some optimism.

7.1 Further work

The results from all components of our evaluation have provided valuable input towards a re-design and re-implementation of this artefact. Comments and suggestions made by the expert evaluators will be considered, and we will look at better ways to implement the HL7 FHIR standard with respect to performance and scalability. We feel that following established standards for health data interoperability is of uttermost importance to secure the development of sustainable eHealth applications.

The current version of the artefact uses simulated patient data. For the development of the next version, we will work on getting access to an anonymised set of real patient data, Furthermore, an expert evaluation of the algorithm that converts the questionnaires to multi-dimensional time series is needed.

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