Reusable Data Visualization Patterns for Clinical Practice*

Fazle Rabbi[1,2], Jo Dugstad Wake[3], and Tine Nordgreen[4,5]

[1]Department of Information Science and Media Studies, University of Bergen, Norway
[2]Department of Computer Technology, Electrical Engineering and Science, Western Norway University of Applied Sciences, Norway
[3]NORCE Norwegian Research Centre, Norway
[4]eMeistring, Bjørgvin DPS, Division of Psychiatry, Haukeland University Hospital, Norway
[5]Department of Clinical Psychology, University of Bergen, Norway
Fazle.Rabbi@uib.no, Jo.Wake@norceresearch.no, Tine.Nordgreen@uib.no

Abstract. Among clinical psychologists involved in guided internet-facilitated interventions, there is an overarching need to understand patients symptom development and learn about patients need for treatment support. Data visualizations is a technique for managing enormous amounts of data and extract useful information, and is often used in developing digital tool support for decision-making. Although there exists numerous data visualisation and analytical reasoning techniques available through interactive visual interfaces, it is a challenge to develop visualizations that are relevant and suitable in a healthcare context, and can be used in clinical practice in a meaningful way. For this purpose it is necessary to identify actual needs of healthcare professionals and develop reusable data visualization components according to these needs. In this paper we present a study of decision support needs of psychologists involved in online internet-facilitated cognitive behavioural therapy. Based on these needs, we provide a library of reusable visual components using a model-based approach. The visual components are featured with mechanisms for investigating data using various levels of abstraction and causal analysis.

Keywords: Data Visualization · Metamodeling · Model Transformation · Visual Analytics · Usability · Health Informatics · guided Internet-delivered treatments · mHealth.

1 Introduction

Digitalizing healthcare systems is considered a major means for meeting current challenges in healthcare [28]. Overall, the potential benefits of digitizing healthcare include increased access to care and the improvement of service quality. These are essential requirements for making health systems responsive and

* Supported by Intromat (www.intromat.no).

sustainable. In addition, digitizing healthcare systems has the potential for enabling the transition from treatment to prevention. In this paper we present results from the ongoing research project Intromat (Introducing Mental health through Adaptive Technology). Part of the project goals is to develop internet-delivered psychological prevention and treatment programs to people with mental health challenges or problems. One of the cases in the project is about increasing adaptive ICT support for eMeistring, a routine care clinic that provides guided internet-facilitated cognitive behavioural therapy (iCBT) in secondary care for adults with anxiety and depression.

Each therapist in the eMeistring clinic is responsible for providing support and treatment to approximately 15 patients. As one of the benefits of internet-facilitated treatments is increased therapist capacity (ca 3 times more patients per therapist), the therapists are in need of user-friendly and effective IT support. The clinical management system currently in use is purely text-based, and the clinic is in need of dashboards for improving the conditions for online clinical practice for both therapists and patients. This can include better overview over patient activity in the system, easier access to patients symptom development, and indicators of patients who are in need of more support. These goals are also relevant to other healthcare practices; for example, healthcare professionals often do not get enough time to look into patients historical information. In order to improve the quality of service, healthcare professionals may be equipped with patient data analytics, including data visualizations. In this paper, we present the results from a study of clinical needs from healthcare professionals involved in guided iCBT, and present a list of reusable visual components. We have conducted interviews with the therapists working in the eMeistring treatment program to gather the requirements for a data support for therapists, and also built insight into patient needs. In this paper we focus on the usability and reusability issues of supporting clinical mental health practice within guided iCBT.

Our aim is to support clinical practice in guided iCBT by providing data visualisations to therapists showing patients activities. Activities are in this context mostly refer to what patients and therapists are engaged in while using digital treatment support systems. The underlying idea is that traces of digital activity, system-generated data can be used to raise awareness about important aspects for the clinical outcomes of mental health therapy. Again, these traces can be aggregated in the form of visualisations. Although there is a scarcity of this kind of work in guided iCBT, examples can be found in other fields. For instance, in educational research, the field of learning analytics focuses on data-driven ways of improving educational outcomes [24] by collecting and analysing traces of what learners leave behind in digital systems [23]. Charleer and colleagues [8] have studied learner dashboards for students and found that visualising student effort (i.e. produced materials, time spent etc.) is only helpful when it highlights how the effort contributes toward the intended learning outcomes of what is being studied. They furthermore find that solutions that empower students and increase their ability to reflect and make decisions, have a more positive effect on motivation, than for example automating the learning trajectory based on data. Corrin [10] and colleagues have studied how analytics can be integrated with a teacher's learning design, and argue the necessity of matching the data visualisations with the pedagogical intent of the teacher. CBT and education share the notion that one of the major change processes or facilitators of improvement is human learning.

Usability: In computer science, a common approach to assessing the value of an application is to evaluate its usability. Poor usability and lack of user-centered design have been described as two of the reasons for low engagement with mHealth apps [27]. In general, ICT with poor usability can lead to situations of low goal-achievement efficiency or the application not being used or being rejected. Usability studies are grounded not only in the social and behavioral sciences but also in the science of design [18]. Through the approach of research-trough design, it is possible to explore ideas to improve practices by building artefacts to support the practice at the same time as ensuring their relevance and validity [30]. This can be ensured by engaging with practitioners within the addressed field, in design of the digital artefacts. A recent review of usability practices in design of digital health applications [13] found that end users such as patients seldom are involved in the design of applications, although they are often involved in post-development evaluation. Here, we advance the state of art mHealth development practice by engaging therapists in the design of the digital environments that are being used to mediate guided iCBT.

Reusability: Model-driven software development may play a significant role in supporting digital health. In current practice, data analysts need to spend a vast amount of time processing data for analysis and producing effective reports. In this paper, we present a model-based approach to develop reusable visual components. With this approach, a data analyst will be able to incorporate visualizations for representing results throughout the process of data analysis. This technique allows the user to visualize data from various level of abstraction. For instance, it allows grouping of activities based on an ontological hierarchy, which permits data visualization from a higher level of abstraction. The visual components are equipped with temporal sliders which allows a user to perform causal analysis. Since our work is related to the topics of visual analytics [16], we clarify the fact that our focus for this paper is in the overlapping part of three research areas which include visual analytics and usability, digital health and model-based information system development (see the Venn diagram in Figure 1). The paper is organized as follows: In section 2 we provide an overview of the research methods that have been used while conducting this research; in section 3 we present the findings from a case study from mental healthcare and present visual artefacts that have been developed; in section 4 we propose a model based system for visual analytics; in section 5 we present related works, and in section 6 the paper is concluded.

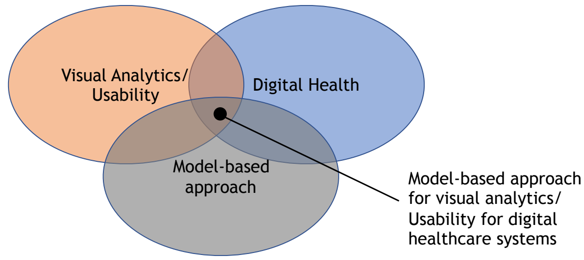

Fig. 1. The focus of this research

2 Methods

We have studied the practice of guided iCBT at a mental health clinic, in order to understand how to support the clinical and therapeutic practices with visualisations of relevant aspects of their activity. Additionally, we have been interested in how to improve the online environment for the patients, in particular in how to help motivate their persistent engagement with the therapy. The methods we have used include interviews and workshops with clinicians. Two to three therapists have taken part in a series of three collaborative workshops. The first two workshops focused on patient and therapist needs. Then a set of low-fidelity drafts for data visualisations were created. In the following workshops, the therapists provided feedback on the perceived usability and value of the visualisations. These feedback were used to improve the draft designs. A final usability and design workshop has been planned to be carried out with all therapists who work at the clinic. The primary focus of this research activity is the investigation of the design requirements reflecting therapists' insight into the program for a better data-driven digital solution. The resulting data material are workshop notes and transcriptions. No personally identifiable information has been recorded, and all the notes and transcriptions are anonymised.

3 Case study: a mental health clinic for guided internet-delivered CBT

Our exploratory study has taken place in collaboration with a mental health clinic – eMeistring – that offers guided online cognitive behavioural theory for the mental health problems of panic- and social anxiety, and depression. The effects of the CBT on the patients mental health are considered positive and long-lasting, also when compared to face-to-face therapy, in line with findings from recent scholarly literature [20, 3, 2, 12, 26]. There are issues with patient dropout, however, also in line with scientific literature findings on mHealth and online mental health therapy worldwide, see e.g. [21, 14]. In the long run, our work is intended to contribute towards lowering the dropout rate, increasing the percentage of successful therapeutic outcomes, and enrich the opportunities for interaction between the patients and the therapists. At an individual patient level, we take as a starting point that there are particular conditions to counselling patients who therapists don't meet or see face-to-face, but only interact with through text in a web-based system, and that this activity can be scaffolded more or less ideally.

Patients are admitted to the clinic by their general practitioners' or other clinical specialist referral. It is also currently possible for patients to contact the clinic directly without a referral. The treatment program lasts 14 weeks, and consists of eight modules covering aspects of mental health problems and CBT. The main activities that the patients are engaged in are reading and reflecting on their mental health problems; completing assignments about the content of each module; and behavioural elements such as behavioural activation. Additionally, they complete self-assessment (MADRS) once a week. All activities except behavioural activation are mediated through a text-based clinical management system. The behavioural activation module is paper-based. Each patient is assigned a therapist, who assesses the patients' progress and provides personal feedback via messages every week. The therapist additionally assesses whether a module needs to be considered as completed by a patient, and, if yes, subsequently assigns the next module.

As mentioned the practice of online mental health therapy is based on different conditions than face-to-face therapy. For example, the interaction between the patient and the clinician in face-to-face therapy is very much temporally and spatially tied. There is a dedicated hour and place for the therapy, which encompasses the relationship between the clinician and patient. In guided iCBT, the patient-clinician and patient-therapy relations are in many ways sustained temporally, and can take place anywhere. One of the treatment strategies in use in the clinic is behavioural activation, which is a common strategy used for treating depression. Behavioural activation [9] is a sometimes standalone component of CBT and involves the "scheduling of pleasurable activities to increase contact with sources of positive reinforcement" [15, p.361]. Ideally, the therapist should be aware of the correlation between the patients' scheduled activities and symptoms, and in guided iCBT this involves making the data available.

Based on our exploration of the problem space in collaboration with therapist representatives from the clinic, we arrived at three main ways of how patients and therapists can be supported with activity data visualisations, and a number of proposals of how to concretely visualise relevant information. The visualisations are drafted as snippets, which easily can be integrated with the digital system in use by the therapists. The following needs are identified:

1. Supporting therapist insight into group of assigned patients
2. Supporting therapist insight into individual patient activity and development
3. Motivating patient persistence

Supporting therapist insight into group of assigned patients. The therapists will presumably be in a better position to support the patient therapeutic process the more he or she knows about the patients needs, development and activities. This need can be exemplified by quotes such as "How do I choose the right person (to treat) first?", and "The least active patients are the least visible in the system". In the current version of the therapy management system, the traces of patient activity available to the therapists are messages sent between them, weekly self-assessment screening results, and patient diaries and responses to tests tied to each module (i.e. "what have you learnt in this module"). It is possible, however, to provide more detailed information, based on the data produced by patients and therapists while using the system. System needs exploration carried out with therapists for this project, revealed three main categories of therapists needs for insight into patients: 1) A way to prioritise who to help first of the patients; 2) To know about how each patient is progressing with the therapy; and 3) To know how much time and effort the therapist has spent on each patient during the therapy trajectory. The first need arises partly because the therapists do not have access to any kind of aggregated views of their patients in the system, and partly because the patients have individual needs for example for follow-up for the duration of the therapeutic process. The state of each patient must currently be assessed by reviewing direct responses to self-assessments and diaries etc. The same observation is the cause of the second need for information. The clinic experiences a high dropout rate (around 60 percent complete the therapy), a common phenomenon in iCBT [26], and has a stated goal of lowering this number. Currently, the therapists have access to the information provided above, in addition to whether the patient has completed a module or not. Insights into each patient activity will enable the therapist to intervene and assist with advice and encouragement, for example in cases where progress is not taking place as expected. The third and final category is insight into how much effort has been exerted by each patient, and is a way to learn about both how much progress can be expected for each patient, but also for the therapist to be able to self-reflect and adjust treatment strategies to ensure a constructive balance of efforts between each patient. Currently, the only source of feedback on this issue is personal memory.

Proposed visualisation: Figure 2 represents a generated view of the progress and activity of each of the patients assigned to a therapist. It is intended to support making decisions about who of the patients to prioritise. The concentric circles each indicate one week of the program (14 in total). Each segment or "cake" in the circle indicates a patient. The colour in each segment indicates how far the patient has gotten since starting. The colour (red - gray - green) and colour grading for each patient indicates trends in the MADRS score, red is negative, green positive and gray indicates stable values. Visualising trends in MADRS scores is based on the previous work of Grieg et al. [11] about supporting guided iCBT with visual analytics. The black lines indicate how many of the modules each patient has submitted. Comparing with the background colour tells the therapist whether a patient is on, ahead or behind schedule. The thickness of the black line indicates how much time the patient has spent online in the system. The grey shadow behind each black line indicates how much time the therapist has spent on each person.

Although the visualisation has the advantage of presenting patient activity and progress data in a condensed way, there is a threshold to how many patients it can present at the same time. From a usability perspective we estimate that it will scale well up to 15 patients, before the information becomes too condensed. However if the number of patients increases for each therapist, we proposed an alternative solution where the same information is presented in a tabular format with patients listed vertically, and progress and significant events are presented horizontally. Due to the limitation of space, this alternative visualisation is not presented in the paper.

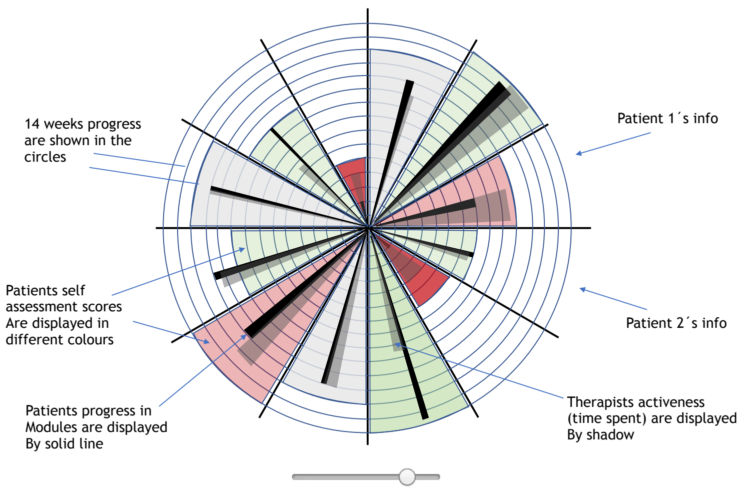

Fig. 2. Therapist overview of patients

Supporting therapist insight into patient activity and development. In addition to have an overview of all patients to be able to prioritise between them, therapists also have a need for insight into the activity and development of each individual patient. Currently, the insights are based on the patients' responses to the module tests, their patient diaries and the MADRS results. The patients additionally keep behavioural activation diaries, but this information is currently paper-based and outside the system they use. The idea is that by visualising the relevant information, the therapists will have better bases for making their therapeutic decisions, and additionally will have further opportunities to make interventions when patients are in danger of dropping out.

Proposed visualisations: Figure 3 is a visualisation proposal that collects items from the patients behavioural activation diary and compares it with their MADRS scores, for therapists to see which activities works well and vice versa. Additionally, the therapist have a need to see which of their patients are in dan-

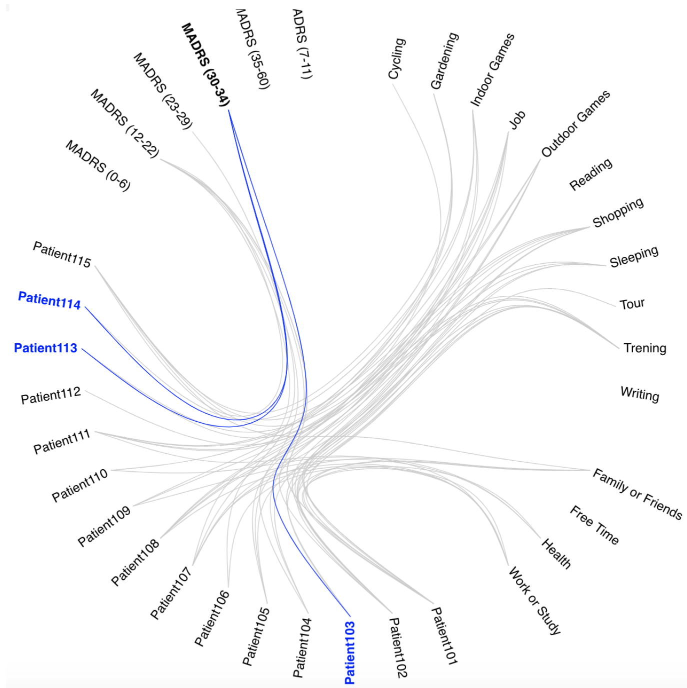

Fig. 3. Connection between patient activity and MADRS score

ger of dropping out. Figure 4 is a draft for a list containing the patients assigned to a therapist who are behind on their modules. This can for example be generated by listing the patients who are behind a specified threshold of expected modules completed, or by listing all patients who are behind with their modules. The list contains a link to the patient page of the persons in question, along with indication of how much time they have spent in they system (green bar) and how many modules they are behind (red squares). To provide the therapist

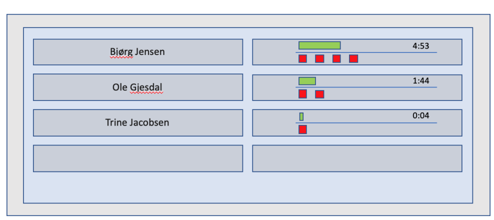

Fig. 4. Patient dropout warning list

insight into how a patient works during the week, we have drafted a table where days of the week are indicated by letters vertically on the left, and hours of the day are displayed horizontally at the bottom. The green bars indicate when patients are online and working in the iCBT management system. The blue dot indicates that a module is completed. The email icons indicate when messages are sent (closed envelope) and read (open envelope). This could be further augmented with data about the platform used when accessing the system, as there are different conditions to system use for example when using mobile platforms compared to a PC. (The system can be accessed using any platform.)

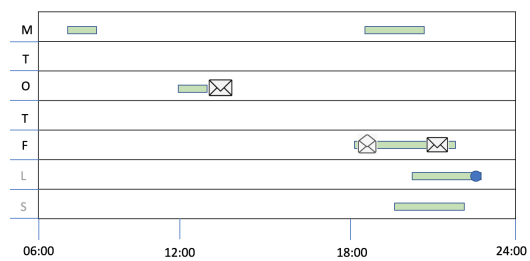

Fig. 5. Patients weekly activity

Motivating patient persistence. We have also aimed to increase the amount of visual feedback provided to each patient. The goal has been to increase the support offered to each patient, and to increase the likelihood of successful therapeutic outcomes. The needs of the patients, as expressed by the therapists can be exemplified as: "Am I doing too much, am I doing too little, am I on the right track?" and "What have I delivered, compared to what I am supposed to deliver?" The current source of feedback offered to the patient comes in form of qualitative assessment messages from the therapists. We aimed to provide more day-to-day and direct feedback based on the activity levels and kinds of the patient, and to increase the patient motivation to continue the therapy.

Proposed visualisations: To support patients continued engagement with the CBT, we propose a refined version of a relatively simple and well known visualisation of progress - a progress bar. It compares actual progress with expected or planned progress, in addition to visualising the amount of messages to and from their therapist. This visualisation is also reported as interesting to therapists, to see if one particular patient is progressing as expected, in a simple way. The dots or arrows in the middle of the progress indicates total weeks of therapy. The colour shaded section (blue in v1 and gray in v2) indicates generic progress as expected, measured by counting weeks from the start. In Figure 6 the actual patient progress is indicated with the vertical slider, and measured by completed modules. The messages are indicated with differently coloured dots, with the patient messages at the top and therapist messages at the bottom. In Figure 7 the patients actual progress is illustrated with the yellow arrow, patient messages with a red speech bubble, and therapist messages with blue speech bubbles.

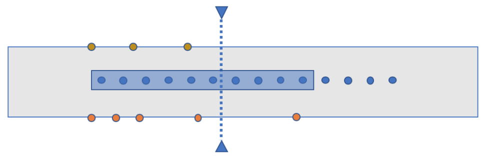

Fig. 6. Therapy progress bar for patients, v1

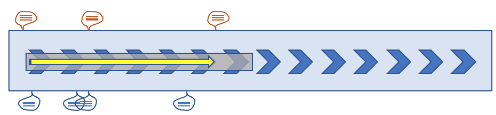

Fig. 7. Therapy progress bar for patients, v2

4 Model based approach for reusable visual components

We propose to use domain specific models for dashboard components. Dashboard components i.e., visualizations, data analysis techniques are associated with an information model. In Figure 8 we present the architecture of our system where we articulate the client server communication by means of an application programming interface (API). A library of model-based visual components are available in the server. When a client e.g., browser requests for a visual artefact, the server sends the scripts for rendering graphics in the client device. Server application fetches relevant data from existing healthcare database and transforms them into appropriate model for visualization. The server maintains the status of the visual component running at the client device. The server application is featured with the following:

- Support for abstraction by using ontologies [22];
- Support for cause analysis using data mining techniques

Besides these features, the visual components are equipped with temporal sliders which enables the user of the system to see the progression of events for a particular time period. The proposed architecture describes the design of our solution space. Figure 9 illustrates how model-driven engineering can be applied in various stages of implementing our system. The figure is adapted from [6] where the concept of extractor and injector were introduced. The idea of using an extractor is to represent the availability of appropriate software artefacts

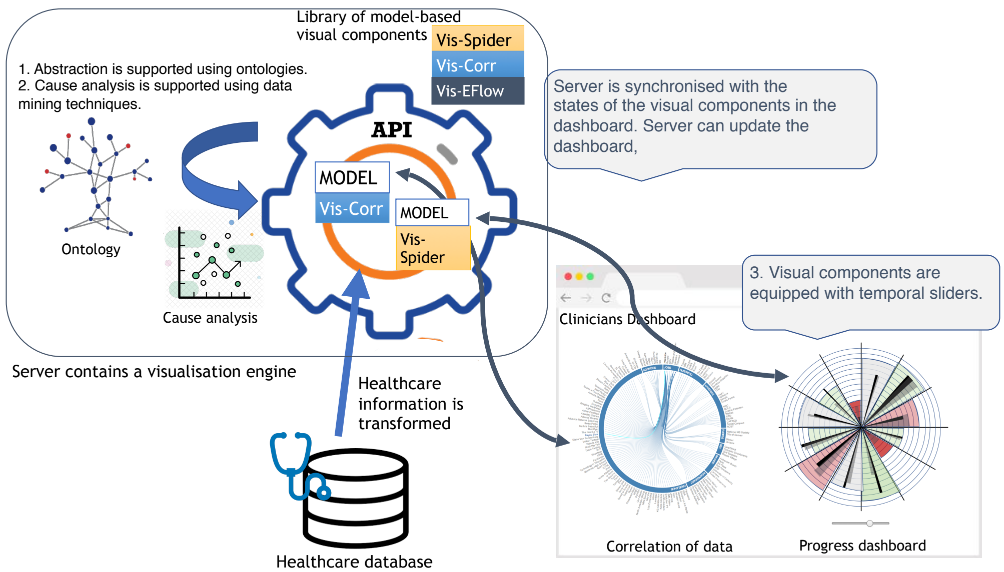

Fig. 8. Architecture design of model based dashboard system

that are able to extract knowledge from a technical space and be able to inject such knowledge in another technical space (called injectors). The problem space consists of requirement specification and domain model which we have described in previous section. The library of visual components are developed by reverse engineering D3 js libraries. The domain model for visualization are specified using graphs which are used for generating JSON code by applying model-to-model (M2M) transformation. In our approach the visual components can be adapted by model-to-text (M2T) transformation. We use M2M transformation for converting healthcare information into suitable data format for the visual components. As mentioned above, in our approach visual components are associated with domain model, Figure 10(a) presents a domain model for the proposed spider-graph. We will refer to this visualization as Vis-Spider. Model transformation techniques can be used to extract this information from an existing health information system and instantiate this domain model with instances. This visual component needs to be connected with other parts of the system such as, the system should allow selecting a patient from the cake view and see the details of patients completion of modules or the correlation of patients symptoms with self-assessment score. The API at the server side mediates the communication between a variety of visual components. Figure 10(b) presents the domain model for visualizing event flow. We will refer to this visualization as Vis-EFlow. The events are associated with case-id (i.e., patients identification), time stamp (i.e., event time), activity and resource information. Many existing

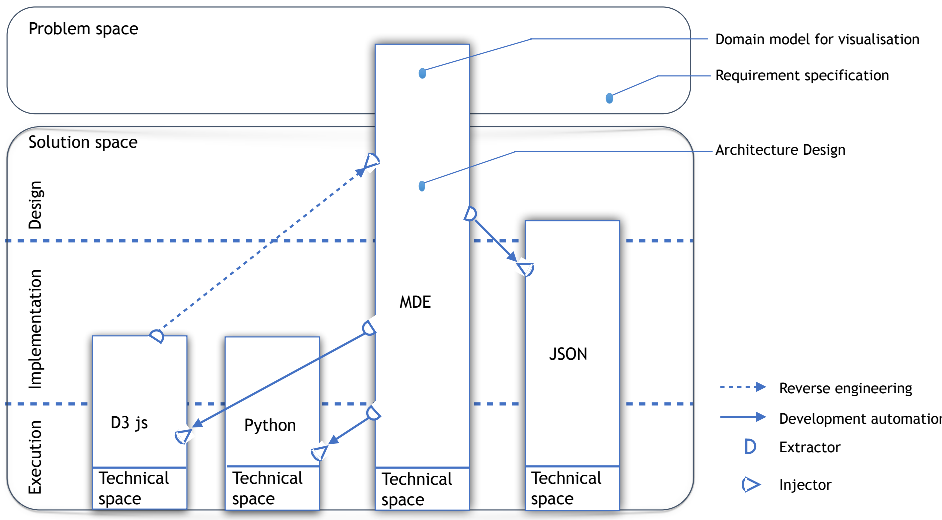

Fig. 9. Technical spaces and coverage

process mining tools use event logs that include these information [1]. In this domain model we have incorporated dimensional information for activities. This allows our event logs to be organized hierarchically. The incorporation of dimensional modeling in event logs permits us to group activities and view information from different perspective. The concept of dimensional modeling originated from data warehousing and business intelligence (DW/BI). Organizations embraced DW/BI techniques in order to handle large amount of information. Dimensional modeling allows us to incorporate following features:

– organization of large amount of data
– process raw data in various ways and turn them into useful information
– show correct information to the right person
– provide useful knowledge to help decision making.

The DW/BI systems emphasize collecting and processing raw data quickly, and turn them into useful information while preserving the consistency of the data [17]. It has been widely accepted by the BI community because of its simplicity and performance in presenting analytic data. In our approach we propose to use dimensional modeling for organizing healthcare information e.g., filtering and grouping events based on patients diagnosis, activities, etc. In our case, dimensional models packages the data in a format that allows simplicity for displaying understandable information to users and also supports developing efficient data analytic tools in terms of query performance. Our event-model allows us to change the level of abstraction in the event logs. We utilize this feature of dimensional modeling for specifying event flow analysis requirements. The purpose of this dimensional model is to provide an easy to use visualization for its

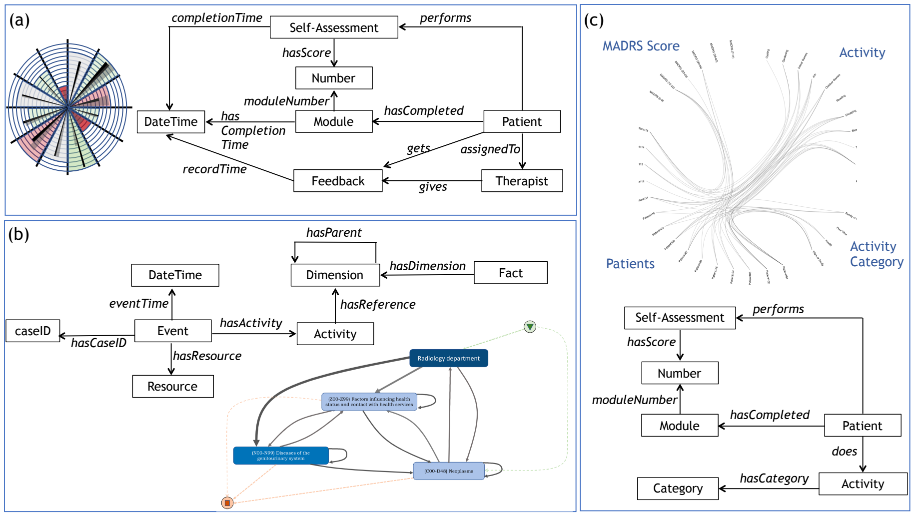

Fig. 10. Domain specific model for (a) Vis-Spider; (b) Vis-EFlow; (c) Vis-Corr

user to investigate care flow from different context. We propose to use ontological hierarchies to provide hierarchical representation of healthcare information along each dimensional model. Traditionally, fact tables are used to store data at the lowest grain e.g., records about physical activity or events. Fact tables always use foreign keys to associate the records/events to their dimensional models. Figure 11 shows a dimensional model where we incorporated healthcare ontologies e.g., SNOMED-CT, ICD-10 ontologies. Fragment of the SNOMED-CT ontology is shown in the figure that links a data from a dimensional model. In Figure 10(c) we present a visualization called Vis-Corr to study correlation of patients activity and self-assessment score. Activities are recorded hourly by patients in a diary, as part of their behavioural activation. In eMeistring this visualization can be used to see how activities carried out by the patient correlate with their MADRS scores (or symptoms), or in other words which activities play a role in reducing the symptoms of depression. Since eMeistring allows patients to write free text for activities, the number of nodes representing activities could be very many in the visualization. To deal with this situation, we propose to use an activity ontology [29] which will allow hierarchical representation of activities in the visualization. The visualization with a temporal slider allows therapists to investigate the effects of various activities and their correlation with depression symptoms. In future we will incorporate a data mining technique which will extract patterns and visualize them with Vis-Corr. For example, the therapists would be able to see if activity-a and activity-b plays a major role in the reduction of depression symptoms. Many CBT treatments are based on the principle of behavior activation. However, therapists currently do not have a visual tool

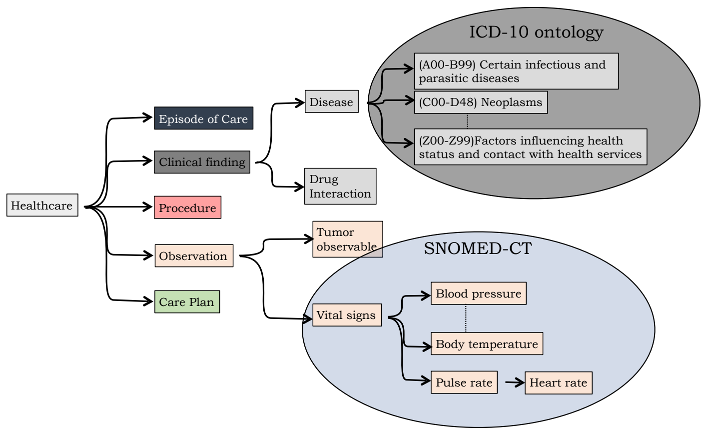

Fig. 11. A dimensional model for specifying data mining/visualization requirements in healthcare

support to investigate how their patients are practicing them. Our proposed method will allow therapists to investigate more into this.

5 Related Work

In [7] the authors proposed an architecture to support model driven software visualization. The visualization artefacts that they proposed are capable of representing the relationship and constraints of software components. In this paper we proposed a different technique to visualize healthcare information. We emphasized on utilizing a model driven approach for the construction of reusable visual components.

In [5] the authors presented a vision for the future of data-driven technology by means of incorporating IoT devices and visualizing healthcare information e.g., bio-markers for monitoring patients physical condition. They urged for the need of using such technology and visualization in healthcare. However they did not provide any information how such system can be developed or the software components can be reused. In this paper we provide a case study and present reusable visual components that can be reused in various healthcare settings.

Keim et al.[16], provided a conceptual framework of how visualization could fit into the phases of information life cycle. They argued for the importance of relevant information and provided a definition of visual analytics. They also provided a list of technical challenges for advanced visual analytics solutions. Our work fits well into the conceptual framework of visual analytics as presented by Keim et. al. and in this paper we address several challenges such as infrastructure, visual representation and level of detail, data dimensionality.

In [4] the authors introduced the idea of using model-based approach for big data analysis to lower the amount of competences needed in the management of a big data pipeline and to support automation of big data analytics. They presented a methodology data analysis steps can be specified using declarative models. However in their approach, authors only considered using scatter plot chart.

Streit et al. in [25] presented a model-driven design approach for visual analysis of heterogeneous data from healthcare. They addressed the issue of how healthcare data from various sources can be linked and how visualization can be used for supporting investigation. They applied their design process to a biomedical use case where they considered visualizing medical data consisting of MR/CT/X-ray, Gene/Protein expression, lab results, disease database, etc. While our work overlaps with their approach in many aspects- in our work we focused on the mental healthcare domain and emphasized on constructing visualization that provides meaningful information for therapists providing internet based treatment. The visualization of data incorporated with an ontology as presented in our approach will facilitate healthcare workers to investigate data from various level of abstraction.

In [19], Medeiros et al. presented an ontology based process mining approach where they discussed about the necessity of relating elements in event logs with their semantic concepts. In their approach they linked event logs with the concepts from an ontology which enabled then to perform concept-based analysis. The idea of using semantics makes it possible to automatically reason or infer relationships of concepts that are related. They distinguished between the application of process mining in two different levels: instance level and conceptual level. They illustrated an example process model to repair telephones in a company. The process model includes three different ontologies: Task ontology, Role ontology and Performer ontology. The idea of using an ontology is for process mining presented in [19] is very similar to our approach. The idea of filtering based on ontological concepts and the idea of grouping nodes by a high level ontological concept is similar. However, in our approach we emphasize on various kinds of data visualization where ontology plays a major role for providing various level of abstraction for healthcare information. While in [19] the authors implemented their technique in ProM, our approach is more general and can be plugged in to several areas in the healthcare system.

Grieg [11] et al. presented an architecture for accessing healthcare data using HL7 FHIR and provided a methodology for visualizing healthcare information in various ways. Their visualization technique include a visualization of clinical observations and self-screening results for individual patients and/or a group of patients. A spider-chart was introduced for visualizing MADRS score of a patient which shows the progression of the symptoms in a single visualization. In their work authors provided an evaluation of the performance of accessing healthcare information using HL7 FHIR API. They pointed out the fact that such architecture based on HL7 FHIR APIs may have scalability problems as HL7 FHIR consists of lot of meta-data information. In our approach we provided an architecture which is more robust in a sense that visualizations are tied to a model. Healthcare information from a variety of sources can be transformed into appropriate format for visualization.

6 Conclusion and Future work

This paper took a starting point in the potential of mHealth and guided Internet-delivered treatments in providing efficient treatment for mental health issues, and increasing overall access to mental healthcare. Through an identified need for, and a large potential in ICT to provide support for clinicians and patients involved in guided Internet-delivered treatments, we have created a set of low-fidelity prototypes for supporting online clinical practice and mental health therapy with visualisations of activity in the online systems used. The needs have been established in dialogue with representatives of clinical personnel working with guided Internet-delivered treatments, and has been crucial in understanding the practice that is addressed through our study. Particularly, we have drafted solutions for therapists to understand and have insight into their patients' activity and need for support, and to help prioritise how to use their time with the patients. We have also focused on what useful and valuable things can be learned about a guided Internet-delivered treatments patient from his or her online activity, and how can this be conveyed to the therapist, to make the therapy as efficient as possible. We have developed an example of how data from patients can be used to help the clinician learn about which of the activities that patients engage in behavioural activation, and how the data can form the basis for the therapist to give substantiated advice to the patient. This work will be tested in a clinical setting were increased quality of user experience and efficacy will be the main outcomes. In addition we will use this work in our industry-research-clinic collaborationship as the industry are offered user-centered tools that improve therapist workflow and increase patient outcomes.

In this paper we proposed to use a model-based approach for visual analytics. We presented how model-based artefacts such as ontology, dimensional models, meta-models could be composed for the construction of reusable visual components. The application of model-based approach for visual analytics will bring several benefits including the reduction of cost, ease of customization, support for model based analysis for the healthcare domain.

The next steps for this study is to validate the results achieved so far, and implement examples in practical settings. Validation involves gathering further usability data, focused on how the visualisation examples give meaning to a wider set of therapists, how understandable they are, and how actionable they are. It is also relevant to study how they can be integrated with the systems currently in use at the clinic. Based on usability and usefulness evidence, the examples should be implemented in practice at the clinic. Everyday use in clinical practice would allow measurement and assessment of long term effect on therapy efficiency and outcomes.

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