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Exploring ways to convey medical information during digital triage

A combined user research and machine learning approach

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Abstract

Exploring ways to convey medical information during digital triage

Linn Ansved & Karin Eklann

The aim of this project was to investigate what information is critical to convey to nurses when performing digital triage. In addition, the project aimed to investigate how such information could be visualized. This was done through a combined user research and machine learning approach, which enabled for a more nuanced and thorough investigation compared to only making use of one of the two fields.

There is sparse research investigating how digital triaging can be improved and made more efficient. Therefore, this study has contributed with new and relevant insights. Three machine learning algorithms were implemented to predict the right level of care for a patient. Out of these three, the random forest classifier proved to have the best performance with an accuracy of 69.46%, also having the shortest execution time. Evaluating the random forest classifier, the most important features were stated to be the duration and progress of the symptoms, allergies to medicine, chronic diseases and the patient's own estimation of his/her health. These factors could all be confirmed by the user research approach, indicating that the results from the approaches were aligned. The results from the user research approach also showed that the patients' own description of their symptoms was of great importance. These findings served as a basis for a number of visualization decisions, aiming to make the triage process as accurate and efficient as possible.

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Populärvetenskaplig sammanfattning

Digitala tekniker kan anses spela en viktig roll för utvecklingen av svensk hälso- och sjukvård. Några av de fördelar som nämns när digitaliserad sjukvård diskuteras är bättre beslutsstöd, ökad medicinsk kvalitet och mer individbaserad vård för patienten. De nya möjligheterna som uppstår kan även medföra utmaningar som påverkar både patient och vårdgivare. Exempel på sådana utmaningar kan vara ökad arbetsbörda för sjukvårdspersonal, hantering av stora mängder patientdata samt organisatoriska förändringar. Välgrundade analyser krävs därför för att säkerställa en effektiv implementering av modern teknik i sjukvården.

En viktig process i vården är triagering; en bedömning av patientens medicinska status och hänvisning till rätt vårdnivå därefter. Digital triagering har blivit allt vanligare i primärvården då vårdpersonal, oftast sjuksköterskor, avgör patientens allvarlighetsgrad baserat på patientgenererad information. Trots att triagering är en viktig del inom sjukvården, har tidigare forskning till stor del fokuserat på diagnostisering utförd av läkare. Eftersom sjuksköterskor precis som läkare är direkt påverkade av ny teknik i deras dagliga arbete, vilket i sin tur påverkar behandlingen och vården av deras patienter, finns det behov att utforska området vidare.

Syftet med uppsatsen var att undersöka vilken information som är viktig att förmedla till sjuksköterskor när de triagerar patienter digitalt. Utöver detta ämnade projektet att undersöka hur sådan information kan visualiseras för att underlätta beslutsprocessen. Detta gjordes genom att kombinera två ämnesområden; maskininlärning och användarcentrerad systemdesign. Genom att sammanföra djupgående kvantitativa dataanalyser med kvalitativa undersökningar kunde studiens syfte uppnås.

Arbetet har bidragit med nya insikter till tidigare relativt outforskade ämnesfält, mer specifikt digital triagering utförd av sjuksköterskor. För att avgöra vilken information som är av störst relevans i ett triageringsunderlag utforskades bland annat tre olika klassificeringsmodeller. Den modell som uppvisade bäst resultat, och även hade den kortaste exekveringstiden, gav en korrekthet på 69.46%. Genom att analysera denna modell kunde de viktigaste informationspunkterna sammanfattas till att vara duration och utveckling av symtom, eventuella allergier mot mediciner, kroniska besvär och patientens självskattade hälsa. Alla dessa faktorer kunde, genom användartester, bekräftas vara viktiga för sjuksköterskor i ett triageringsbeslut vilket påvisade att resultaten från de två ämnesområdena överensstämde. Från användartesterna kunde det också konstateras att patientens egna beskrivning av sina symtom var av stor vikt. Dessa forskningsresultat låg till grund för en rad prototyper, vars mål var att göra den digitala triageringen mer träffsäker och effektiv.

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Acronyms

CI Contextual Inquiry.

NaN Not a Number.

PAEHR Patient Accessible Electronic Health Record.

PHR Personal Health Record.

RFE Recursive Feature Elimination.

VAS Visual Analogue Scale.

Terminology

Triage: a process of understanding the patients' symptoms and prioritize them accordingly. This way, resources available in a healthcare center are being matched with each patients' needs.

Report: a medical report, or anamnesis if you will, consisting of information that the patient provides when initiating contact with a healthcare center and fills out the questionnaire. The report serves as a basis for how healthcare professionals choose to triage and treat the patient.

Questionnaire: when initiating contact, the patients are asked to fill out an intelligent questionnaire, designed to ask relevant questions to the case at hand. Based on the answers provided, a medical report is created.

Reason for contact: based on their symptoms, the patients are asked to choose one reason for contact, e.g. 'stomach pain', prior to filling out a questionnaire. Their choice affects what questions are being asked in the questionnaire.

INTRODUCTION

The first chapter deals with the very core of the project; the project formulation and the research question that is addressed. Furthermore, the project scope and the thesis outline are presented.

1 Introduction

Ensuring sufficient quality of treatment and care is a pressing issue for health authorities worldwide. Currently, healthcare is undergoing heavy digitalization which has the potential to reform several fields. Digital healthcare can be considered to be a key enabler for addressing increasing demands for improved care and putting healthcare systems on a more sustainable cost trajectory. For instance, the capability and availability of healthcare technology have the potential to increase medical quality, streamline processes and offer more personalized care.[1] Internationally, there is an ongoing shift towards increased patient participation and empowerment as patients are encouraged to take part in collecting and interpreting their own data.[2] Patients can have quick and easy access to personal medical information and health records, which can improve the care provided and the overall patient experience.[3] As a consequence, healthcare professionals may also benefit from more patient-centered care through easier access to important patient information. Beyond this, digitized healthcare could also enable for the caregivers to offer more efficient care and reach higher levels of satisfaction at work.[4]

The introduction of health-related technical innovations is however accompanied by major concerns; many originating from health care professionals.[5] Increased workload and privacy risks have been considered to be some of the most relevant barriers when discussing successful implementations of the technology.[4] Early experiences with patient-centered services point to many unintended consequences and challenges, affecting patients as well as caregivers, that need to be taken into consideration when designing future healthcare services and applications. The causes of the problems are complex and varied since healthcare work is highly institutionalized and involves multiple stakeholders, including private and public funding arrangements. Thus, a collaborative approach needs to be taken where every stakeholders' concerns are addressed in order for healthcare technology to reach its full potential.[2] Given that digital healthcare plays an important role in developing our society for the long term, it should be in everyone's interest to make this process as efficient and successful as possible.

1.1 Problem formulation

An important process in the practice of medicine is *triaging*, which is used to match resources available in a healthcare center with each patient's needs. This is often performed by nurses whose tasks involve understanding the patients' medical conditions and prioritizing them accordingly. Despite the centrality of triage in healthcare practices, most research is focusing on diagnosis done by physicians rather than the triage performed by nurses. A reason for this may be that diagnosis is considered to be the very basis of many medical processes. Much less work has therefore been conducted on how nurses perceive, store, process and communicate patient-generated information.[6] Nowadays, nurses are given the opportunity to triage patients digitally. Since nurses, just like physicians, are directly affected by the technology in their daily work which in turn affects the treatment and care of their patients, there is a great need to explore the area further.

There is sparse research investigating how digital triaging can be improved and made more efficient. The issue raises the question of whether a human being's work should or could be assisted by a decision support algorithm. Maybe it is not about replacing the health care professionals, but rather looking for ways to facilitate their work and decrease their workload. In order to do this, determining what information is relevant in order for a nurse to perform efficient triaging is critical. Having this in mind, combining the two fields of user research and machine learning could investigate the issue from different perspectives. The hope with this project is to contribute with valuable knowledge regarding how triaging can be made more efficient and thus provide sound bases for the nurses to determine the best level of care for their patients.

1.2 Aim and research question

In this project, the two fields of user research and machine learning are combined in order to make use of a holistic view and obtain a better understanding of the challenges and possibilities that the triaging process implies. By doing so, this project aims to take advantage of a detailed data analysis combined with a broader user perspective. To investigate the information needed in the triage process, the following question is formulated:

What information is critical to convey to nurses when making an accurate triage decision?

By answering the above-stated question, the project aims to determine *what* information is important and *how* it best can be visualized to facilitate nurses' reasoning process. The hope is to enable a better user experience for nurses and to provide an interface that makes it possible to quickly form an opinion of the patients' needs and medical status.

1.3 Project scope

The most obvious limitation to the thesis is that a case study has been carried out in collaboration with one single company, meaning that only one digital platform has been investigated. As for its users, only nurses have been considered when exploring ways to convey medical information. Furthermore, the information investigated by the two different approaches has been gathered from one single healthcare center. When performing the data analysis, only questions of multiple and single choice character were investigated, as analyzing free text is beyond the scope of this project. The consequences of the presented limitations are further discussed in Chapter 10.

1.4 Thesis outline

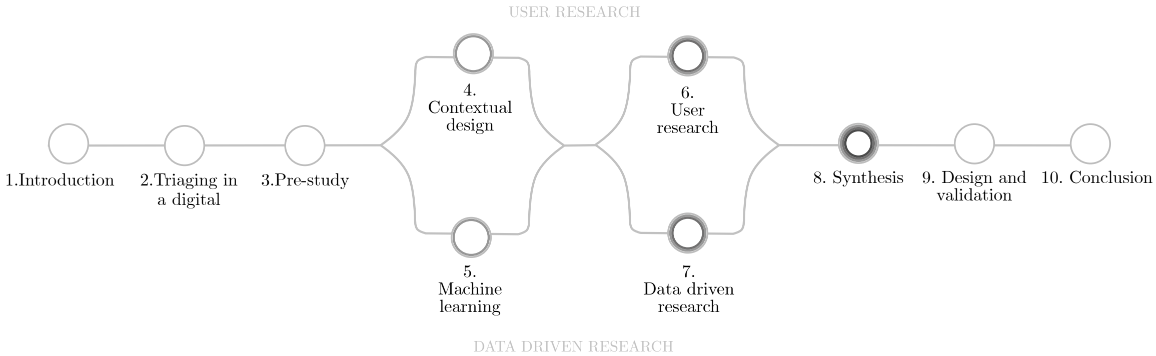

Figure 1: An illustration of how the thesis is structured.

As seen in Figure 1, this thesis consists of ten chapters. A brief introduction to triaging in a digital environment is given, followed by a presentation of *the Company* that the project has been carried out in collaboration with as well as the product used when triaging patients. A choice has been made to divide the theory, method and results chapters among the two approaches respectively. The following two chapters therefore present theoretical frameworks regarding contextual design and machine learning. After this, the two consecutive chapters present research and implementation as well as results and discussion for the two approaches. At last, the results from each scientific field are being merged and further discussed, and prototypes for how to best visualize the medical reports are presented. The report ends with a conclusion and final words.

TRIAGING IN A DIGITAL ENVIRONMENT

The second chapter presents a brief background, starting with the process of triaging and online communication. This is followed by a description of ethical aspects relating to the usage of personal patient data. Lastly, the chapter is ended with a short presentation of related work.

2 Triaging in a digital environment

An important part of nurses' daily routines is to triage patients, i.e. to understand the patients' medical condition and prioritize them accordingly. Triage is a unique form of nurse-patient encounter that often includes quick, yet accurate and patient-safe assessment.[7] This way, the patients with the most severe symptoms is ensured priority in their treatment and care. However, the nurses' decisions are often based on minimal and inadequate information and involve communication difficulties which can make the information hard to interpret.[8][9] It is therefore common that the nurses' prior knowledge and interpretation skills affect the diagnosis made, thus leading to variance in prioritization.

The medical practice has been described as "the art of managing complexity"[10, p.583] since medical professionals need to process a maximum amount of information in a minimum amount of time while constantly having the patients' best in mind.[10] Research suggests that designers need to create healthcare technology that considers the fact that nurses base their decisions on previous experiences, in highly complex situations. Furthermore, nurses tend to look at the problem from different angles depending on the medical data provided and rarely make decisions without interacting with colleagues.[11] Not only does the technology need to provide fast data that is relevant to the case at hand, but also to match the nurse's workflow and way of reasoning. Succeeding in doing so may result in improved clinical performance and more widely used systems.[12]

2.1 Mediated communication

Traditionally, the interaction between patient and provider occurs in examination rooms that are private and intended to enable for patients to share personal feelings and information. The introduction of new healthcare technology may affect the potential liability of diagnosing when the nurse is not able to see the patient in-person to interview, examine and observe. Part of nurses' assessment and diagnosing processes include factors such as responsive feedback and understanding of the patients' vulnerabilities and distress.[13] Whereas face-to-face communication can be thought of as a closed loop, where the sender of information obtains feedback as soon as the information is received by the other, sending information electronically might result in other ways of exchanging information, for the better or worse. One positive aspect with online communication is that time and space limits are changing, enabling nurses and patients to participate in the conversation when and where it suits them. Online communication might also lower the threshold for contacting a healthcare center. Researchers have found that 75% of participants in an online mental health discussion forum thought that it was easier to discuss their private issues on the internet than by doing so face-to-face.[12] Furthermore, text-based media requires the patients to reflect on what to write and why, which can be thought of as a new zone of reflection. Some patients might therefore find it easier to communicate their concerns and health questions online, and nurses may be provided with more concrete, accurate information. Furthermore, new opportunities arise for nurses to respond in ways that might contribute to building trust with the patients, e.g. using a personal, more informal language in writing.[12] When patients' and providers' decisions about healthcare priorities align, improvements are seen in the patient's health status, functional status and self-reported satisfaction - metrics for which nurses are held accountable.[14]

On the other hand, the introduction of healthcare technologies may pose new challenges for healthcare providers as their decisions to a great extent are based on information that patients choose to provide. The patients' values, what they consider meaningful, influence their priorities and decisions about what information to share and how as well as their strategies for coping with a specific illness.[15] Differences in life situation, background and mental and physical condition can cause variation in how patients use the technology and communicate with the provider.[16] Such variations, as well as spelling and accuracy in language, contribute to how a text is interpreted and might affect trust and attitudes towards the other part.[17] As patients are entering information related to their symptoms on a digital platform, they might provide data based on their beliefs rather than on the basis of logical argument. Patients might think that they suffer from a medical condition because they have previous experiences from it, people in their surroundings are suffering from the same illness or simply because their symptoms match the ones associated with it. Data that does not endorse arguments whose conclusion they believe, might thus be left out or framed to support their beliefs. If nurses are unaware of this phenomenon when reading the information provided by the patient, the quality of care and treatment is at risk. Additionally, patients might only share information that they think is of high priority for the nurses, thus risk leaving out information that could have been crucial for making a successful diagnosis. Discrepancies between what patients want to share, or think that they should share, and what nurses find useful might lead to miscommunication and nurses struggling with finding relevant data.[18] It is therefore of high priority that healthcare technology supports honest communication between patient and nurses, enabling for quick feedback.

Healthcare technology has been framed as a means to bridge the knowledge gap between patients and providers, and might in the long run make the patient-provider relationship less characterized by hierarchy.[19] The introduction of so-called 'expert patients', who can engage with their providers as lay experts, may contribute to reducing the amount of missing information and patient anxiety.[20] However, the idea of active patients also potentially shifts the responsibility for the patient's health, diagnosis and treatment from the nurses to the individual patient.[21] This shift, in turn, may lead to increased workload for healthcare professionals or have a negative influence on the patient-provider interaction, e.g. 'no decision about me without me'.[22] Additionally, interested and active patients have shown to be more concerned about errors in care and to be more likely to lack trust in their clinicians.[23] Again, delivering patient-centered technology requires an in-depth understanding of not only the technology itself but also the concerns and needs of every stakeholder, particularly of patients and nurses.

2.2 Ethical aspects

The introduction of Personal Health Records, PHRs, has contributed to making vast amounts of medical data available electronically. It has also provided patients with online access to their own health data.[24] Along with the progress of advanced machine learning and data mining techniques, the data can, with the patients' permission, provide significant opportunities in healthcare. However, increasing patient empowerment and engagement has also lead to data and user-related challenges such as quality issues, safe storage and secure processing. In this project, the usage of personal patient data has consequences on several levels, spanning from analysis to visualization. When using personal patient data for machine learning analyses it is important to preserve privacy. The process of anonymization often needs to be undertaken to delete any instance of information that can identify or be derived from a specific individual.[25] Dealing with the challenges that come with using confidential, digital patient data requires analyzing questions like how we should deal with new types of medical errors caused by the introduction of healthcare technologies and defining where the responsibility lies. In the healthcare industry, a so-called 'super-humanistic' approach is often applied, making the professionals ultimately responsible for every action they take. Errors that at a first glance are considered to be a result of the human factor might in fact not be. It is often the clinicians that risk being held responsible for an accident, even though the error could be a result of poor hardware or a careless designer failing to understand the end users.[26] In medicine, the technology is often used in a high-tension environment with a great number of devices and users, and if this is not taken into consideration it could result in consequences just as severe as a traditional equipment failure.

2.3 Related work

One study that is of high relevance for this master thesis explores nurses perception of Patient Accessible Electronic Health Records, PAEHRs, that was first introduced in Region Uppsala, Sweden in 2012. Prior to this study, no research had focused on how nurses' working environment in primary healthcare is affected by such new services. The research concludes that nurses experienced an altered contact with their patients in several ways, e.g. patients came better prepared to appointments which led to more in-depth, and sometimes time-consuming, discussions. The introduction of the service also led to uncertainty among patients who were unable to fully understand their own medical records. Even nurses felt uncertain about how and when to best communicate medical findings with the patients. However, nurses experienced an overall improved contact with patients as they could participate more actively in their own treatment. Furthermore, the authors stress the fact that there is a need for more knowledge and education on how to use online health services, both for healthcare professionals and patients.[6]

Research discussing the nursing profession can be equally important for this project, since the nurses' way of perceiving themselves is likely to affect their attitudes towards using healthcare technology. Being identified with a nursing professional identity highly affects the way a person thinks of the profession; what being and acting as a nurse really means.[27] Previous research has described the nursing profession as a calling and a lifetime commitment with a strong feeling of serving the patients. Some of the most important personal characteristics mentioned are generosity, curiosity, stress tolerance and knowledge sharing.[28] The authors further conclude that emotion work is a fundamental part of nurses work practices. Skillful, emotional management is done with the aim of creating a caring atmosphere around the patients.[29] When introducing new technology that has the possibility to drastically change traditional work practices, one could suggest that the technology must be designed to support nurses values and personal characteristics that are considered important for their profession.

When it comes to models for auto triage there is limited research. Up to this date, no such models have been developed to be successful enough to put in practice. Auto triage is a complex task, one of the biggest challenges being to analyze individuals' beliefs and ideas on what their problems are and how they should be addressed. Automating the decision support and predicting the level of care for patients, needs to have a high performance rate if it is going to replace humans performing the same task. However, the availability of electronic health records opens up the opportunity to use this type of information with the aim to assure the correct treatment for every patient and is a large asset to future healthcare. Despite the increased availability of data, challenges arise regarding the low quality of the data. Medical records have shown to often include incomplete or even incorrect data.[30]

Despite the sparse existing research on auto triage, there are some researchers who have tried managing the task. A study regarding the usage of electronic health record variables to predict medical intensive care unit mortality showed that the model achieved a diagnostic improvement with a factor of 16.26. The model could also provide an improvement in the specificity and sensitivity of patient mortality prediction over existing prediction methods. Another research study, done in 2013, aimed to develop a clinical artificial intelligence framework that could 'think like a doctor' and learn to decide a suitable treatment for patients. This attempt was done by using decision processes and dynamic decision networks. The results indicated that such a framework outperforms the current models of healthcare, decreasing the cost per unit with approximately 60% while at the same time obtaining a 30-35% increase in patient outcomes.[31]

PRE-STUDY

The third chapter presents the results from a pre-study that was conducted prior to investigating ways to convey medical information to nurses during triage. More specifically, a description of the Company that the project has been carried out in collaboration with and their platform is being presented.

3 Pre-study

This project has been carried out in collaboration with a start-up company focusing on digitizing Swedish primary care; from now on referred to as *the Company*. Prior to investigating ways to convey medical information to nurses during triage, a pre-study was conducted. The intention was to form an understanding of *the Company* and their platform, and consequently describe the context in which the project is undertaken. This was done by performing a number of semi-structured interviews with *the Company's* employees as well as by going through their product in detail. The employees contributed with relevant information relating to their own area of expertise, e.g. customer success, medical or product and tech. This way, an understanding of why and how the project should be realized was formed. Additionally, with the previously described purpose and scope in mind, a number of suggestions for what results could be achieved were discussed and formulated. Since digitizing of the medical industry can be thought of as a fast-paced, ever-changing field the suggestions have only served as initial indications, or ideas, of what the result could point to.

One such suggestion was that, given the patient's reason for contact and characteristics, different information is needed to make a triage decision. It could be that some information always is of high interest and should be presented to the nurses no matter the patient's reason for contact. Examples of this could be age, gender and the patient's own rating of his/her health. In contrast to information that is always of interest, other information may be of importance depending on the specific case at hand. For example, if a patient is suffering from nausea and abdominal pain it could be relevant to know if he/she experiences chest pain as it may indicate that the patient is having a heart attack. Other times when the patient is suffering from for example fever, such information may not be as relevant to know. Given this, nurses might look for information in different ways depending on the patient's reason for contact. As a consequence, the information should preferably be visualized differently for each specific case to enable a more efficient triaging process.

In the subsections below, the result of the pre-study is being described, starting with a description of *the Company* and their product. Moreover, the nurses' general workflow is described in short as well as the different types of information that the nurses read when triaging a patient.

3.1 The Company

The Company was founded in 2016 and has since then offered white-labeled, business-to-business solutions to digitize the patient journey for primary healthcare providers. *The Company* claims that while other digital solutions available on the Swedish market tend to focus on specific patient groups and care chains, they apply a holistic approach and strive to include all steps of the patient journey. Their intentions are to free-up time for healthcare professionals, obtain better medical quality as well as increase patient engagement and satisfaction. At the time of writing, around 20% of Sweden's patients have access to *the Company's* solutions.

3.2 The platform in short

As of today, *the Company's* services consist of a digital platform that acts as an extension to existing healthcare providers. Patients are able to asynchronously interact with a medical practitioner online, by first safely logging in to the service using BankID, a Swedish mobile identification system. Before proceeding with the process, the patients must answer whether their symptoms are life-threatening or not and if so contact an emergency unit directly. Otherwise, the patients are presented with a chatbot and asked to create their own medical history by answering an intelligent questionnaire as seen in Figure 2. Initially, the patients are asked to choose among a fixed number of symptoms and to answer a number of questions that are generated based on their reason for contacting. Once the questionnaire is completed, a medical report is created consisting of the patient's medical and personal information which serves as a basis for how the healthcare professionals proceed with the patient. The goal of the questionnaire is to include relevant, yet brief, information regarding the patient's reason for contacting, thus enabling effective treatment and the right level of care. Once the healthcare professional has read the medical report, he or she can chat with the patient to ask additional questions. In the chat environment, the provider can also prescribe medication or redirect the patient to a digital meeting with another professional such as a physician, psychiatrist or specialist. If needed, the patient can be scheduled for a physical consultation at a healthcare center. Lastly, the physician can, with the patient's consent, end the appointment and add it to the patient's medical records.

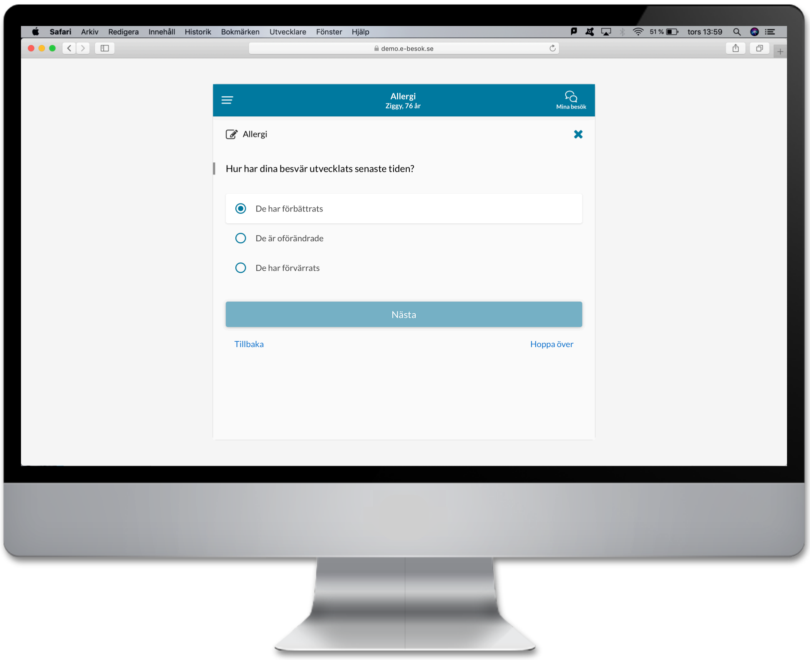

Figure 2: The patients are asked to fill out a questionnaire when contacting the healthcare center.

The platform is reportedly developed with the patients in mind and allows the patients to reply in the chat whenever it is convenient. The aim is for the platform to support the entire patient journey, from initial contact to follow-up. *The Company's* digital tool enables the practitioners to make better use of their resources since time spent on taking the patients' anamnesis is reduced. This creates more time to provide the best possible treatment and to treat more patients simultaneously. In Figure 3, the above-mentioned process is being visualized, starting from initial contact to treatment and documentation.

The most common outcomes for patients are; physical doctor's visit, digital doctor's appointment, referral to primary practitioner on call or self-care, i.e. patients not needing professional treatment. The scope of this project is hence limited to those four options.

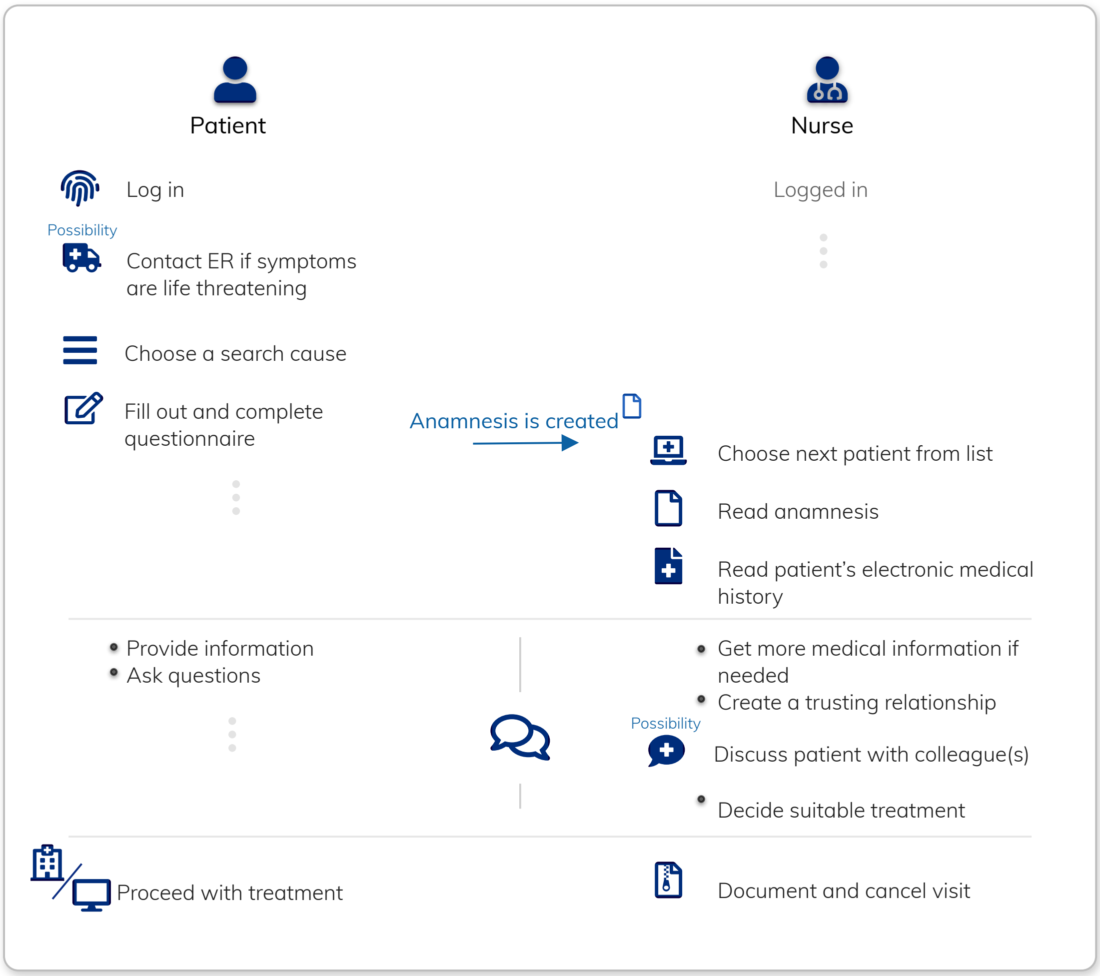

Figure 3: The steps taken by the nurse and patient during a patient encounter.

3.3 The medical report

Based on the reason for contacting and the medical information provided by the patient in the questionnaire, a report is generated as seen in Figure 4. The questionnaire is dynamic and built upon artificial intelligence techniques where the questions are generated from previous answers given by the patient. Since the report summarizes the information provided in the questionnaire, it may vary in length and detail. However, it always follows the same general structure with two main sections; background (*Bakgrund*) and current state (*Aktuellt*). One feature supported by *the Company's* platform is that the nurses can choose to view an extended version of the original report (*Utökad rapport*). By doing so, it is possible for the nurses to analyze information that is considered to be less important for making a decision, e.g. questions that the patient has not answered. This way, the original report (*Standardrapport*) can be kept intuitive and concise.

The information included in the report can be of the following varying types:

- **Free text.** The patients are always asked to describe their symptoms with their own words in the questionnaire. The length and detail of the information provided may vary greatly from patient to patient and a maximum length of the answers is therefore set. In the report, the patient's own words are presented along with subheaders and quotation marks but follow the same font, color and size as the rest of the report.

- **Scales.** The patients are frequently asked to make use of scales that are designed to help asses their symptoms, e.g. the patients' pain ranging from none to an extreme amount of pain. The Visual Analogue Scale, VAS, is a measurement for subjective attitudes or characteristics that cannot be directly measured. It is a well-known scale, used worldwide in clinical research to measure the frequency or intensity of various symptoms.[32] VAS can be displayed in a number of ways but is in the report presented in a free-text format, ranging from 0-10. Additionally, the patients are always asked to estimate their current health status (*Självskattad hälsa*) with the scale ranging from 0-100, where 0 corresponds to the worst possible health status and 100 to the best. Motivations to why the scale is not ranging from 0-10 like VAS is that a higher value corresponds to a better health status, whereas a higher value in VAS correlates to a worse status.

- **Answers to single/multiple choice questions.** A few questions in the questionnaire, e.g. *Do you have a fever?*, are single-choice questions, i.e. require only one answer from the patient such as *Yes*, *No* or *I don't know*. Based on the relevance of the question, the patient's answer might be displayed in the original report no matter what the patient chooses to answer. Other times, the information may be presented only if a certain answer has been chosen. Shorter sentences relating to the patient's answers are generated and presented in the report, separated by line breaks. For multiple choice questions, only the chosen alternatives are initially displayed in the report. By choosing an extended version of the report, it is possible for the nurses to see all the alternatives that the patients can choose from, including the ones that were not selected. Such information is displayed in smaller, gray font.

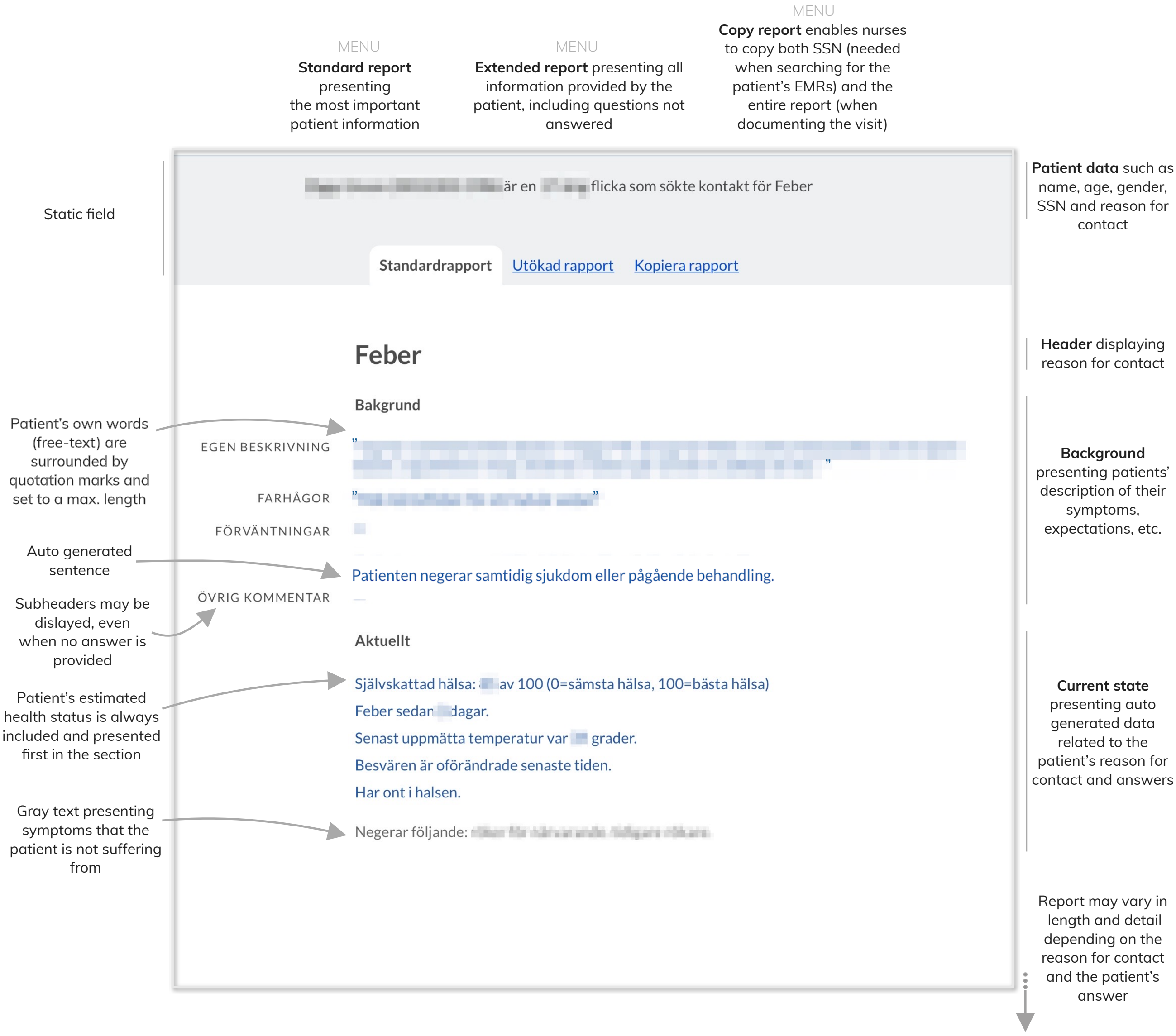

Figure 4: A brief description of the medical report.

- **Duration and dates.** The patients are always asked to estimate how and when their symptoms first started as well as how they have evolved with time. Such information is presented in shorter sentences and separated by line breaks.

CONTEXTUAL DESIGN

The fourth chapter presents a theoretical framework relating to one of the two chosen approaches, namely user research and design. Each of the three subsections describes one part of the design process, ranging from data collection through testing sessions to product concepts and final prototypes.

4 Contextual design

Contextual design is a user-centered approach for collecting field data based on the user's needs and behaviors. The data is later used to drive ideation, construct new product concepts and design, or re-design, any kind of technological product. It was first introduced in 1988 and has since then become an established design process, perhaps since it considers the fact that a product always is part of a bigger process or work structure. Thus, the designers are given a chance to 'own the complexity' of the technology and base their decisions on the very end users of the product. In this thesis, contextual design has been chosen to be the theoretical framework for the user research approach since it, in contrast to other commonly used frameworks, puts the users in the center of the design process and lets them be experts in how to interact with the technology. This way, the designers can make use of a deep understanding to design products that actually fit into people's lives. By observing the users in their natural context, while they are interacting with the product in their own unique way, the designers are given the opportunity to reveal important insights.[33] Failing to consider how the users interact with the technology might lead to a mismatch in the users' and designers' mental model of a task, as defined in the usability and functionality of an interface. Consequently, the technology might be short-lived and lead to frustration; both for the users when not getting what they need from the system and for the designers when the users do not interact with the technology as initially expected, leading to more work.[34]

The design process is divided into three main phases; *data collection and interpretation, consolidation and ideation,* and *design and validation.* First, field data is collected to get an understanding of the users' needs, desires and motivations to use the technology. Secondly the gathered data is analyzed and a shared view among the members in the design team is ultimately created. During this phase new product concepts can be invented based on the user data. Thirdly and last, the concepts created in the previous phase are realized into actual designs and further testing is carried out.[33]

4.1 Data collection and interpretation

When gathering user data, a possible mistake is failing to discuss design requirements with the users or expecting them to provide a complete, detailed picture of how the technology is or will be used. The users might not know what they want, just like the designers might not know what to ask. One commonly used data gathering technique is Contextual Inquiry, CI, where the users are observed in their natural environment while interacting with the device. Over time, the designer can ask questions to get an in-depth understanding of how the technology is used, and gather aspects that the user is unaware of or does not know how to articulate. This way, tacit knowledge and unconscious aspects may be revealed. When interacting with the user, one relationship structure that has proven to be successful is the master/apprentice model where the users are considered to be the experts or the masters in the context, guiding the designer in their work. The interviewer on the other hand, takes the role as apprentice and may consequently adopt some characteristics associated with the role such as inquisitiveness, humility and attention to detail.[33]

Before gathering data, a project focus needs to be established by defining the settings, who the users are and what their natural environment is, as well as the problem(s) to be solved. This way, the designers know better what to pay attention to when observing the users and may help steer the conversation into a relevant context. The designer is additionally guided by four main principles that have been constructed for running a successful interview. The first one is *context*, which relates to when the designers observe and discuss what the user is doing and why, in their own environment. Detailed re-telling of specific events, so-called retrospective accounts, can be used to understand what has happened outside the interview session, thus leading to a more thorough understanding. By observing ongoing work, the user can reveal values, emotions and motivations towards the product and give the designer detailed and rich context insights. The second principle *partnership* deals with how the designers collaborate with the users and 'share the power' to direct the interview. Instead of formulating predefined questions, the designer should let the user lead the session towards the most important aspects. Third, the principle of *interpretation* relates to how the designer turns facts from the observation into hypotheses. These are shared with the user during the session and the user is encouraged to discuss the hypotheses with the designer so that a mutual understanding can be created. Since the hypotheses can be considered to be the very foundation of the future design, it is important that the designer understands the user correctly. The users are known to not let designers misinterpret their motives behind their actions and are therefore likely to rephrase the interpretation until it fits their own thoughts. The fourth and last principle *focus* encourages the designer to steer the conversation to topics that fall within the project scope and ignore the rest. Even the users could, by knowing the predefined focus, steer the conversation.[33] Once the CI is completed, the designers are encouraged to sum up all the findings in interpretation sessions, which enables the design team to understand the data from an in-depth user perspective.

4.1.1 Think aloud

One additional method, not included in the contextual design framework, that effectively can bridge the knowledge gap between user and designer is when the users are instructed to talk out loud while interacting with the technology. Think aloud can be considered to be an effective method to gain insight into the way humans solve problems as well as their cognitive processes. A verbal protocol is created and used as raw data, and substantial interpretation and analysis are needed to get a deep insight into how the users interact with the technology. To use think aloud early in the design process, the designer may obtain user-specific knowledge before forming own ideas of how the system should be used. As a consequence, the users' and designers' conceptual models might not differ as much, which can result in more efficient systems being designed with fewer iterations.[35] In contrast to

CI, where the designer should have an open mind and let the expert user set the scope, the think aloud approach gives the designer a chance to test strict and predefined hypotheses.

4.2 Consolidation and ideation

After the team has collected in-depth user data, the sometimes challenging process of making sense of the information and reach a shared decision on what product concepts to focus on begins. To bridge the gap between design and data, it is essential to not only transfer knowledge but also understanding, insight and a 'feel' for the users and their lives. Since the findings tend to be complex and detailed, the first steps in sorting the data may feel overwhelming. Contextual design therefore offers a great number of models and diagrams to use, each showing different points of views of the user's world. One such model is the affinity diagram, sometimes referred to as the KJ Analysis, which is commonly used as a first step in the process of structuring data. Notes gathered from the interpretation session performed in the previous phase are written down on post-its and arranged in groups in a bottom up-manner where each group points to a single issue or insight that derives from the data. This way, complex and detailed data can result in a single hierarchical structure that is easy to read and interpret.[33]

An important part of the second phase is the ideation process, which takes place after the data has been structured in a more comprehensible way. Contextual design supports ideation through team-based workshops with the goal to understand, in detail, how the technology can facilitate users' lives. The workshop is introduced by analyzing the affinity diagram individually, trying to link the data to possible design ideas. The ideas with the greatest potential are later sorted out by the team and grouped together for further exploration. It is essential that the whole team is brought together in a shared direction so that creative, spur-of-the-moment ideas can be created. Later, a visioning session is conducted where product concepts are identified and the first designs ideas realized.[33]

4.3 Design and validation

The last phase in contextual design focuses on giving the product concepts defined in the previous phase a look, structure and function that supports the initial values of the users. The process of this phase is designed to follow an agile mentality, with just enough thinking and prototyping to be able to effectively create a design and refine it after each iteration. Due to the challenges of creating a product where all parts coherently should work together, it may help to divide the design into a number of layers, ranging from abstract to specific. Holtzblatt and Beyer, the authors of the book *Contextual Design*, think of the first layer as a *practice design*, which deals with the information and functions that the system should support. The second layer, named *interaction design*, relates to how the user is navigating in the system, independently of the visual look. The focus lies on both the screen itself and the content that is being presented. Thirdly, the *visual design* layer, deals with the graphical interface such as design principles and detail of interaction.

Naturally, testing is a necessary part of the design process, used to identify possible flaws and ensure that the design fits the users' initial needs. The testing phase is an integral part of the design process and should thus be included in almost every iteration. At the beginning of the process, basic prototypes, often on paper, are being presented to the users. This way, they are not overwhelmed with a complete system too complex to comment on, but are instead given a chance to analyze the most important functions. As time passes, the prototypes can be more detailed and realistic.[33] In the redesign process, comparisons of the designers' and the users' mental models as well as the old and the new systems are conducted to identify flaws in the original system and uncover potential problems with the redesigned one.[36]

MACHINE LEARNING

In the fifth chapter, a brief introduction to the basic concepts of machine learning are presented. The concepts of classification are explained, followed by descriptions of the different classification algorithms and evaluation metrics used in the project.

5 Machine learning

Most machine learning problems belong to one of two categories; *supervised* or *unsupervised* learning as seen in Figure 5. In general terms, supervised learning builds a model that takes one or several inputs to predict an output. Unsupervised learning on the other hand, have access to inputs but no outputs. There are two typical kinds of supervised learning; classification and regression. The difference between these two can be explained by the variable output types, which can be characterized as either quantitative or qualitative. This project is narrowed down to focus on supervised learning and specifically classification.[37]

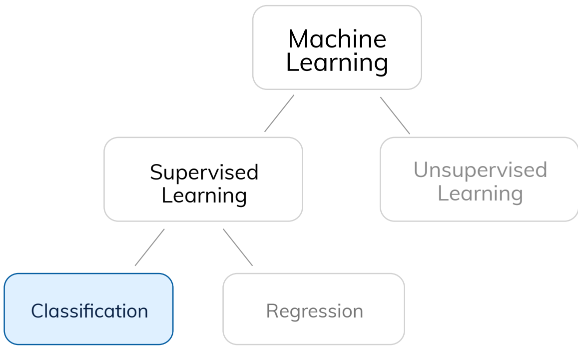

Figure 5: A brief description of categories belonging to machine learning.

5.1 Classification

Classification can be described as the "task of assigning objects to one of several predefined categories".[38, p. 145] It can be used for various applications, two examples being filtering spam emails from real emails or classifying what songs a user of a music streaming platform will like based on previous preferences. Classification aims to learn a model which, for each input data point x, can predict its class $y \in \{1, ..., K\}$.[37] The class, or label if you will, can for example be true/false or spam/not spam. When training such a classifier, the idea is that the model learns by adapting to labeled training data. The classification model is specified in terms of the conditional class probabilities as shown in Equation 1:

$$Pr(y = k|\text{x}) \text{ for } k = 1, ..., K. \tag{1}$$

where k represents the class, ranging from 1 to K, and x represents a vector or matrix containing observations and their features. Note that Equation 1 is a conditional probability; given the observed predictor x the probability that $y = k$ is wanted.

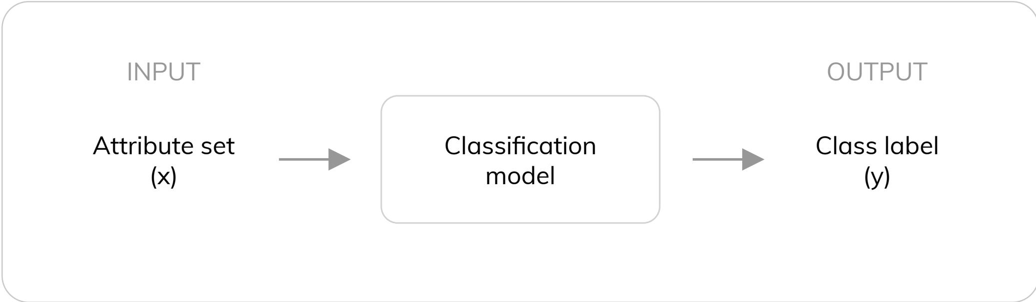

Figure 6: A classification model takes an attribute set as input and classifies it to an output label.

Training and test data

Partitioning the data from the original data set is necessary when implementing machine learning methods. Most of the data is used to learn, or train, our model and is referred to as *training data*. The remaining part of the original data set makes up for the *test data*, seen in Figure 7, for which the trained model can be verified to see how well it performs on unseen data. The split between training and test data should always be done randomly.[39]

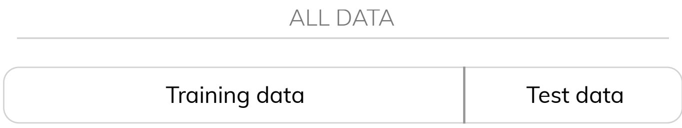

Figure 7: The original data set is split into training and test data.

Error

When estimating the test error rate, which is the error given when running the trained model on the test data, one can hold out parts of the training data and treat it as test data, while training the classifier. This method is known as cross validation and has a few different approaches, one being k-fold cross-validation. The data is split in training and validation data k times as seen in Figure 8, each time letting the validation data be a new subset of the original data set. For each new validation set, the data error is estimated. After all iterations are done an average of all estimated errors is determined.[39]

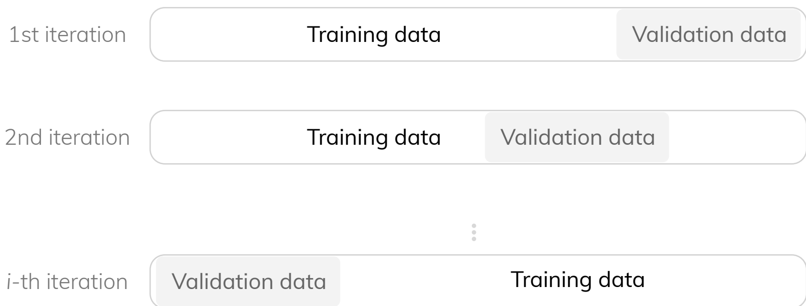

Figure 8: The original data set is split into training and validation data k times, each time letting validation data be a new subset.

The training error rate, which can be determined when the trained model is applied on the training data set, is a common approach when determining the accuracy of the estimate $\hat{\mathrm{f}}$.[37] This metric gives the proportion of incorrectly classified observations and can be calculated as:

$$\frac{1}{n}\sum_{i=1}^{n} I(y_i \neq \hat{y}_i), \tag{2}$$

where $\hat{y}_i$ represents the predicted class label for the ith observation using $\hat{\mathrm{f}}$, and y_i is the correct class. $I(y_i \neq \hat{y}_i)$ is the indicator variable that equals to 1 if $y_i \neq \hat{y}_i$ and equals to 0 if $y_i = \hat{y}_i$. If the indicator variable equals to 1 it means that the ith observation was classified incorrectly. Thus, Equation 2 gives the proportion of misclassified observations.

The training error rate, as seen in Equation 2, computes the fraction of incorrect classifications based on the data used to train the classifier. The test error rate, on the other hand, is obtained by applying the trained classifier to the test data set on the form (x_j, y_j) and can be defined in a similiar way as the training error rate:

$$\frac{1}{n}\sum_{j=1}^{n} I(y_j \neq \hat{y}_j), \tag{3}$$

with the difference being which part of the data set is used. In Equation 3, $\hat{y}_j$ represents the predicted class label for the jth test observation with predictor x_j. The optimal classifier is the one having minimal misclassification test error, thus being the model which assigns each prediction to the most likely class given its input value.[39]

Overfitting

Very complex models, for example polynomials of high degree, can lead to overfitting. This phenomenon can be explained by a model being trained to follow the errors, or noise in the training data, too closely.[37] This can lead to the model not yielding accurate estimates of the output on data not being part of the training data set. One general rule of thumb is that the likeliness of overfitting becomes greater as the number of input features grows, while increasing the size of the training data set can reduce potential overfitting. Analyzing this, it becomes clear that choosing the right number of features is an important part of model selection. The process of finding the best classifier can be divided into two steps; *model selection* which defines the 'hypothesis space' followed by *optimization* which finds the best hypothesis.[40]

When having a data set with a large number of input features it is often valuable to use regularization to avoid overfitting. The idea of regularization is to modify a learning algorithm with the intention to reduce its generalization error while not affecting the training error. It is an efficient way to, without overfitting to the training data set, train models to perform better on unseen data. Two common methods for this are *lasso regression* and *ridge regression*, also known as L1 and L2 regression respectively. The distinction between the two regularization types can be determined by studying the penalty term in the cost functions as seen below in Equation 4 and Equation 5, which both show a multiclass penalized logistic regression minimizing the cost function. The two regularization types can mathematically be expressed as:

$$\textbf{Ridge } min_{\beta_0,\beta}\frac{1}{2}\beta^T\beta + C\sum_{i=1}^{n} log(exp(-y_i(x_i^T\beta + \beta_0)) + 1) \text{ and} \tag{4}$$

$$\textbf{Lasso } min_{\beta_0,\beta}||\beta||_1 + C\sum_{i=1}^{n} log(exp(-y_i(x_i^T\beta + \beta_0)) + 1), \tag{5}$$

where x is a matrix of shape *number of samples∗number of features*, β is a vector $\beta = (\beta_1, \ldots, \beta_p)$ which represent the coefficients to x, β_0 is the y-intercept and C is the optimal value for the inverse of regularization strength. The number of classes determines the number of β-coefficients; for a binary classification problem the vector β would only hold β_1 whereas a problem with 4 output labels would have a vector $\beta = \{\beta_1, \beta_2, \beta_3\}$.

5.2 Classification algorithms

5.2.1 Logistic regression

Despite its somewhat misleading name, logistic regression is a model used for classification and not regression problems.[41] When using logistic regression, one is interested in modeling the probability that the response variable y belongs to a certain class[37], given the observation x, which mathematically can be expressed as:

$$p(x) = Pr(y = 1|x). \tag{6}$$

For a binary class problem this can be solved by using the logistic function:

$$p(x) = \frac{e^{\beta_0+\beta_1 x}}{1 + e^{\beta_0+\beta_1 x}}. \tag{7}$$

Equation 7 holds for multiclass problems as well, but the difference being that β_1 is replaced by the vector $\beta = (\beta_1, \ldots, \beta_p)$, where p is the number of classes minus 1. For the binary case, the model makes predictions based on the probability that the input value belongs to a default class (class 0). A probability greater than 0.5 indicates that the default class should be the predicted output, while a probability less than 0.5 results in the prediction being the other class (class 1). The logistic model is learned using maximum likelihood.[37] In maximum likelihood, estimates of β_0 and β_1 (seen in the logistic function Equation 7 above) are chosen such that these estimates yield a probability close to 0 and 1 respectively for two binary classes. This is done by maximizing the likelihood function [39] which can be formalized as the mathematical equation:

$$\ell(\beta_0, \beta_1) = \prod_{i:y_i=1} p(x_i) \prod_{i':y_{i'}=0} (1 - p(x_{i'})). \tag{8}$$

In Figure 9 a decision boundary when using logistic regression for two-dimensional input data is illustrated.

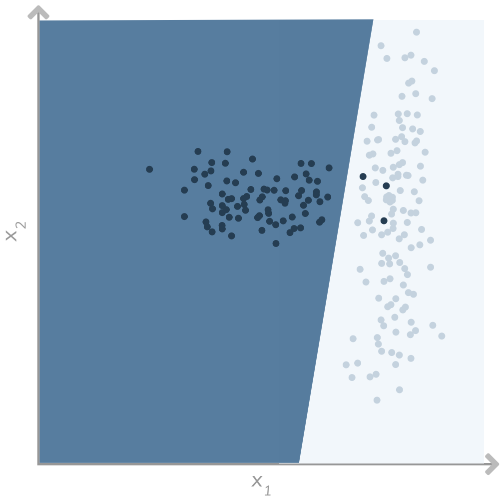

Figure 9: Logistic regression for K = 2 classes, generating a linear decision boundary learned from the classifier, here represented by the intersection between the dark and light blue fields. The dark blue dots represent training observations from one class, and the light blue dots represents the other class.

The logistic regression model can also be used for problems with more than two classes, multinomial logistic regression, where a common approach is to use one-hot encoding followed by replacing the logistic function with a softmax function described by Equation 9. The one-hot encoding is implemented by replacing the output y_i with a K-dimensional vector y_i. Below is an example with $K = 3$, that is outputs that can take on one out of three different classes.

Vanilla encoding	**One-hot encoding**
$y_i = 1$	$y_i=[1,0,0]^T$
$y_i = 2$	$y_i=[0,1,0]^T$
$y_i = 3$	$y_i=[0,0,1]^T$

Having the output in a vector-valued format, a vector-valued version of the logistic function is also introduced which is being referred to as the softmax function:

$$softmax(z) = \frac{1}{\sum_{j=1}^{K} e^{z_j}} \begin{bmatrix} e^{z_1} \\ e^{z_2} \\ \vdots \\ e^{z_K} \end{bmatrix}, \tag{9}$$

where z is a K-dimensional input vector. The outputs given by the softmax function sum up to 1, each element ranging from 0 to 1. Combining the softmax function with the concept of linear regression the class probabilities can be modeled with the multi-class logistic function:

$$Pr(y = k|x_i) = \frac{e^{\beta_k^T x_i}}{\sum_{l=1}^{K} e^{\beta_l^T x_i}}, \tag{10}$$

where the number of estimated parameters increases along with k, the number of output classes. Just as for binary logistic regression, the parameters can be learned by using maximum likelihood.[42]

5.2.2 Random forest

The random forest classifier relies on the concept of fitting a number of decision tree classifiers on different subsets, originating from the original data set, and averaging them. A decision tree is a method for decision support which has a tree-like structure where each branch represents a decision. Depending on the structure of the tree, it can have a varied number of branches with varying depths. It follows a hierarchical structure where the decision process starts at the the top-most item, also known as the root. Every part of the tree that is not either a root or a branch is known as a leaf, which represents the output label. Each non-leaf node is labeled with an input feature whereas each leaf node is assigned with a class, or the corresponding class probability. An example of a decision tree is illustrated in Figure 10.

Instead of only looking at the result from one single decision tree, random forest uses several trees and takes the average as the final result. This approach can enable powerful predictions, as it may not be sufficient to rely upon the result of one single classification model. The idea is that the averaging, also known as *bagging*, will improve the accuracy and reduce the chances of the classifier to be overfitted; resulting in a more stable prediction.[43] The bagging method, or *bootstrap aggregation* if you will, reduces the variance of an estimated prediction function. Research has shown that this works especially well for trees since they are unpruned, meaning that the trees are deep and often have high-variance and low-bias characteristics. The bootstrapping concept relates to random sampling with replacement.[39]

The algorithm can be explained by the following steps:

1. For $b = 1$ to B:
   (a) Choose a bootstrap subset $Z*$ of size N from the training data set.
   (b) Construct a random forest tree T_b by choosing a random number of input features. Split the tree based on best split-point, that minimizes the misclassification error, among the various features. This is done for each terminal node in the tree, until minimum node size n_{min} is reached.
   (c) Make a class prediction.
2. Make the overall class prediction by taking majority vote C from all B trees.

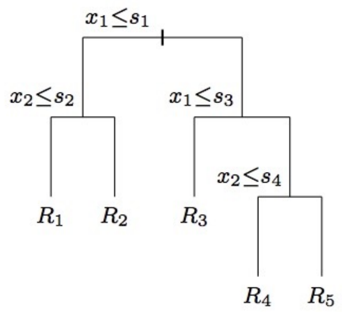

Figure 10: Example of a decision tree, having terminal nodes R1, R2, R3, R4 and R5.

The trees used in random forest are not very dependent of each other, since the algorithm uses bootstrap sampling from the original data set. This creates an overall reduction in the misclassification error. Three common error measures to determine the best split point are misclassification error, entropy and gini index.[42] Considering two classes, where the proportion in the second class is represented by r, the three splitting criterias can be calculated as:

$$\text{Misclassification rate } = 1 - \max(r, 1-r), \tag{11}$$

$$\text{Gini index } = 2r(1-r) \text{ and} \tag{12}$$

$$\text{Entropy/deviance } = -r\log r - (1-r)\log(1-r). \tag{13}$$

5.2.3 XG-Boost

XG-boost is a Python library, relying on gradient boosted decision trees. This is quite easily interpreted from the algorithm's name, which stands for "extreme gradient boosting".[44] The algorithm has become popular and frequently used in machine learning projects, much thanks to the high performance and powerful execution speed it has proven to provide. Having some similarities to the random forest algorithm described above, XG-boost makes use of the boosting concept. Boosting is an ensemble technique just like bagging, but with the big difference being that updated models are being added in order to correct the errors made by previous models. This continues until no further improvements can be done. A consequence of this is that the model can cause overfitting in the training data. To avoid this, one can apply a weighting factor for the corrections made by new trees. This weighting factor is also known as the learning rate.[45]

For many learning algorithms, like logistic regression, we aim to minimize a cost function which can be determined by an algorithm like gradient descent. However, for very large data sets gradient descent can become very computationally heavy and therefore implementations and modifications to the algorithm have been developed. For regular gradient boosting, the gradient descent is used to optimize the parameters (optimizing being to find the parameters causing minimal loss) as well as to find the objective function that best approximates the data. This adds a lot of complexity since the number of parameters to optimize for no longer have a fixed value. Instead, the optimization can come to change as the objective function alters.[46] What separates XG-boost from normal gradient descent boosting, is that it uses both the first and second order gradients to calculate the loss function, whereas normal gradient descent boosting only uses first-order gradient.[45]

5.3 Evaluation metrics

To evaluate the performances of machine learning classifiers, there are a number of different evaluation metrics that can be analyzed. Depending on the model, data type and what issue is being investigated different metrics are of relevance.

Confusion matrix
A confusion matrix, which can handle outputs of two or more classes, is often used as an evaluation metric. The confusion matrix gives an easily interpreted overview of how well a classifier performs, in terms of number of correct and incorrect predictions. Presented below in Table 1 is an example of a confusion matrix for binary classification, resulting in a two-dimensional matrix. The actual class can be found on the y-axis while the predicted class is found along the x-axis.[47]

Table 1: Confusion matrix with 2 classes.

		Predicted	
		Yes	No
Actual	Yes	100	0
	No	10	80

- True positive (TP); number of correctly predicted class examples. *Items of class Yes belonging to class Yes.*
- False negative (FN); number of incorrectly predicted examples belonging to the class. *Items of class Yes predicted to class No.*
- False positive (FP); number of incorrectly predicted examples not belonging to the class. *Items of class No predicted to class Yes.*
- True negative (TN); number of correctly predicted examples not belonging to the class. *Items of class No predicted to class No.*

For multinomial classification algorithms, with outputs of k classes, the number of correctly predicted examples will be represented by the diagonal of the $k * k$- dimensional matrix. For a model with 100% performance accuracy, i.e. predicting all classes correctly, the matrix would have positive values along the diagonal and zeros elsewhere. A confusion matrix of 4 classes is illustrated below in Table 2.[47]

Table 2: Confusion matrix with 4 classes. The correctly predicted observations (true positives) are found along the diagonal.

		Predicted			
		Class 1	Class 2	Class 3	Class 4
Actual	Class 1	TP_1	E_{12}	E_{13}	E_{14}
	Class 2	E_{21}	TP_2	E_{23}	E_{24}
	Class 3	E_{31}	E_{32}	TP_3	E_{34}
	Class 4	E_{41}	E_{42}	E_{43}	TP_4

By using confusion matrices like the ones presented in Table 1 and Table 2, it is possible to calculate different measures to evaluate the performances of classification models.

Accuracy

One commonly used metric when evaluating classifiers is accuracy, which shows the relation between the observed predictions and the correct predictions[47] as seen in Equation 14.

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}. \tag{14}$$

Making use of the terms in the confusion matrix as described above, accuracy could also be calculated as:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \tag{15}$$

However, accuracy as an evaluation metric does not take into consideration what type of error the classifier makes. Making this distinction can be critical, since some errors can be considered to be worse than others. Consider for example the process of filtering spam e-mails from non-spam e-mails. Deleting an important e-mail could be considered to be a bigger mistake than letting a spam e-mail through a filter to the inbox. In cases where the type of errors a classifier makes matter, accuracy may not be a sufficient performance metric. Hence further metrics, displayed below, have come to be widely used as complements to accuracy.[47]

Precision

The equation for the precision metric can be defined as:

$$Precision = \frac{\text{TP}}{\text{TP + FP}} \tag{16}$$

and illustrates the proportion of all positive predictions, TP + FP, that were correct, TP. For the case when there are 4 classes, the overall precision can be calculated by determining the precision for each class and then averaging them. FP is the sum of values in the corresponding **column** (excluding TP). For example, the precision for *Class 1* could be calculated as:

$$Precision_{Class1} = \frac{\text{TP}_1}{\text{TP}_1 + \text{E}_{21} + \text{E}_{31} + \text{E}_{41}}. \tag{17}$$

Recall

The equation for the recall metric can be defined as:

$$Recall = True\ Positive\ Rate\ (TPR) = \frac{\text{TP}}{\text{TP + FN}} \tag{18}$$

and illustrates the proportion of actual positives, TP, that was identified correctly. In the multiclass case, again the recall is calculated for each class and the overall recall achieved by averaging them. FN is the sum of values in the corresponding **row** (excluding TP). An example of how to calculate the recall for *Class 1* could be expressed as:

$$Recall_{Class1} = \frac{\text{TP}_1}{\text{TP}_1 + \text{E}_{12} + \text{E}_{13} + \text{E}_{14}}. \tag{19}$$

Specificity

The equation for the specificity metric can be defined as:

$$Specificity = True\ Negativ\ Rate\ (TNR) = \frac{\text{TN}}{\text{TN + FP}} \tag{20}$$

which illustrates the proportion of actual negatives, TN, that are identified correctly. In the multiclass case, again the specificity is calculated for each class and the overall recall achieved by averaging them. TN is the sum of **all** columns and rows excluding that class's column and row. FP is the sum of values in the corresponding **column** (excluding TP). An example of how to calculate the specificity for *Class 1* could be expressed as:

$$Specificity_{Class1} = \frac{\text{TN}_1}{\text{TN}_1 + \text{E}_{21} + \text{E}_{31} + \text{E}_{41}}. \tag{21}$$

To fully evaluate a model, one needs to study both precision and recall. However, it is important to note that there often is a trade-off between these two metrics. Having a model with high precision typically results in a reduced recall and vice versa.[48] Consider a problem having two output classes, where one of the classes is seen as the event of interest. Recall, or true positive rate, tells us about the accuracy in the event population. Specificity, or true negative rate, measures the rate to which non-events are classified as non-events. The false positive rate is defined as one minus the specificity.

USER RESEARCH

The sixth chapter presents the user research process, starting with data collection and ending with discussing product concepts. Insights from the user studies relate to the nurses' usage of the platform, online communication and, more importantly, the report in detail.

6 User research

6.1 Data collection

The first step in using a contextual design approach was to get a rich understanding of how nurses, with varying expertise and attitudes towards new healthcare technology, use *the Company's* platform. In order to address the project's research question, an understanding of what information is important during triage was formed. A number of healthcare centers from different regions in Sweden were initially contacted and asked to participate in the data collection. Due to healthcare centers often struggling with issues such as understaffing and heavy workload, only one of them could find the time to participate in the study. A total number of four nurses were participating in qualitative data collection sessions, all of them with varying experiences from working in healthcare and with digital tools. Additionally, the nurses had different roles within the nursing team. Such variance is of high relevance for the study, since the design of the report ideally should support a wide range of needs and applications.

All of the nurses participating in the study use *the Company's* platform in their daily work and, more specifically, communicate with the patients in an online chat. Some healthcare centers using *the Company's* platform are instead communicating with their patients over the phone and are thus likely to be using the report differently. When discussing the symptoms directly with the patients over the phone, they are more likely to follow the structure of a traditional patient-nurse encounter according to *the Company's* employees. Thus, they might not use the report to the same extent, resulting in them having different attitudes and needs towards it when being compared to nurses who are communicating with their patients in the chat. If the results of the interview sessions would have been based on nurses who are using the report in fundamentally different ways, one would lack the kind of detailed user information that is of high importance for the study. Therefore, a decision was made to not invite nurses who are communicating with their patients over the phone, and instead keep the data collection short, yet of high quality.

Early in the process it was decided that the interview session should consist of two main parts, focusing on different areas of the reports' functionality and usage. The data collection took two hours in total for each nurse and had one hour allocated for each part. An interview guide was initially created to keep the interviews on topic and ensure comparability between the two parts. The topics covered in the guide were related to the nurses' triaging process, their attitudes towards the system and their patients as well as the reports' structure, content and design. Before conducting the interview sessions, a pilot study was carried out with two employees at *the Company* to evaluate the structure of the test and ensure that the right questions were being asked. As previously mentioned, it is of high importance that the participants feel relaxed and comfortable with sharing personal data, something that was kept in mind when collecting the data.

Part 1 - think aloud

The first part was designed to better understand the nurses' reasoning process when reading the report and deciding on an appropriate level of care for the patient. Areas of particular interest were *what* patient information the nurses were looking for and *how*, i.e. in what order, they were looking for it. Instead of using real patient data, 20 test cases were created and uploaded to the platform. Given the scope of the project, five reasons for contacting were used when creating the cases (*headache*, *depression*, *fever*, *stomach pain* and *ear symptoms*). The test cases were designed to reflect reality and varied, apart from the chosen reasons for contacting, in details, severity of symptoms and personality of the patient. Before conducting the first part of the interview session, a project focus (Appendix A) was established and later shared with every nurse participating in the study. This way, the nurses were given a chance to better know what to pay attention to and keep the conversation relevant.

During the interview session, the nurses were asked to verbalize their clinical assessment while navigating on the platform and reading the test cases. When suitable, they were asked to explain their way of reasoning and discuss areas of improvement. Screen and sound recordings were used to efficiently store the testing data and put all attention to the nurses when performing the tasks.

Part 2 - Contextual Inquiry

The first part was designed to get a better understanding of nurses' cognitive thinking and reasoning processes, and did not reflect a natural working environment in healthcare. The nurses were, for instance, not able to use the chat to communicate with the patients or to read up on their medical records. The second part was therefore designed to give a more in-depth understanding of how the nurses were using the platform in real-life. Contextual Inquiry was carried out, where the nurses were asked to perform everyday tasks on the platform while being observed. During the second part, the nurses could read authentic reports while communicating with their patients, checking their medical records and using advisory support if needed. A master/apprentice approach was taken, enabling for the nurses to explain how they interact with the platform and answer questions that were of particular interest for the interviewer. Every session was documented by using notes and sound recordings. Just like in the previous session, a project focus (Appendix A) was created and shared with the nurses prior to the observation. The main goal was to observe factors that the nurses were unaware of or unable to describe with their own words. Additionally, the observations enabled the designers to identify areas of improvements and specific pain points previously unidentified. Whenever possible, the second part was carried out prior to the first one so that the nurses would take the role as 'experts' from start and thus feel more comfortable with participating in the sessions. This way, a relationship between the interviewer and the nurse could be established, leading to the nurses being more relaxed when discussing issues related to the report.

6.2 Consolidation and ideation

Shortly after the interview sessions had been completed, the data collected was transcribed and stored for future purposes. Transcribing within a short limit of time enabled for an immediate repetition of the session and made it easy to identify key takeaways as well as patterns relating to previous sessions. In order to make the complexity of the data more manageable and bring the data from all the nurses together into a single, coherent view, an affinity diagram was created. Firstly, notes gathered from the interpretation sessions were printed on post-its in random order. A number of general themes could be distinguished and the post-its were later arranged into smaller groups relating to a design or functionality problem. When writing the notes, four colors were used to represent the themes seen below in Figure 11.

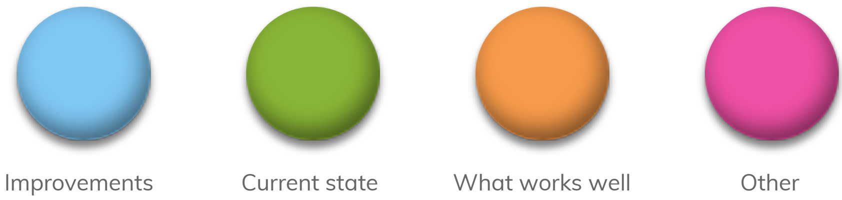

Figure 11: Colors referring to themes found in the interpretation sessions.

By creating an affinity diagram, the designers were forced to discuss every observation made from the data collection, ranging from specific issues to general topics expressed by many nurses. Finally, a single hierarchical structure was created as seen in Figure 12 and used as a basis when trying to link the data to possible design ideas.

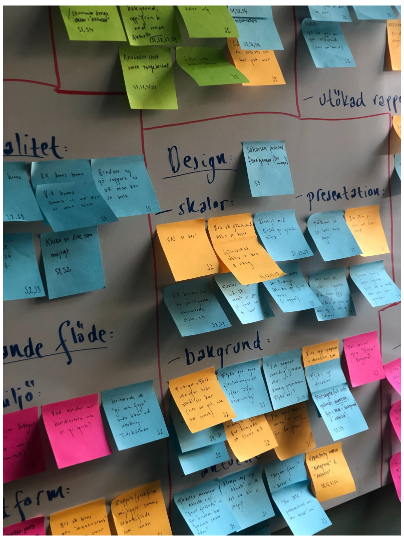

Figure 12: Affinity diagram created to link the user data to possible design ideas.

6.3 Results

The affinity diagram enabled for the design team to understand, analyze and drive ideation from the user data, resulting in a number of product concepts listed below. Worth mentioning is that the nurses were using the platform and medical report in surprisingly similar ways, independent of the patients' reason for contact or the nurses' prior experience. Therefore, the findings have been summarized in a list below, without differentiating the nurses apart. In Section 6.4., a more detailed discussion relating to the product concepts can be found. The themes do not only relate to what data is important for nurses to know when triaging patients but do also consider other factors and work structures that may affect their reasoning process and thus have implications on the redesign of the report. For instance, the design and structure of the questionnaire are factors that are not directly related to the purpose of this project but nevertheless may play a big part in what and how a patient chooses to answer. The content and quality of the report may thus be affected and as a consequence, the nurse's first impression of the patient. Data collected relating to general work processes is not presented with the aim to broaden the perspective of the project, but rather to contribute with important insights relating to what, and how, the information should be included in the report.

Patient generated information:

- The nurses always looked for the patients name, sex, age, social security number and reason for contact prior to doing anything else.
- The nurses read the background carefully from top to bottom, which was said to be the section of highest relevance. More specifically, the patients' own descriptions of their symptoms and reason for contacts were said to be very important.
- The nurses tended to skim through the current state, actively looking for specific information. However, some information such as duration of symptoms, the estimated health status, the progress of the symptoms and current diseases or treatments were always of interest.

Design and functionality:

- The nurses almost always needed to scroll down to see all information included in the report.
- Depending on the reason for contact and the patients symptoms, some information was said to be critical for the nurses to know and should perhaps be highlighted.
- The structure of the report, consisting of background and current state, seemed to fit every nurse.
- The estimated health status was a valuable feature for the nurses, but the scale (ranging from 0 to 100) seemed to be confusing.
- The nurses expressed a wish to shorten or rephrase information presented in the current state, while other parts could be more detailed. Information relating to duration were

often incorrect or contradictory.
- The nurses preferred when the medical information was presented in text-format but claimed to want some information to be visualized differently (e.g. different figures, colors).

Navigation on the platform:

- The nurses always started the patient encounter by reading the patient's report.
- The patient's medical records were read to form an understanding of the patient's history. These were accessed by manually copying the patient's social security number.
- Sometimes, the nurses discussed the patient's symptoms with their colleagues or looked up medical information online. This way, they were said to be given a better understanding of the patient's needs, personality and treatment compared to a physical encounter.
- The nurses introduced themselves to the patient in the chat and always asked follow-up questions relating to the case at hand. The extended version of the report was rarely looked at, even though it was said to contain important information.
- Once a decision had been made for how to treat the patient, the encounter was, with the patient's consent, ended. The entire report was manually being copied and inserted into the patient's medical records.

Communication between nurse and patient:

- It was important for the nurses to keep the report visible when chatting with the patients.
- The chat was an important tool for communicating with the patients, creating a shared understanding of their treatment as well as to reduce the patients' level of stress.
- The nurses could ask questions to the patient in the chat, even though the information was included in the report, to create a trusting relationship.
- Some nurses were carefully reading through their answers when chatting with the patients while others wrote an answer without reading it through.

General observations:

- The nurses wanted to know what the questionnaire looked like and what questions that had been asked since it may affect the patient's answers.
- The nurses tended to be treating a great number of patients at the same time.
- The introduction of a new platform had changed existing work routines as well as organizational and social contexts.
- The nurses felt motivated to establish new routines and acquire knowledge needed to make use of the technology.

6.4 Discussion

Based on the product concepts previously described, a more thorough discussion is being held below. To enable a better understanding of the data collected, the discussion follows a different structure compared to the results mentioned above; starting by presenting the nurses' usage of the platform and, more specifically, the report in detail. The discussion relates to what information seemed to be most important when triaging patients, as well as the design and functionality of the report. This is followed by describing online communication, new working routines and changing team dynamics.

6.4.1 General workflow

This section describes the following product concepts; navigation on the platform and patient generated information. In general, every nurse participating in the data collection was positive towards using the platform and digitizing healthcare. The platform was said to enable the nurses to be 'detectives' prior to contacting the patients which, in contrast to traditional patient encounters, may contribute to them having a better understanding of the patients' history, needs and personality. Additionally, the nurses are given the opportunity to discuss the patient's symptom with each other, both in person and by using the team chat, and to read up on a certain diagnosis online. If a nurse is newly graduated or unused to digital tools in healthcare, this might be particularly useful since it can make them feel more confident in their profession and decisions. One nurse (N2) expressed her frustration over the fact that healthcare practitioners tend to focus on only one aspect of the patient's symptoms, failing to consider the bigger picture. By using the platform however she felt like she was given a chance to understand the patient's situation as a whole which, according to her, might result in patients getting the right care and treatment from the very beginning.

Every patient that has initiated contact and completed the questionnaire is presented in a list, ordered by time, to the nurses. Whenever the nurses have time, they can start a new patient encounter by choosing one of the patients from the list, resulting in them being responsible for the treatment of the patient. Common for every nurse participating in the data collection was that they started the encounter by reading the medical report to get an understanding of the patient's symptom and reason for contacting. Thereafter, the nurses presented themselves in the online chat by using a standardized message, followed by a more specific question or comment relating to the patient's symptoms. One nurse (N2) stated that this was done to build trust and make the patient feel listened to. No matter what information was included in the report, one important part of the process was for the nurses to form an understanding of the patients' previous history which was done by reading up on their medical records. To access the medical records, the nurses needed to manually copy the patients' social security number and insert it into the search field in the medical records. Since this process is handled manually, yet completed for every new patient, there is a small risk that the wrong social security number will be copied, resulting in the nurses reading another patient's history and basing their decisions on the wrong information. Even though the nurses seemed well aware of the risks that may come with copying the social security number manually and hence used to double check that they were doing it right, it is important that the platform is designed with this in mind, preventing it from happening.

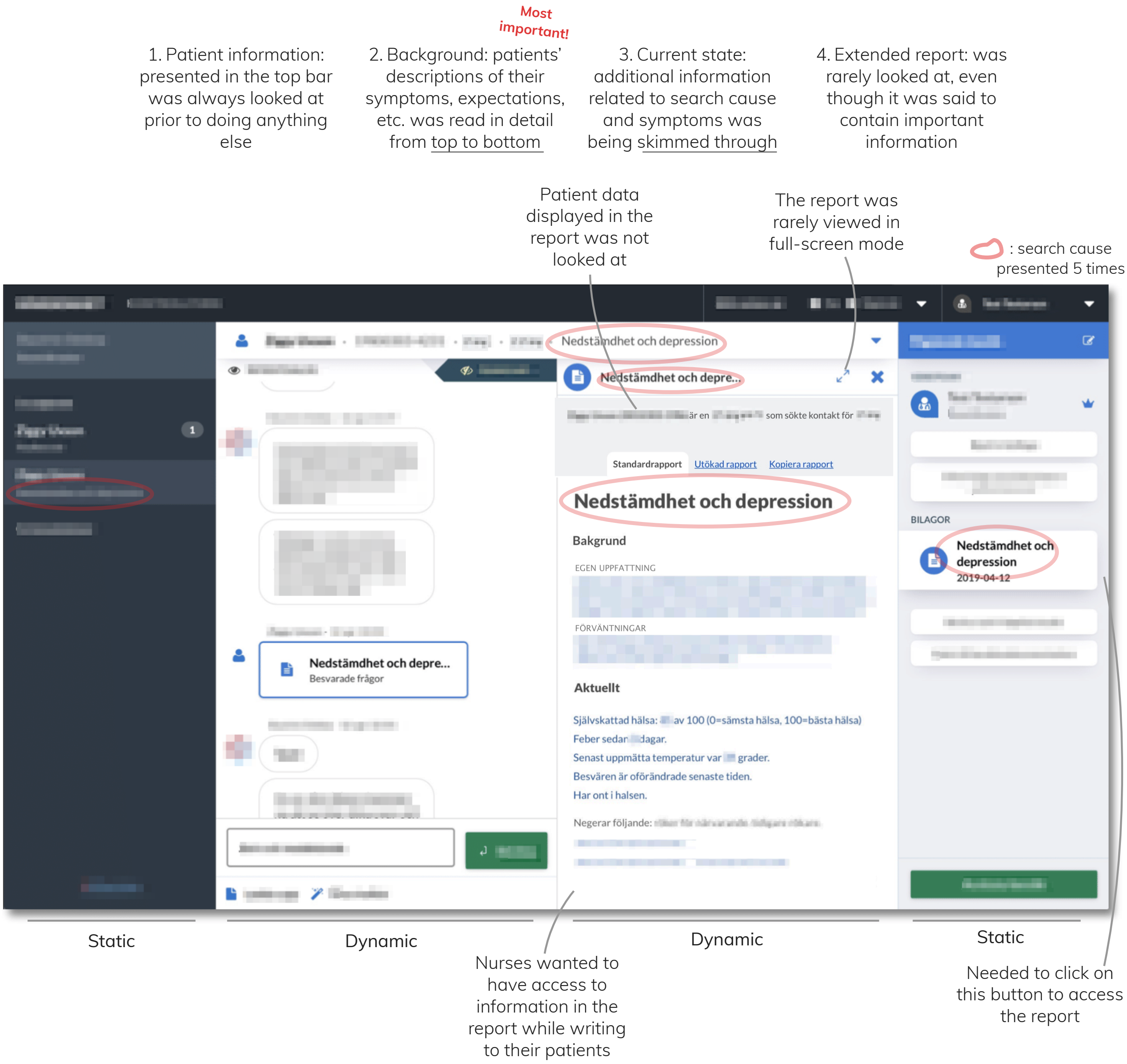

Figure 13: A brief description of how the nurses used the platform.

Every nurse participating in the study stated that once they had formed an opinion of the patients' symptom and prior history, they always asked follow-up questions to the patients in the online chat. The reason for this might be that the information presented in the report was inadequate or contradictory, leading the nurses to ask more in-depth questions to be able to form a complete understanding of the patients' current state.

During the observations, the nurses seemed well aware of the fact that patients might leave out important information when completing the questionnaire or frame the answers so that their symptoms would support their ideas of what they might suffer from. By communicating with the patients online and reading the patients' medical records, the nurses may be presented with information not included in the report and thus form themselves a different idea of how to best treat the patient. As seen in Figure 13, an important feature for the nurses was to keep the report visible when communicating with the patients in the chat. This way, the report could function as a base and enabled the nurses to double check information previously read. A few nurses (N2, N3) complained about the fact that they often needed to scroll up and down to see the entire report, particularly in cases when the patient had provided a lot of information in the questionnaire. Quite reasonably, they wanted to reduce the amount of scrolling as well as the number of 'clicks' so that they better and faster could navigate on the platform.

Once the nurses had formed an opinion of the patients' symptom, they tended to search for health-related information online and take part in frameworks for clinical reasoning to form a better understanding of the patients' illness. In some cases, the nurses were basing their decisions on common frameworks, e.g. deciding that a patient was suffering from an illness since he experienced three out of four symptoms related to that illness. Once the nurses had decided the patients right level of care, they explained their decisions to the patients in the chat, answered questions if there were any and ended the appointment with the patients' approval. Lastly, the appointment was added to the patients' medical records which was done by navigating to the upper menu, choosing *Copy report (Kopiera rapport)* and inserting it to the medical records. The nurses participating in the testing all claimed that it was easy to document the visits this way. In Figure 14, the nurses' sources of information is being presented.

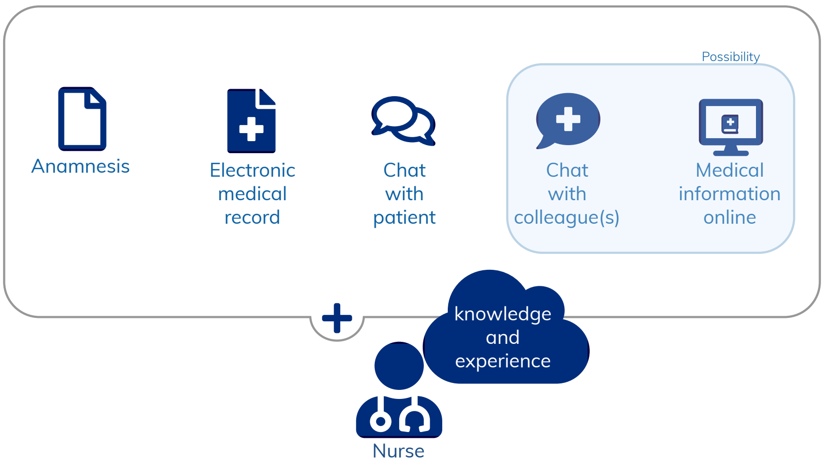

Figure 14: The nurses' different sources of information.

6.4.2 The report

This section describes the following product concepts; patient generated information and design and functionality. Common for every nurse participating in the study was that they all thought that the report was a great tool for quickly forming an opinion of the patient's symptom and needs. The nurses used the report in more or less the same way and had, considering their different experiences and roles within the nursing team, surprisingly similar attitudes towards the design and functionality of the report. For instance, when being presented with a new patient, the first thing every nurse did was to look for the patients' personal information such as name, age, sex and reason for contact. The patient's information is displayed in a number of places on the platform, but the nurses tended to look at the top border above the chat and not elsewhere. One nurse (N3) thought that it was excessive to present the same information that many times and argued that one would be enough. When navigating between different views or manually copying the patients' social security number, such patient information needs to be visible and easy to find. Secondly, every nurse read the first part of the report, the background, carefully from top to bottom prior to doing anything else. Thereafter, the nurses moved on to the second part, the current state, containing more detailed information relating to the patients' reason for contact. Even though this information was important for nurses to know when forming a decision, they tended to skim through the section, actively looking for specific information related to the symptoms. As seen in Figure 15, the nurses' workflow when navigating through the report is described in general.

None of the nurses used the extended version of the original report much when searching for patient data, although every nurse said that it contained important information relevant for the triaging process. One nurse (N2) claimed that she was likely to use the extended report once she had created better routines from working digitally. During the observations, the nurses often asked questions to the patients whose answer was provided in the extended report, without them knowing about it. This observation was confirmed by nurses saying that they were more likely to ask in-depth questions in the chat, than to look at the extended report. By doing so, the nurses claimed to be given a better understanding of the patients since they were formulating their own answers in free-text format, something that was preferred over auto-generated answers. On the other hand, it could cause frustration among the patients when needing to provide the very same information again. As a consequence, such behavior from the nurses may lead to a more ineffective triaging process, both for nurses and patients. A reason to why the nurses were not using the extended report, even though they seemed to think that it was a valuable feature of the platform, may be that it contains far more information than the standard report and might thus be hard to interpret. In contrast to the standard report, the extended version may require some time before the nurses can understand the content correctly. Referring back to the nurses who said that they wanted to reduce the number of 'clicks' on the platform, the process of finding the extended version is in fact quite ineffective. The nurses tended to look at the second section of the report when wanting to take a look at the extended version. As a consequence, they needed to scroll up to the main menu, choose the extended report and then scroll down to find the information they were looking for. Perhaps the navigation could have been made easier, enabling the nurses to keep their focus on the same part of the screen.

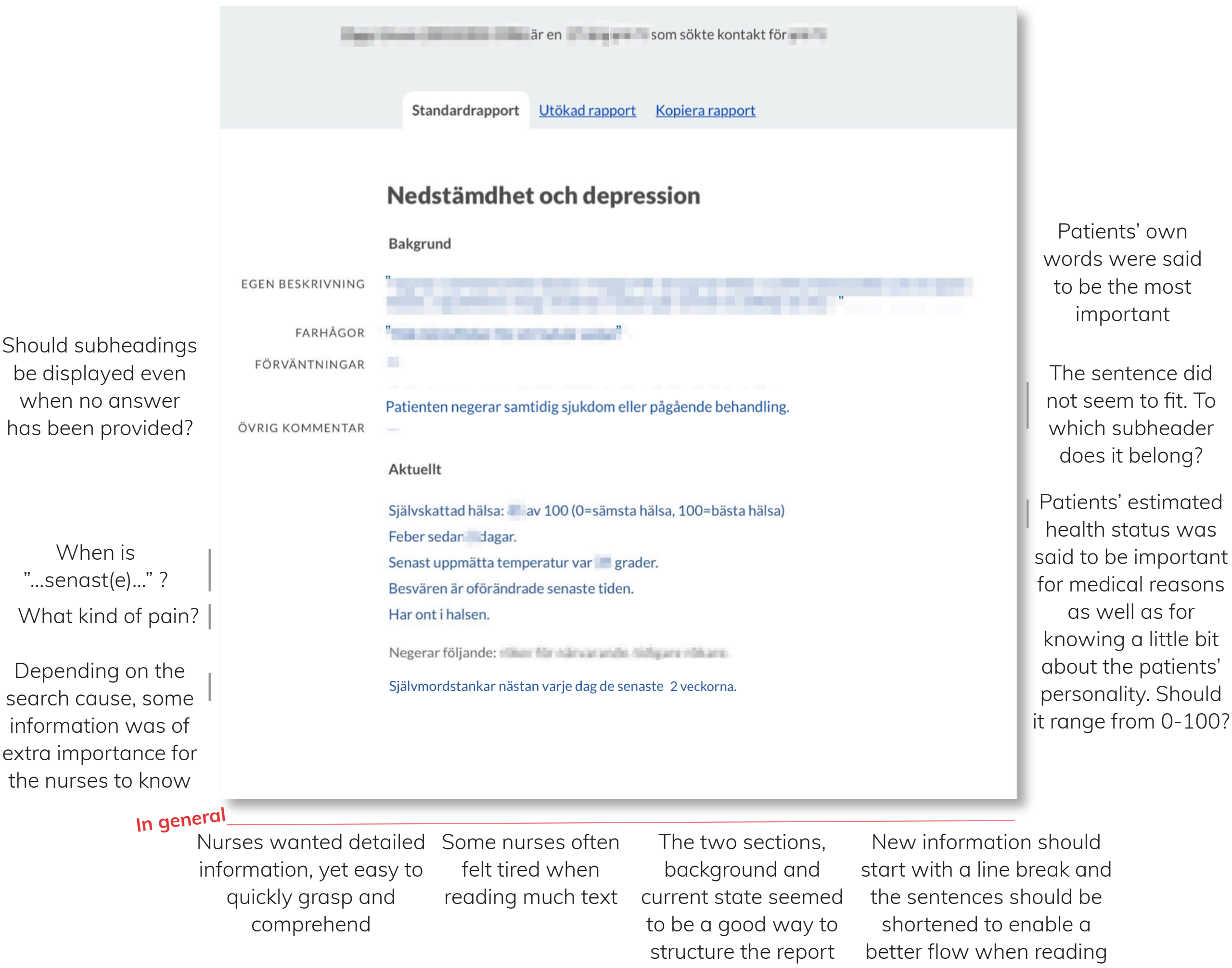

Figure 15: A brief description of how the nurses used the report.

Every nurse thought that the structure of the report, being divided into the background and current state, was suitable and efficient when wanting to quickly form an opinion of the patients' health. Presenting the information in a text-based, straightforward way with headers to the left seemed to fit every nurse. However, a few nurses explained that they often felt tired and unfocused when reading much text-based information and that they were positive towards other ways of visualizing the information. By doing so, one nurse (N4) pointed out that nurses who are not comfortable with the Swedish language could be given a better chance to fully understand the information. The majority of the nurses also thought that the design of the report, i.e. the choice of colors, fonts, text size and so on, was pleasant to look at although it could be tiring to look at for a long time. One nurse (N4) therefore suggested that other colors could be used to highlight important information.

Background

Every nurse said that the far most important information in the report was the patients' descriptions, in their own words, of their symptoms and reason for contacting. Not only could the nurses form an understanding of the patients' symptoms but also get an idea of the patients' personalities based on their way of expressing themselves. Therefore, it seems suitable that such information is placed at the top of the report, being the first thing that the nurses see. The patients' expectations were also considered to be important information and one nurse (N2) suggested that she would rather like to have that information placed right next under the patients' descriptions of their symptoms to enable a better flow when reading the report. With such a question, the patients are encouraged to formulate their expectations from the visit which gives them a reason for reflection and may make it easier for the nurses to meet their needs. As seen in the Figure 15, every piece of information presented in the background follows the same structure: a header is placed above, or next to, the information and the patients' answer is placed below. There is, however, one such answer that does not follow the same structure which seemed to distract and confuse the nurses. If the patients had answered that they don't suffer from any current diseases or are part of any treatments, the sentence *Patienten negerar samtidig sjukdom eller pågående behandling* was presented in the middle of the section without a header. Every nurse agreed that the information was important to know, but did not know to which header the information belonged. As for the times when the patient had not answered a question, the headers belonging to such a question were often still included in the report with empty question marks below. This way, the nurses could know that the patient had not answered the question and would thus not look for the information elsewhere in the report. There seemed to be different attitudes towards this design choice. Some nurses (N1, N4) thought that it was disturbing to see headers over empty answers and wanted them gone, while others claimed that it was good that the headers were still displayed since they otherwise would look for the information elsewhere.

Current state

The second part of the report starts with the patients own estimation of their current health. Every nurse thought that the information was valuable and important when triaging patients, especially in cases where the patients were showing signs of suffering from depression. Not only does the scale describe how the patients are feeling, but it also tells the nurses a little bit about the patients' personality. If a patient had initiated contact for, let's say, a sore throat and ranked their current health to 30 out of 100, the nurses knew that this patient might need some comforting and kind words, prior to discussing medical conditions. Every nurse thought that the placement of this scale was good but they did, however, criticize the fact that it ranged from 0-100. Since the scales used in healthcare settings tend to range from 0-10, they did not seem to know the reason why 100 suddenly was chosen to be the maximum. Neither did they know how to interpret, for example, 72 out of 100. One nurse (N4) wondered how such an answer differed from 71 or 73 and asked herself if and how it should affect her decision when triaging the patient. As for the VAS-scale, every nurse thought that it was a valuable and good measurement since pain is subjective and can be hard to describe. A few nurses commented on the fact that the first scale was presented along with a description, saying that 0 equals to the worst possible health and that 100 equals to the best, whereas no description was presented along with VAS. They asked themselves if a description was even needed since they look at the same reports all day long and know what the scales mean.

Based on the patients' symptom and way of answering the questionnaire, the information included in the current state may in some cases be quite extensive, leading to a relatively long report. Even in cases where the information is short and concise, some nurses (N1, N3, N4) wanted to lump together or shorten parts of the information to enable a better flow when reading it. For instance, one could write *issues have gotten worse* instead of *issues have gotten worse recently*. One important observation was that the formulation *...have not...*, used in the extended version when describing symptoms that the patient is not suffering from, confused one nurse (N4) who in fact thought that the patient was suffering from the symptoms. Such formulations need to be rephrased to avoid misunderstandings and, in the worst case, the wrong treatment. In contrast to the first section, subheadings are sometimes used and have a similar design like the rest of the report. Such a subheading is often used when the patient has answered a free-text question and is thought to give the reader a better understanding of what question the patient has been answering to. However, none of the nurses claimed to be reading the subheadings and they thought instead that it was disturbing.

Early in the reasoning process, every nurse was looking for the duration of the patient's symptoms as well as a description of how the symptoms had started and evolved. However, the report only provided the nurses with parts of the needed information and they therefore often needed to ask follow-up questions to the patients relating to duration. For instance, when reading that the patients' symptom had been worsened (*Besvären har förvärrats*) they wanted to know in what way and for how long. Similarly when reading how much fever a patient was having (*Senast uppmätta temperatur var*), they wanted to know when the patient last checked the temperature. Such information, important for every nurse to know independent of the patients' symptom or reason for contact, could have been included in the questionnaire from the very beginning, enabling for a more efficient triaging process. Another area of improvement is that when patients were answering questions relating to their use of alcohol and drugs, they were asked to provide an answer in their own words. Since such information can be highly subjective, it could be hard for the nurse to know what a 'normal' intake is for the patient. By changing the structure of the questionnaire, e.g. making the patients choose how many units per month they are drinking, the answers might be easier for the nurses to interpret.

The questionnaire

One issue that many nurses pointed out was that the report often presented the same information in different places and ways or contained information that was contradictory, leading to trouble when trying to form a complete view of the patients' health status. This goes against the very fundamental idea of the report: to keep it simple and short yet to be rich in information. One reason for this issue may be that it is hard to know what information the patients have provided when answering to free-form text questions. Such questions are included at the beginning of the questionnaire and depending on what the patients choose to answer, they may later be presented with questions whose answer they have already provided. Since the platform not yet supports the possibility to interpret information in free-form text, a result may be that the patients need to provide the same information twice. An effect for the nurses may thus be that the same information is presented more than once in the report or that the information is contradictory if the patients have interpreted two similar questions differently, leading to different answers. Another implication may be that the patients tend to answer *no* or *see above* to questions whose answer they have already provided, leading to information presented in the wrong sections in the report. One issue that almost every nurse pointed out was that information relating to the duration, i.e. how long a patient had been suffering from a symptom, often was contradictory. The patients tended to describe in free-text that they had been suffering from a symptom for a longer time than stated in other sections when choosing the answer from a drop-down menu. Since such information is said to be of high relevance for the nurses, they often need to ask follow-up questions related to duration. One reason for this might be that the patients interpret the question *How long have you been suffering from your symptoms?* as a question for how long their symptoms have gotten *worse*. As with all information presented in the report, the structure and design of the questionnaire highly affect what the patient chooses to answer, and in what way. It is therefore surprising that none of the nurses participating in the study had seen what the questionnaire looked like and therefore lacked an understanding of what questions the patients were being asked. When discussing the questionnaire with the nurses, everyone expressed a wish to see what it really looked like. If the nurses better knew what process the patients have been going through prior to initiating contact, it is likely to affect the communication between nurses and patients, thus affecting the patients' overall experience from the visit.

Every piece of information included in the standard report has, in advance, been decided to be of the highest priority for the nurses. The relevance of the question asked in the questionnaire, as well as the patients' answer, determine if the information should be included in the standard or the extended report. During the observations, it has been clear that the nurses seem to forget that the report and the questionnaire are designed to support more than one illness related to the patient's chosen reason for contact. As a consequence, they often thought that information included in the report, particularly in the extended version, was redundant. Additionally, given the patient's reason for contact, some information was pointed out as particularly important. For instance, when the patients seemed to be suffering from depression, the nurses always wanted to know if they did, or did not, have suicidal thoughts. The standard report only presented such information if the patient had such thoughts and if not, the nurses were encouraged to read the extended version which they rarely did. Due to the relevance of the information, the nurses suggested that it not only should be included in the standard report but also should be given a different placement and design. Currently, it is given the same design as the rest of the information and may be placed anywhere in the second part of the report. In cases when the report was relatively long, the nurses needed to scroll down to the very end of the report to see such information which could lead to frustration.

6.4.3 Online communication

This section describes the following product concepts; general observations and communication between nurse and patient. During the observations it was evident that nurses not only form an opinion of the patients' treatment and needs based on the medical information provided, but also on the patients' way of expressing themselves and answering to questions in the chat. The nurses were constantly looking for information that could reveal who the patient really was. Understanding the needs and personality of the patient was considered to be of great importance since the nurses wanted to communicate with the patients on their own terms. For instance, one nurse (N2) said that it was important to address every patients' concerns and that she treated patients differently depending on their level of anxiety and stress. One characteristic relating to the nursing profession is, as mentioned above in Chapter 2, knowledge sharing which almost every nurse participating in the data collection mentioned. They seemed to want to educate the patients and encourage them to better understand their illness by reading medical information online as well as their own electronic health records. Almost every nurse tended to include links to relevant websites in the chat so that the patients better could understand their illness and consequently take a more active role in their own treatment. Many sites, such as Vårdguiden 1177, are written so that patients with no prior medical knowledge can understand the information provided. By encouraging the patients to read relevant medical information online and ask questions that might arise, the nurses could save valuable time that otherwise would have been spent explaining the patients' condition in-person or over the phone. Consequently, nurses could treat more patients at a time. Almost every nurse claimed that they experienced a shift in patients playing an increasingly important role in their own treatment and care. As a result, patients were described as less mistrusting and stressed, and the nurses felt like their decisions regarding healthcare priorities and treatment were more aligned with the patients'.

During the data collection it was evident that the online chat was an important feature of the platform, not only because it enables an exchange of medical information but also because the nurses could communicate with their patients. Even if it would have been possible to create a report that would cover every important aspect of the patient's symptom and history, the nurses would probably still initiate contact with their patients since it relates to what being and acting as a nurse really means. In line with Miller et. al's research, one nurse (N2) emphasized that her task was to serve the patients and ease their concerns by discussing their symptoms online. She could ask questions to the patients, whose answer she had already read in the report, just to create a trusting relationship and make the patient feel listened to. The very same nurse expressed the importance of communicating with the patients in a more casual way, not by using complicated medical terms hard to understand. Another nurse (N1) used to ask her patients about their hopes and expectations from the visit, so that she could provide the best possible care and make the patients satisfied. These observations show that the nurses strove to maintain their roles as listening, understanding professionals trying to create a caring atmosphere around the patients.

There seemed to be various attitudes among nurses regarding online communication. The majority claimed that it was easier to discuss symptoms online since the patients, in contrast to communicating over the phone or in person, tended to be less mistrusting and critical towards the nurses. Some patients seemed to take greater responsibility for their own health as they were better prepared for the meeting, leading to a more effective, direct communication with the nurses. The patients were also described to be less stressed and aggressive when discussing their symptoms online compared to a physical meeting, possibly due to the fact that they can answer the nurses whenever, and wherever, it suits them. Additionally, they can initiate contact at any time of the day, which the nurses thought was a key reason for why the patients felt more relaxed. As a result, the nurses did also describe their working environment to be less stressful. However, a few nurses explained that it could be hard to find a perfect balance in how many patients they should treat at the same time since they had no control of when the patients would answer. There were times where the nurses wanted to start a new patient encounter but hesitated since they could risk feeling overwhelmed with answers at a later time. Treating a big number of patients simultaneously might lead to a more efficient workflow but can also cause underlying stress for the nurses when working. For instance, when conducting the first test session with one nurse (N2) she explained that she felt stressed since she did not know if and how many of her patients would answer during the session. One additional aspect that needs to be considered when treating many patients simultaneously is that the nurses need to be very careful not to confuse the patients with each other. One nurse (N2) explained that she needed to do a lot of double checking before writing to a patient, to make sure that she had chosen the right one from the patient list. Just as with any new technology that requires new routines and knowledge to efficiently be implemented and used, the nurses might feel more confident with time in handling many patients simultaneously. When redesigning the report, however, it is important to create an interface with this risk in mind.

In contrast to the nurses that felt positive towards communicating with their patients online, a few nurses thought that is was harder to create a caring atmosphere around the patient and to understand the patients' needs and concerns when writing. A reason for the varying attitudes might be that the nurses had different abilities and experiences from expressing themselves in text. During the observations, it was obvious that some nurses were more careful about what and how to write an answer to the patients than others. While some of them read through the message more than once to make sure that there were no spelling mistakes, others sent the message directly without reading it through. Some patients might prefer a casually written answer, over an answer full of medical terms hard to understand. Others may feel uncertain and lack trust in nurses that express themselves in a casual way. Regardless, it would have been good if the platform was designed to support the functionality of deleting and changing messages that already have been sent. Another idea could also be to make use of a digital writing assistant, ensuring that the messages are mistake-free before sending them to the patient.

6.4.4 New routines

This section relates to the product concept named general observations. The process of first introducing *the Company's* platform to the healthcare center could be thought of as a disruptive factor, changing existing work routines among the nurses and their coworkers. For the platform to be efficiently implemented and used, new knowledge must be acquired relating to technology but also organizational and social context. The healthcare center must go through a learning process and make organizational, interpersonal and cognitive adjustments to form new routines better adapted to the platform. Almost every nurse claimed that they were likely to change their way of interacting with the device once they were more familiar with it. In fact, they were motivated to establish different working routines and acquire new knowledge in order to make use of the benefits that may come from working digitally. In the healthcare center visited, one nurse was given the role as 'coordinator' and sorted the incoming patients to the right instance based on the severity of their symptoms. If done carefully, the rest of nurses were not presented with patients listed at another healthcare center or in need of emergency care, which could result in a reduced level of stress and anxiety at work. As a consequence, every nurse could work at a steady pace that was suitable for their level of experience and skills. Despite the positive impact a coordinator might have on the workflow, a few nurses expressed concerns relating to such a structure. What happens when the coordinator is not working? The coordinator can be considered to be an expert in handling the incoming patients and is thus an irreplaceable part of the nurses' workflow. In the healthcare center visited, the coordinator was also the team leader, likely to influence the technology learning process in several ways. She had the power to influence other nurses' attitudes towards the platform and, in this particular case, enhance their motivation and effort to use the platform. Additionally, she could along with other experienced nurses contribute to creating team stability among the nurses who were working digitally. As a consequence, the nurses may feel more secure in trying new routines and could more easily coordinate their actions.

DATA DRIVEN RESEARCH

The seventh chapter presents the data analysis process; from pre-processing of the data to implementation and results. An analysis of the differences between the applied models is presented along with the results, and the chapter is ended with a recommendation for what results to bring forth to the combined discussion.

7 Data driven research

7.1 Approach

A big part of the project was dedicated to performing necessary pre-processing steps, followed by the below listed approach:

1. To get a sense of how well and at what rate different classifiers perform without having undertaken any tuning or modifications, initial tests were made. Simple classifiers were built and run to get a rough estimate on how well they would perform without tuning or adjustments. The following step was to continue building and tuning the different classification algorithms.

2. Tuning each model by performing gridsearch and cross validation.

3. Evaluating performances of the different models.

4. Determining most important features for each model.

5. Analysing most important features for model with highest performance.

All code used to develop and perform the various classification algorithms, as well as the different pre-processing steps, was written in Python using Jupyter Notebook. There were mainly three Python libraries used; Numpy[49], Pandas[50] and Scikit-learn[51], the later being Python's open source machine learning library. Numpy and Pandas were mainly used for pre-processing and data handling while Scikit-learn was used to build different classifiers, followed by various evaluation methods originating from the same library.

7.2 Data and pre-processing

One of the most critical factors when developing good classifiers is access to a lot of high-quality data.[52] During this project, the different classification algorithms have been performed on one specific data set. At the beginning of the project, the data set consisted of approximately 3000 medical cases, whereas towards the end of the project the dataset was extended to a little over 6000 cases. The reason behind this was that *the Company's* platform had been up and running for a longer period of time, thus generating more cases and patient data which could be collected. Initially, the algorithms were developed based on the earlier data set. Towards the end of the project, the same algorithms could be run on the larger data set, generating higher accuracy. The following sections will aim to describe the data set more thoroughly; how the data was obtained and its characteristics. A brief description of the pre-processing steps of the features is also included. The data set was anonymized by employees at *the Company* where all information that could be used to identify an individual was deleted, such as social security number and name.

7.2.1 Data set

An important aspect to mention is that the data-driven research has not analyzed any information given by the patients in free text. Instead, machine learning algorithms have only been performed using multiple and single choice questions. It is possible that this analysis is too narrow, since it does not consider the patients' symptoms described with their own words and how this type of information affects the triage decision.

The final data set consisted of 6067 medical cases with 2588 features each. These were loaded into a data frame using Python's pandas library. One medical case corresponds to one row in the data frame, while each individual feature is represented by a column. Each feature corresponds to a question in the medical questionnaire described in Chapter 3. Since only approximately 10-15 questions are being asked to each patient seeking medical treatment, most parts of the data frame consisted of questions (features) not being answered, generating NaN-values (Not a Number). The label(s) for each case, along with the case id, was received in a json-file format. Important to mention is that the ground output labels for each case was generated by scanning each case's data and search for specific keywords. This process can of course have generated incorrect or inaccurate labels, but on the other hand the triage process when performed in the medical field does not always have an unambiguous answer among different caregivers.

One hot encoding

As previously described, a lot of the input features originally constituted of multiple answer alternatives to multiple choice questions. One hot encoding transforms categorical labels, i.e. variables containing label values rather than numerical values, into vectors of zeros and ones. The length of the vectors is equal to the number of categories given as input features. This procedure is often necessary since categorical values usually don't have a natural ordered relationship, and encoding such categorical values with numbers would simply feed the classifier with misleading information. Examples of how the one hot encoding was used is shown in Table 3 and Table 4. However, the dataset used for this project contained a lot of NaN-values meaning that the question (the input feature) was never posed to the patient and thus lacking an answer. Since there is a distinction between a missing answer due to a question never being asked and a possible answer not being chosen while being asked a question, NaN-values has been translated into the value -1, false-values mapped to the value 0 and true-values to the value 1. Illustrations of this can be found below in Table 5 and Table 6.

Table 3: Example of a multiple choice question from the platform and corresponding answers.

patient id	**Have you had any of the following after your neck injury?**
1234	Numbness, pain in legs
1235	Reduced muscle strength
1236	Numbness, pain in legs, pain in arms

Table 4: One hot encoded multiple choice question.

patient id	**Have you had any of the following after your neck injury?_numbness**	**Have you had any of the following after your neck injury?_reduced muscle strength**	**Have you had any of the following after your neck injury?_pain in legs**	**Have you had any of the following after your neck injury?_pain in arms**
1234	1	0	1	0
1235	0	1	0	0
1236	1	0	1	1

Table 5: Example of a single choice question and corresponding answers.

patient id	**Are you sensitive or allergic to any medicine?**
1234	No
1235	NaN
1236	Yes

Table 6: One hot encoded single choice question.

patient id	**Are you sensitive or allergic to any medicine?**
1234	0
1235	-1
1236	1

In the first example, all three patients were posed the question *Have you suffered from any of the following after your neck injury?*, and therefore a non-answer is interpreted as a negating answer and thus mapped to the value 0. In the second example, the patient with id 1235 was never being asked the question *Are you sensitive or allergic to any medicine?* and therefore that was encoded to the value -1. As described in previous sections, a patient has to state their reason for contact, e.g. *headache*. There are approximately 200 different reasons for contact and those have been handled as any other input feature. Thus, the one hot encoding approach has been applied for the reasons for contact as well.

Integer encoding
Some input features had the format of strings. Those were converted to numerical values. For example, the length of a patient was given as '168 cm' which was converted to the integer '168'. The gender feature was given as 'male' or 'female' which were encoded to 1 and 0 respectively. After performing the pre-processing the data set ended up having approximately 2700 input features, while for each case there are only between 15-20 of these features containing information.

7.2.2 Grid-search

The models described above have hyperparameters, which can be described as external characteristics of a model that cannot be learned within the estimators. The values of a model's *hyperparameters* must be defined before the training process is initiated, as they are passed as arguments to the classifier. To give a few examples; the tree depth when using decision trees or the penalization norm for logistic regression are both hyperparameters. The regular input parameters, on the other hand, can be estimated from data and can be described as internal characteristics of the model. Grid-search is a common method to find the optimal hyperparameters for a certain model. This has been done by choosing the hyperparameters giving the highest accuracy. The hope is that those hyperparameters will improve the classifiers ability to make better predictions.

7.2.3 Feature selection

An important part of the data pre-processing is the selection of input features. Putting an effort in analyzing what features the model should take as input can reduce dimensionality, clean the data set from irrelevant data, increase learning accuracy and improve the result considerably. However, this implicates challenges to many feature selection models in terms of efficiency and effectiveness. It is highly likely that a high dimensional data set, containing a large number of input features, holds irrelevant information which impairs the performance of the model. There are two main categories that feature selection algorithms fall under; filter models and wrapper methods. Without taking any specific machine learning model into consideration, filter models select what input features to use based on analyzing general characteristics of the given data. Wrapper models need to be given a specific machine learning algorithm and evaluates the performances of the features in order to filter out which features to use. For each new given set of features, the wrapper model forms a hypothesis from which it later finds the features resulting in higher performance. Thus, using the wrapper model for feature selection requires a higher computational effort compared to the filter model.[53]

As mentioned, feature selection is normally a part of tuning the classifier to improve its performance. But since the aim of this project is to investigate what information is of high importance in order to perform an efficient and successful triaging, investigating the most important features answers the problem and serves as part of the result, rather than tuning it. To determine the 10 most important input features for the three classifiers, two different approaches have been taken and the achieved results are presented below. The first approach used was the wrapper method Recursive Feature Elimination, RFE, followed by mean decrease impurity as computed by feature_importances_ in Scikit learn. The latter approach was only possible to perform on random forest and XG-Boost since there exists no such attribute for the logistic regression model in Scikit's library.

Wrapper method: Recursive Feature Elimination

The goal of Recursive Feature Elimination is to choose the most important input features by recursively using smaller input subsets. The feature importances are initially determined by training the estimator on the original data set. The features shown to be less important are pruned from the data set repeatedly until the number of desired input features is reached.[54] The 10 most important features, of equal importance, when performing RFE for 3 different classifiers are presented in the result section, starting at Table 7.

7.3 Result

7.3.1 Recursive Feature Elimination

Table 7: The 10 most important features for the multi class models, having 4 classes.

Random Forest	**XG-Boost**	**Logistic Regression**
Did your Issues start with an injury?	Do you have Issues from the skin surrounding the wound?	Have you tried any treatment(s) for your issues?
Did your Issues start immediately?	Do you have any of the following?_liquid or blood from ear	For how long have you had your vertigo?_5 days
Are you under medical treatment for any diseases?	Are you under medical treatment for any diseases?	For how long have you had your respiratory distress?_5 days
How would you rate your current health?	How would you rate your current health?	Does any of the following apply to your scalp?
How have your issues evolved recently?_gotten worse	Does any of the following apply to your scalp?	Did you loose consciousness when damaging your head?_no
If you have any symptoms, can you derive them from a certain cause?	Have you had or do you currently have a cold (coryza, sore throat)?	Issue_bruises
Age	Issue_fever	Issue_ear concern
Gender	Issue_pinworm	Issue_palpitation
Are you sensitive or allergic to any medicines?	Issue_uro concern women	Issue_pinworm
Issue_pinworm	Issue_wound	Issue_vaccination advice

Table 8: The 10 most important features for the binary class models, having 2 classes.

Random Forest	XG-Boost	Logistic Regression
Did your Issues start with an injury?	Do you have any of the following?_stomach ache	Have you tried any treatment(s) for your issues?
Did your Issues start immediately?	Do you have any of the following?_sore throat	For how long have you had your vertigo?_5 days
Are you under medical treatment for any diseases?	Are you under medical treatment for any diseases?	For how long have you had your respiratory distress?_5 days
How would you rate your current health?	How have your Issues evolved recently?_gotten worse	Does any of the following apply to your scalp?
How have your Issues evolved recently?_gotten worse	Issue_appointment doctor reschedule	Did you loose consciousness when damaging your head?_no
If you have any symptoms, can you derive them from a certain cause?	Issue_bruises	Issue_bruises
Age	Issue_ear concern	Issue_ear concern
Gender	Issue_leg	Issue_palpitation
Are you sensitive or allergic to any medicines?	Issue_pinworm	Issue_pinworm
Issue_pinworm	Issue_vaccination advice	Issue_vaccination advice

When determining the feature importances for random forest and logistic regression, the resulting 10 most important features are the same for their respective multiclass model and the binary class model, as seen in Table 7 and Table 8 above. The reason for trying out binary classification was to investigate whether such a classifier would perform better compared to the multi-classifier. These two classes were set to be 'Self care' and 'Not Self care'. For XG-Boost, the results for the multiclass model does not cohere with the binary model. Furthermore, the features with the highest importances differ between the different classifiers.

7.3.2 Mean decrease impurity

As a comparison to determining the most important features through the RFE approach, the mean decrease impurity [55] [56] as computed by feature_importances_ in Scikit learn was used. It returns an array where all values sum up to 1. The higher the number, the more important the feature is. The results of this approach for the XG-boost and random forest classifiers are presented in Figure 16 and Figure 17, respectively, below.

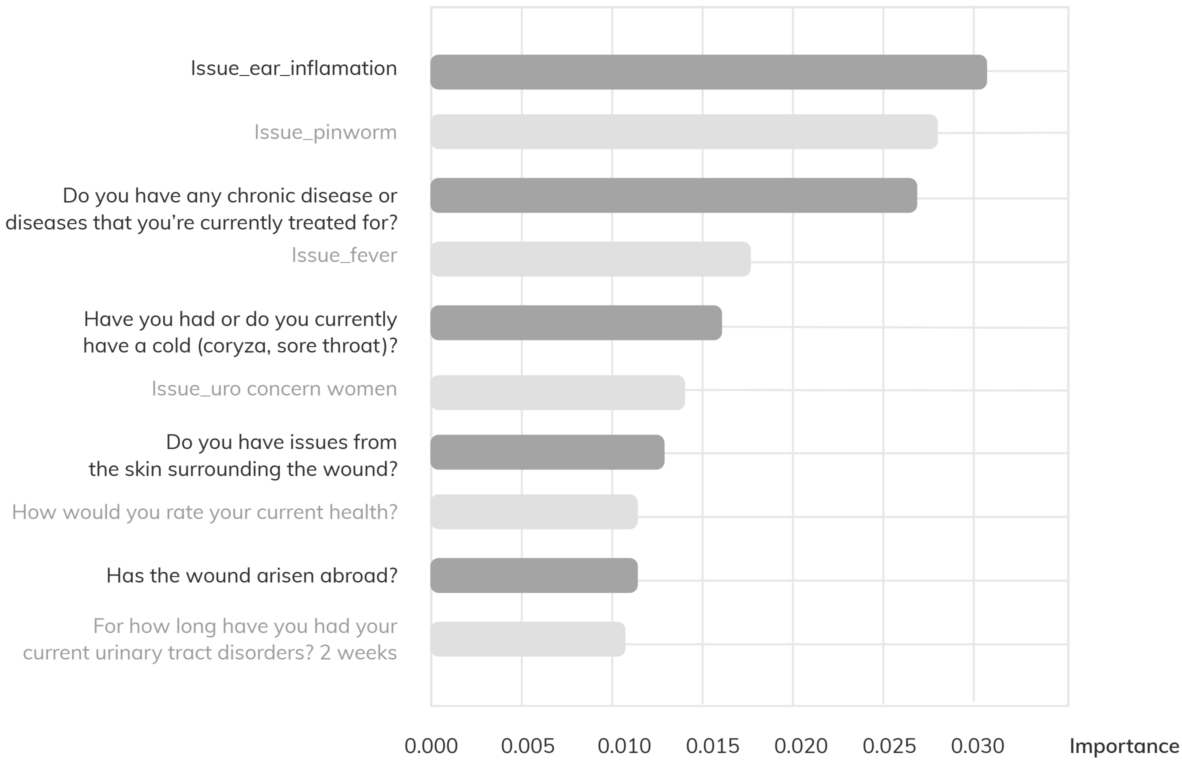

Figure 16: Feature importances for the multiclass XG-boost classifier

A comparison between the most important features as stated by the RFE approach, shown in Table 7, with the ones given when using mean decrease impurity was done only for the multiclass models. As seen in Figure 16, it can be concluded that 7 of 10 features were the same when using RFE compared to mean decrease impurity for the XG-boost classifier. The remaining 3 most important features, unaligned for the two different approaches, according to RFE was *Do you have liquid or blood coming out of your ear?*, *Does any of the following apply for the skin in your scalp?* and the reason for contact *wound*. The other approach stated that the remaining 3 features should be *Ear inflammation*, *Has the wound arisen abroad?* and *For how long have you had your current urinary tract disorders?_2 weeks*. The fact that the results differ is not remarkable per ce since they are simply two different approaches. However, it can be analyzed further which one of these shows the "better" result.

As stated above, two different approaches were undertaken when investigating the 10 most important input features for the different classification models, and the results achieved are presented above. However, since the classifiers are of varying characteristics and based on completely different concepts and mathematical grounds, as described in Chapter 5, one of the three had to be chosen in order to be able to compare the results with the findings from the user research methods. Out of the three classifiers tested, random forest turned out to perform marginally better compared to XG-Boost and logistic regression, see Table 9, also having the shortest training time. Because of this, the random forest classifier and its 10 most important input features were chosen to be compared to the results from the testing sessions with the nurses.

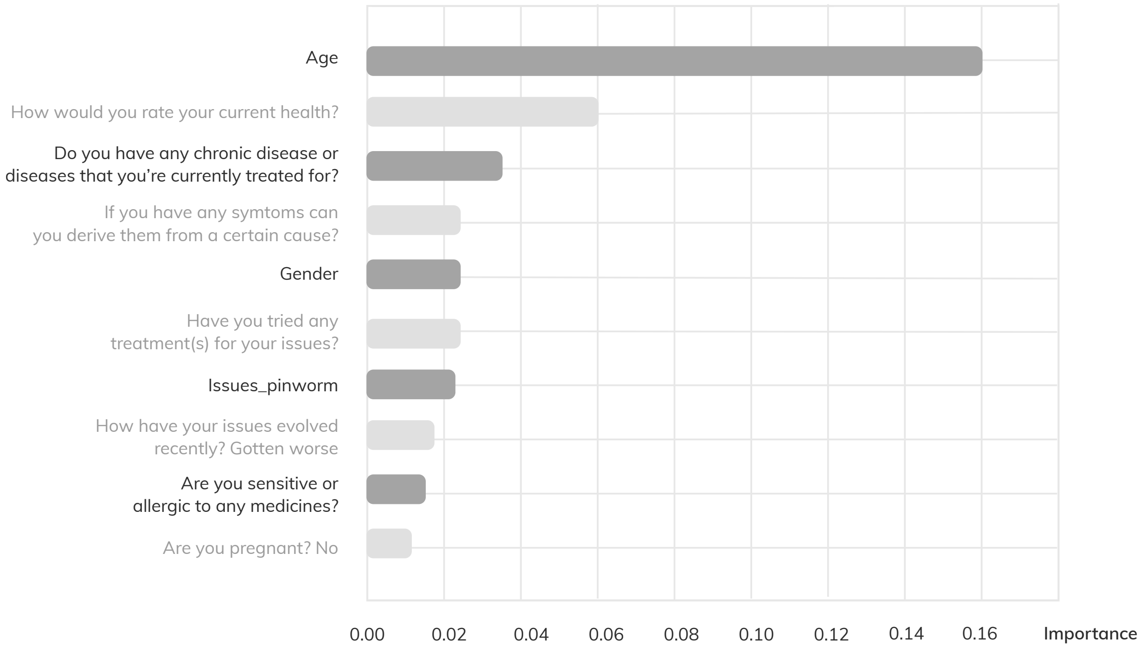

Figure 17: Feature importances for the multiclass random forest classifier.

When applying two different approaches to determine the 10 most important features for the random forest classifier, the results were completely aligned except for two parameters; the RFE approach determined the questions *Did your issues start immediately?* and *Did your issues start with an injury?* to be two of the 10 input features affecting the outcome the most. In contrast, Scikit's built-in feature selection attribute indicated that the two aforementioned questions should be replaced with *Have you tried any treatment(s) for your issues?* and *Pregnant_no* in order to find the 10 most important features. Both approaches listed *Pinworm* to be one of the 10 features, which can seem a bit remarkable. When investigating this further, it turned out that the medicine for this issue, normally distributed by Swedish pharmacies not requiring any prescription, ran out and resulted in an increased number of patients contacting their health centers to get help in relation to this matter. Thus, it is likely that this parameter showed to be important since there was a large number of patients reaching out for help to get treatment for their pinworm issues, resulting in a large number of cases in the dataset having this input feature. With this in mind, one reason to why some data points are listed as important could be because of their frequent occurrence in the data set. For example, every patient is being asked to fill in their age, which is listed to be one of the 10 most important features.

Furthermore, it is quite interesting that 8 out of 10 input parameters were the same, both for the binary and multiclass model, all of them in fact being quite aligned with the initial suggestions made in Section 3. The features differing from each other, *Did your issues start immediately?* and *Did your issues start with an injury?* vs. *Have you tried any treatment(s) for your issues?* and *Pregnant_no*, all seem to be important to include in the decision support when triaging. Of course, the *Pregnant_no* feature could be excluded from all male patients and because of this one could argue that this is not an important feature for all patients, although very much so for female patients.

7.3.3 Classification performance

Table 9: Training and validation accuracies for 3 different classifiers on the new data set.

Model	Baseline - 2 classes	Accuracy prior to tuning - 2 classes	Accuracy after tuning - 2 classes	Baseline - 4 classes	Accuracy prior to tuning 4 classes	Accuracy after tuning - 4 classes
Logistic regression	0.6347	training 0.7124 validation 0.6974	training 0.6823 validation 0.6931	0.6856	training 0.6922 validation 0.6936	training 0.6823 validation 0.6931
Random forest	0.6347	training 0.9651 validation 0.6749	training 0.7181 validation 0.7002	0.6856	training 0.9503 validation 0.6678	training 0.6992 validation 0.6946
XG-boost	0.6347	training 0.7106 validation 0.7024	training 0.7106 validation 0.7024	0.6856	training 0.6978 validation 0.6930	training 0.6978 validation 0.6930

Table 10: Evaluation metrics. 'Default HP' indicates the default hyperparameters as determined by Scikit learn. The higher value the better.

Model	Precision	Recall	Specificity
Logistic regression default HP	0.379	0.269	0757
Logistic regression tuned	0.173	0.250	0.750
Random forest default HP	0.583	0.301	0.780
Random forest tuned	0.298	0.256	0.750
XG-boost default HP	0.424	0.264	0.754
XG-boost tuned	0.424	0.264	0.754

In order to analyze and evaluate how well the different classifiers performed, some kind of comparison measurement was required. This baseline reference point was chosen to be the majority class; showing how accurate the classification would be if the class having the most observations would be assigned for all predictions. All results presented in Table 9 are generated from running the models on the new data set, containing approximately 6000 medical cases. As previously mentioned, a smaller data set was used at the beginning of the project but as time progressed more data could be gathered and all the data up to this date has been used for evaluating the classifiers. Also, the below-presented results are generated from using the models for multi- classification. The reason for trying out binary classification was to investigate whether such a classifier would perform better compared to the multi-classifier. These two classes were set to be ‘Self care’ and ‘Not Self care’. Since the result only showed to be marginally better when using this approach, the further analyses are being done for models having 4 output classes, as this was the original idea being more accurate to how the platform is used in practice. Studying Table 9, it can be stated that the validation accuracy does not differ significantly between the different classifiers.

Logistic regression

The logistic regression models have marginal better performances compared to the majority-vote classifier, but the difference is so small that one cannot exclude the possibility that this result was obtained by chance. When training the logistic regression model with 4 output labels with the default hyperparameters the following result is obtained.

Table 11: Confusion matrix for a logistic regression model, using default hyperparameters, obtained from validation data. The actual class can be found on the y-axis while the predicted class is found along the x-axis.

	Digital appointment	**Physical appointment**	**Primary practitioner on call**	**Self care**	
Digital appointment	0	1	0	57	58
Physical appointment	0	5	6	67	78
Primary practitioner on call	0	1	10	412	423
Self care	0	5	9	1248	1262
	0	12	25	1784	n = 1821

As the confusion matrix in Table 11 shows the model does not classify any cases to a digital appointment. According to the model 12 cases need to be scheduled for physical doctor’s visits whereas 25 cases should be referred to the Primary practitioner on call. The remaining 1784 cases from the validation data set do not need any medical treatment, according to the logistic regression classifier using default hyperparameters.

Table 12: Confusion matrix for a tuned logistic regression model, obtained from validation data.

	Digital appointment	**Physical appointment**	**Primary practitioner on call**	**Self care**	
Digital appointment	0	0	0	58	58
Physical appointment	0	0	0	78	78
Primary practitioner on call	0	0	0	423	423
Self care	0	0	0	1262	1262
	0	0	0	1821	n = 1821

When performing hyperparameter optimization and cross-validation for the logistic regression model, the best norm used in penalization was concluded to be lasso regularization, as described in Equation 5. The optimal value for the inverse of regularization strength, which is represented by C in Equation 5, was found to be 0.001. Like in support vector machines, smaller values for C specify stronger regularization. As seen in Table 12, the consequence of using these optimized hyperparameters was that all cases were classified to be treated as self-care. According to Table 9, there seems to be no difference in performance, in terms of accuracy, between the model classifying all cases to self-care and the model that distributes its predictions among physical appointment, primary practitioner on call and self-care.

Random forest

Table 9 shows the accuracies for the majority-vote classifier along with the random forest classifier. However, using the default hyperparameters for the random forest model resulted in severe overfitting; the accuracy for the training data set was 0.9503, which differs significantly from the validation accuracy which was determined to be 0.6678. Looking at the confusion matrix in Table 13, it can be seen that there is a broader distribution among the classified observations, compared to the tuned model as seen in Table 14. It seems like when training the model with default hyperparameters, it adapts too well to the training data. When applying the same model on the validation data, the broad distribution among classes is not as advantageous. Instead, a less overfitted model and higher accuracy for the validation data is achieved when tuning the model by using the optimal hyperparameters;

- The number of trees was chosen to be 200.
- The function to measure the quality of the split was chosen to Gini impurity.
- The number of input features to consider when looking for the best split was determined to be the square root of the total number of features.

- The maximum depth of the tree was chosen to be 4.
- The minimum number of samples required to split an internal node was chosen to be 1.

When using those optimal hyperparameters, all observations except for 5 are classified to the majority class (self care). 4 observations are classified to physical appointments, whereas only a single observation is classified to primary practitioner on call. It seems like it is more advantageous for the model to classify the observations to the dominant class, in terms of receiving the highest accuracy, compared to the broader distribution among the classes used in the model with default hyperparameters.

Table 13: Confusion matrix for a random forest model, using default hyperparameters, obtained from validation data.

	Digital appointment	**Physical appointment**	**Primary practitioner on call**	**Self care**	
Digital appointment	1	0	4	53	58
Physical appointment	2	5	16	55	78
Primary practitioner on call	3	4	103	313	423
Self care	13	17	125	1107	1262
	19	26	248	1528	n = 1821

Table 14: Confusion matrix for a tuned random forest model, obtained from validation data.

	Digital appointment	**Physical appointment**	**Primary practitioner on call**	**Self care**	
Digital appointment	0	0	0	58	58
Physical appointment	0	2	0	76	78
Primary practitioner on call	0	0	0	423	423
Self care	0	2	1	1259	1262
	0	4	1	1816	n = 1821

XG-boost

As seen in Table 9 the XG-Boost classifier does not perform much better than classifying all cases to the dominant class. The XG-Boost classifier with default hyperparameters has the same accuracy as the tuned version, shown in Table 15 and Table 16 below.

Table 15: Confusion matrix for a XG-boost model, using default hyperparameters, obtained from validation data.

	Digital appointment	**Physical appointment**	**Primary practitioner on call**	**Self care**	
Digital appointment	0	0	0	58	58
Physical appointment	0	4	2	72	78
Primary practitioner on call	0	1	5	417	423
Self care	0	1	8	1253	1262
	0	6	15	1800	n = 1821

Table 16: Confusion matrix for a tuned XG-boost model, obtained from validation data.

	Digital appointment	**Physical appointment**	**Primary practitioner on call**	**Self care**	
Digital appointment	0	0	0	58	58
Physical appointment	0	4	2	72	78
Primary practitioner on call	0	1	5	417	423
Self care	0	1	8	1253	1262
	0	6	15	1800	n = 1821

The XG-Boost model using default hyperparameters classifies the observations in the exact same way as does the tuned version. Thus, it seems that looking for the optimal learning rate, which was determined to be 0.1, did not make any difference in terms of classifying. Although the multiclass XG-Boost model had an execution time of almost 5 days it did not manage to perform better than the Random Forest model. Both Table 15 and Table 16 show that no observations were classified as Digital appointment, 6 to Physical appointment, 15 to Primary practitioner on call and the 1800 remaining as self-care. This is pretty close to classifying all 1821 observations to the majority class, self-care. However, the model performs marginally better compared to this baseline measure. It is possible that classifying those 21 cases to classes not being self-care, is what causes the marginally better accuracy (0.6930 compared to 0.6856).

As seen from the results above, all three classifiers perform quite equally, Random Forest being marginally better. Random Forest had the absolute shortest execution time, followed by Logistic Regression. Despite XG-Boost's long execution time, the accuracy did not show

to be any better compared to the other models. Furthermore, the accuracies for the different classifiers are not much better than the baseline, obtained from classifying all observations to the majority class. Observing the confusion matrices, it can be seen that the few observations being classified to some other class then self-care is the reason behind the marginally better performance compared to the baseline measure.
In this project, the optimal hyperparameters are referred to as the hyperparameters bringing the highest validation accuracy. However, interesting to note is that choosing those hyperparameters decreases the values for the other evaluation metrics, as seen in Table 10. For both the random forest and the logistic classifier the values for precision, recall and specificity decreases when choosing the hyperparameters obtained from gridsearch. For the XG-boost classifier all evaluation metrics, including accuracy, are indifferent, indicating that the gridsearch did not have any impact. This leads one to conclude that maybe accuracy was not the best evaluation metric for this particular case.

7.3.4 Summary

The three classifiers turned out to perform equally well, not resulting in a higher accuracy compared to when classifying all cases to the majority class. The multiclass logistic regression model obtained a validation accuracy of 0.6931, XG-boost had a 0.6930 validation accuracy whereas random forest resulted in 0.6946. However, by studying other evaluation metrics, shown in Table 10, it can be argued that accuracy as a performance measure was not the best for this project, since choosing hyperparameters to increase accuracy resulted in a decrease of the other evaluation metrics.

Given the highest validation accuracy, the random forest model showed to be marginally better than the other two, also having the shortest execution time. The two approaches used to determine the 10 most important input features for the multiclass random forest model had 8 out of 10 features in common, stated to be important. These were found to be:

- *are you under medical treatment for any diseases?*
- *how would you rate your current health?*
- *how have your issues evolved recently?_gotten worse*
- *if you have any symptoms,can you derive them from a certain cause?*
- *age*
- *gender*
- *are you sensitive or allergic to any medicines?*
- *issue_pinworm.*

SYNTHESIS

In the eighth chapter, the results from the two fields, user research and machine learning, are compared and summarized.

8 Synthesis

The results from the two fields, user experience and machine learning, turned out to be surprisingly aligned and showed many similarities. Specifically when looking into what data is important to include in the report in order for a nurse to make an efficient triaging. Worth mentioning is that both of the approaches were, in fact, pointing to the same general result no matter who was participating in the data collection or what feature selection model was applied to the random forest classifier. This serves as a proof for why the results can be said to be of high relevance, even though the scope of the project did not enable for a thorough investigation in terms of available data. However, important to mention is that if another machine learning algorithm would have been chosen, the results would have differed. The factors that were shown to cohere between the machine learning and user research approaches are listed below, ordered by relevance as determined by the data analysis approach. The bold header correlates to one of the features said to be most important according to the random forest classifier as presented in Table 7 and Figure 17, while the text below it relates to result(s) from the user research. This section is written in a short and straightforward manner, since a more detailed analysis of the machine learning and user experience results can be found in Chapter 6 and Chapter 7 respectively.

- **Age**
  The nurses were always looking for the patients' personal information prior to doing anything else, in order to form themselves an opinion of who the patient was. Such information included name, age, gender and reason for contact. The nurses tended to look for patient data on the top border, even though it was being presented on a number of places on the platform.

- **How would you rate your current health?**
  Every nurse thought that the patients' own estimation of their own health was valuable and important when triaging patients, especially in cases where the patients were showing signs of suffering from depression. Not only did the scale describe how the patients were feeling but also told the nurses a little bit about the patients' personality. If a patient had initiated contact for, let's say, a sore throat and ranked their current health to 30 out of 100, the nurses knew that this patient may be in need of some comforting and kind words, prior to discussing medical conditions. The patients' estimation of their own health was presented first in the second section of the report, the current state, but should perhaps be given a higher prioritization given its importance.

- **Are you under medical treatment for any diseases?**
  An important part of the nurses triaging process was to read up on the patients medical history, including allergies, ongoing or chronic diseases and treatments. Such information was provided both in the report, written by the patients themselves, and in their medical records. The results when applying the RFE approach for the multiclass random forest model showed that the question *Have you tried any treatment(s) for your*

issues? was an important question which goes in line with the results from the user research.

- **If you have any symtoms, can you derive them from a certain cause?**
  Every nurse read the first section of the report, the background, carefully from top to bottom. If the patients had any ideas of what was causing their symptoms, a description in their own words was included in this section and said to be relatively important by the nurses. Even though the description was read carefully by every nurse, they did not necessarily share the same ideas of what the underlying problem was.

- **Gender**
  As written above, the nurses were always looking for the patients' personal information prior to anything else. The results of the user research did not, however, conclude that age was more important than gender as the data analysis suggests. Age and gender could be of varying importance, depending on the specific case at hand.

- **How have your issues evolved recently? - Gotten worse**
  Included in the second section of the report, the current state, was information relating to the duration and progress of the patients' symptoms. Even though such information was presented in a random order, often in the middle of the section, it was said to be of high relevance for the nurses. Preferably, the nurses wanted to read the duration and progress shortly after reading the patients' general description of their symptoms. The user research did not only point to that the answer *Issues have gotten worse* was the most important, but rather that any answer indicating how the symptoms had started and evolved was of high interest. This is further suggested by RFE approach for the multiclass random forest model, concluding that *Did your issues start immediately?* and *Did your issues start with an injury?* are relevant. Worth mentioning is that information given by the patients relating to the duration of the symptoms were often incorrect or contradictory, leading to frustration among the nurses and more follow-up questions to the patients.

- **Are you sensitive or allergic to any medicines?**
  As written above, it was important for the nurses to read up on the patients' medical history, including allergies, ongoing or chronic diseases and treatments. The user research did not, however, conclude that information regarding allergies was more important than the patients' diseases and treatments (just) as the data analysis suggests.

Referring back to the initial suggestions, stating that some information always is of high interest and should be included in the report no matter the patient's reason for contact, one could say that every factor presented in the list above relates to such information. The suggestions also stated that the relevance of some information is determined by the specific case at hand; who the patient is as well as the reason for contact and symptoms. Based on the results from the user research, this part of the suggestions can be said to be true. For instance, when the patient seemed to be suffering from depression, the nurses always wanted to know if they had or had not suicidal thoughts. Another example could be that nurses wanted to know the answers to a different set of questions when the patient was pregnant. Using the mean decrease impurity approach for the multiclass random forest model suggested that pregnancy was one important factor, which could be thought of as an indicator that the suggestions are true, e.g. the patient's condition (in this case, being a woman) highly affects what information should be included in the report or not. However, the suggestions also states that the nurses are likely to read the report differently, depending on the patient's reason for contact. It was during the data collection sessions evident that the nurses read the report in surprisingly alike ways, independent of the patient's symptoms, age, gender, etc. This suggests that the nurses' working structures and routines decide how the report is being interpreted and read, rather than the patient's reason for contact. If this had been known prior to initiating the project, the reasons for contact could have been excluded from the data set and not treated as any other input feature.

One major difference between the user research and data analysis approach is that the patient's own words are not included in the latter approach since the scope of the project did not enable for such an analysis of free-text format. However, it was during the data collection evident that the patient's descriptions were considered to be the far most important information by the nurses. Such information, e.g. the patients explaining their reason for contact or expectations from the visit, was placed at the top of the report, being the first thing that the nurses read. When redesigning the report, such information needs to be given prioritization even though the data analysis could not confirm this conclusion.

Another major difference is that the user research is not only investigating what information is important for the nurses to know during triage, but also the structure and design of the report. The data analysis is instead analyzing every source of information, independent of each other, which leads to a more narrow and thorough investigation of what data is important. One can think of the results of the data analysis to be the guideline in terms of what information is important to include in the report, while the results of the user research can be pointing to how such information should be presented (design and placement).

Since previous research about combining the fields machine learning and user experience is sparse, there are not any references to compare the results with. The platform itself and the process of performing triage digitally also lacks support from previous research. However, the findings discussed above indicates that only investigating what information is important to present in the report is insufficient. Instead, such an analysis should be completed by using insights from a qualitative study, like Contextual Inquiry. Important to mention is that there seems to be a trade-off between having a clean report being efficient to work with and not leaving any important information out. Therefore, the combination of machine learning and user research has enabled a holistic view, where a deeper as well as broader understanding of how the triaging process could be made more efficient has been given.

DESIGN AND VALIDATION

Based on the discussion previously held relating to what information to convey to nurses during triage, suggestions for how to best visualize medical information is presented in the ninth chapter.

9 Design and validation

The two approaches, user research and machine learning, researched what information was of importance for nurses during the triage process. Not only is the content of the medical report relevant to examine, but the presentation of such information is of equal importance. Therefore, the previously described results have served as a basis when moving into the third and last part of contextual design, namely the design and validation phase. During this phase, the focus has lied on giving the product concepts described in Chapter 8 a look, structure and function that supports the initial preferences of the nurses. Initially, paper and pen sketches were created, dealing with the general flow of the platform. Since the report is not isolated from the platform, but instead highly dependent on what functions are included in the interface surrounding it, a first step was to broaden the perspective and design a work-flow that hopefully could suit the nurses better. Thereafter, the sketches were combined to enable intuitive navigation through the system and make sure that necessary functions were included. At last, the focus was put into the visual look and graphical interface. The digital design app Sketch was used during the two last steps of the process.

Below, a few parts of the final prototypes are being presented, along with a short description of the motives behind them. More figures, and bigger ones, are included in Appendix B. Important to mention is that the prototypes have been designed without considering current limitations, such as access to patient data.

9.1 The prototypes

Figure 18 displays what the prototype looks like once a new patient encounter has been accepted by the nurse. He or she is presented with the report, and nothing else, since it was the first thing that every nurse looked for. Once the nurse has read the report, it is possible to navigate to the standard view, presenting the report in combination with the chat shown in Figure 25. When doing so, one alternative could be to automatically copy the patient's social security number, since it was done for every new patient when wanting to read the medical records. However, this can also be done manually by the nurse whenever he/she wants to by clicking on the patient's social security number. A choice has been made to distinguish between more static patient information presented in the top menu and information that is specific to the current encounter. The idea is that once the patient initiates contact with a healthcare center, he or she can create a 'profile' consisting of personal information such as name, age, habits, allergies and diseases, etc. Every time the patient uses the platform again, he or she can either confirm that the information is still valid or change it. This feature was suggested since the nurses wanted to form themselves an opinion of who the patient really was and to be more aware of the patient's risks and ongoing diseases.

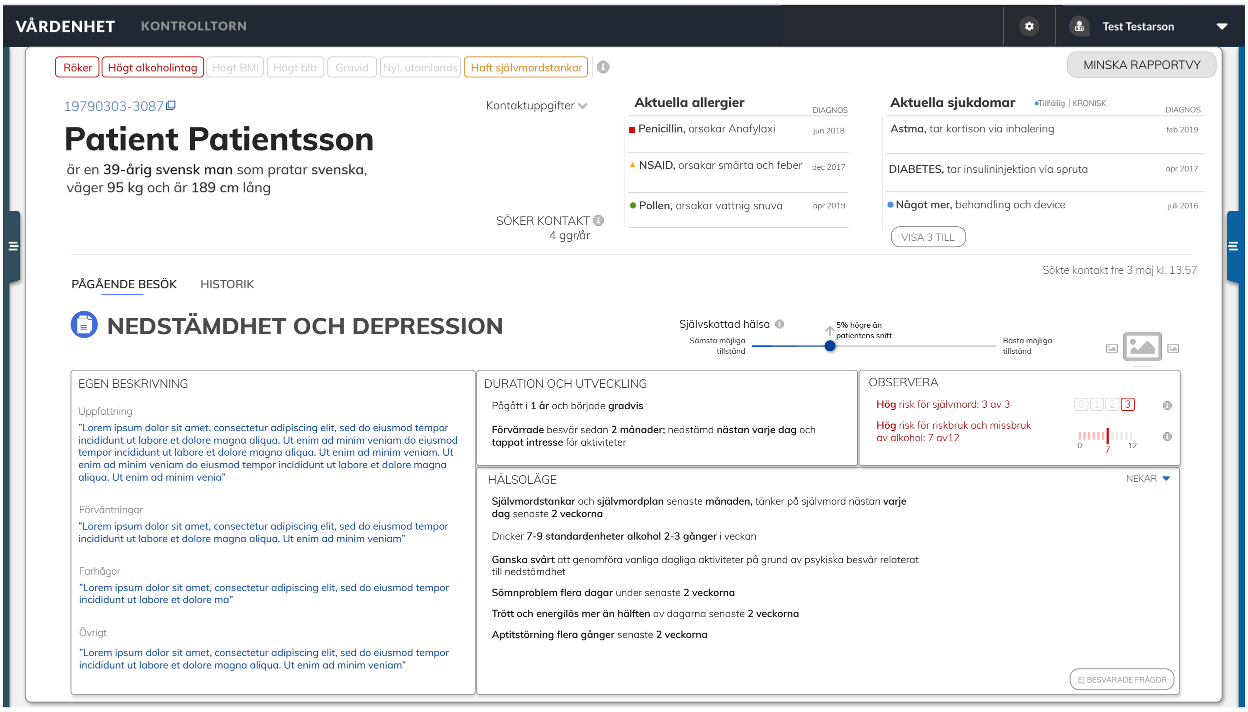

Figure 18: A view of the report when a new patient encounter has begun.

The platform is designed to be kept simple, yet intuitive, and to enable the nurses to get access to more information if wanted. For instance, when placing the mouse over one risk factor presented in the upper left corner, more information is shown as seen in Figure 19.

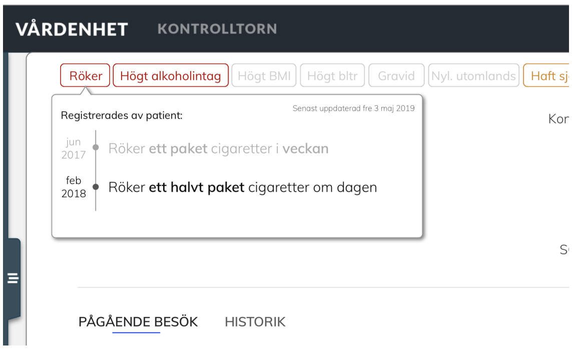

Figure 19: Possible to obtain more information when hovering over the information.

It is, just as before, possible to see a list of all the active patients when hovering over the left menu as seen in Figure 20. Similarly, when hovering over the right menu as seen in Figure 21, information relating to the healthcare team is displayed. The hidden sidebars are just one out of many ways to visualize the interface and another option would be to introduce a static side menu. When deciding how to design the platform, it is important to present the most relevant information at first, i.e. the medical record, to enable for a clean and intuitive interface.

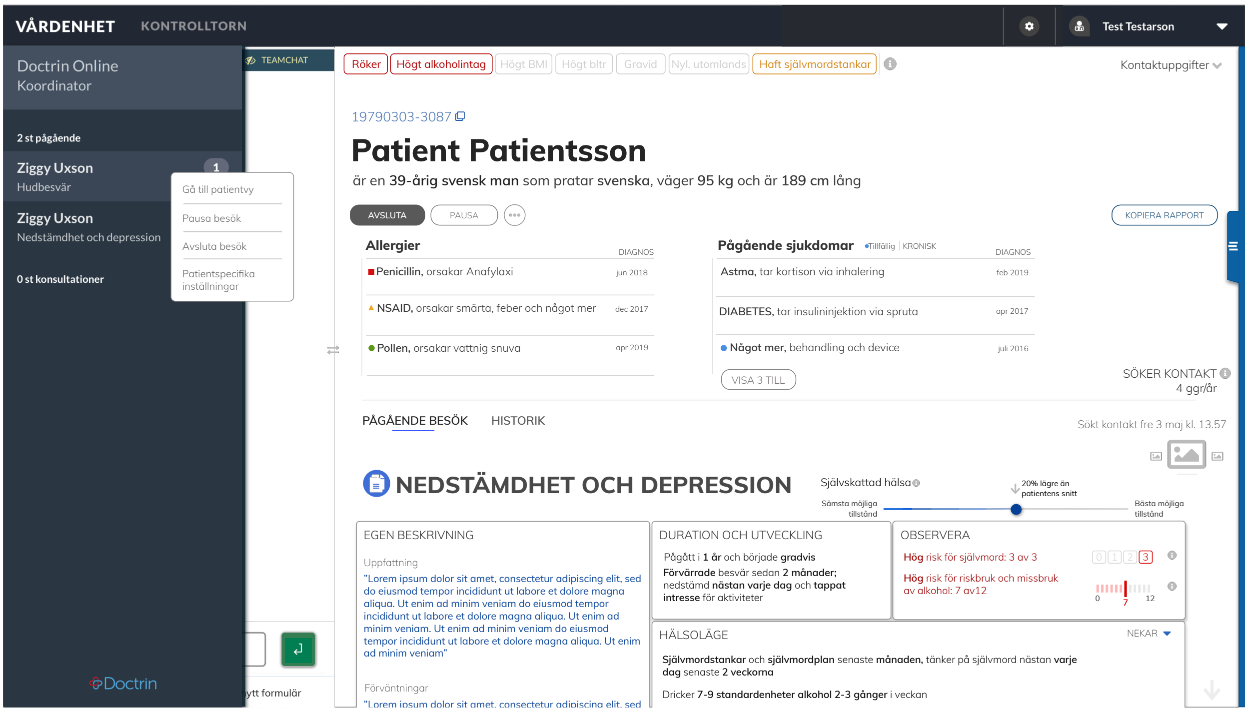

Figure 20: Hovering over the left side menu enables the nurses to see a list of all their active patients.

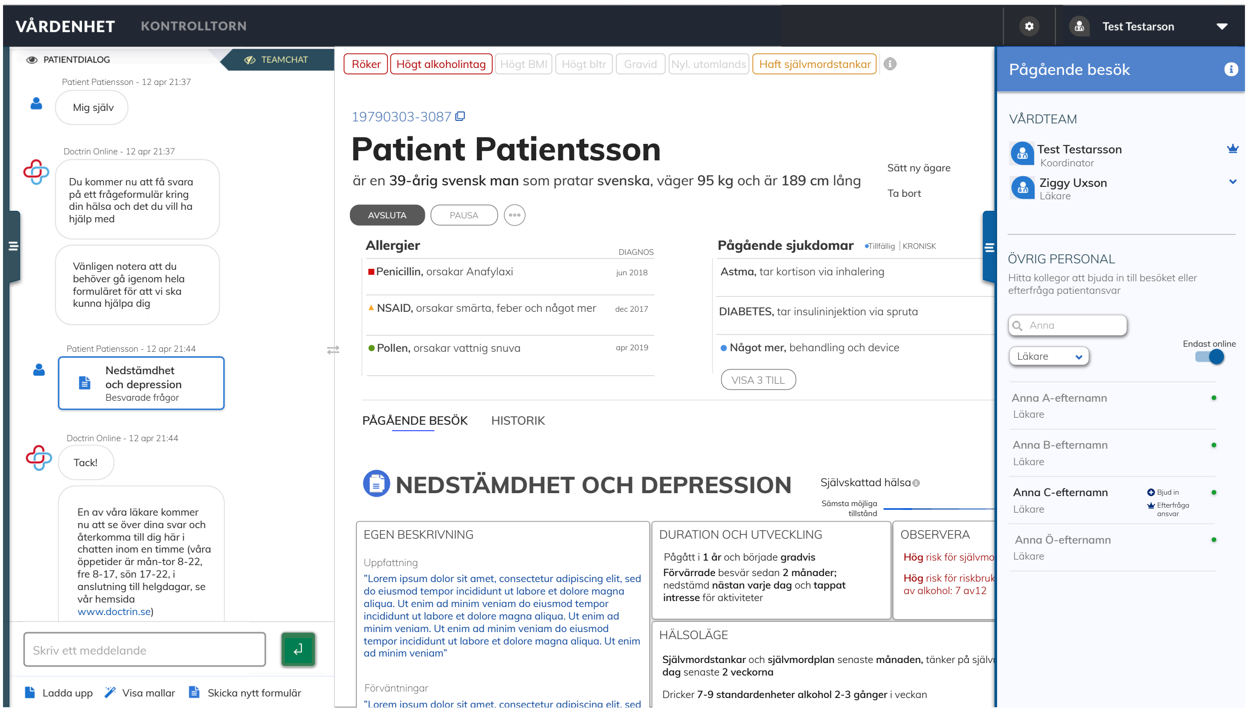

Figure 21: Hovering over the right side menu enables the nurses to see information specific to the case.

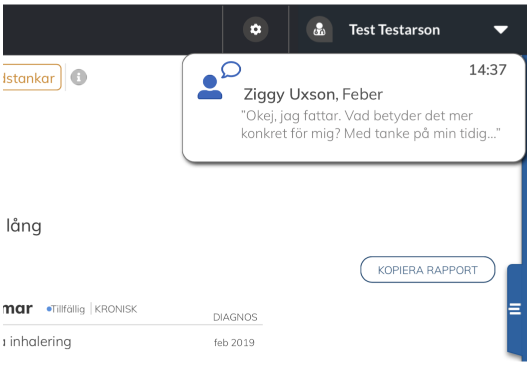

Figure 22: A message notification indicating that the patient has written a message.

Figure 23: Unread messages.

Due to the fact that the left menu initially is hidden, the nurses need to be notified when one of their patients writes a message in a chat. As seen in Figure 22 and Figure 23, the message is displayed in the upper right corner for a short period of time and an envelope is presented on the left menu, indicating that there are unread messages waiting to be read. Furthermore, as seen in Figure 24, another feature is that more specific settings have been introduced, such as the possibility to choose between dark or light mode since there were mixed opinions among the nurses for how the interface should be designed.

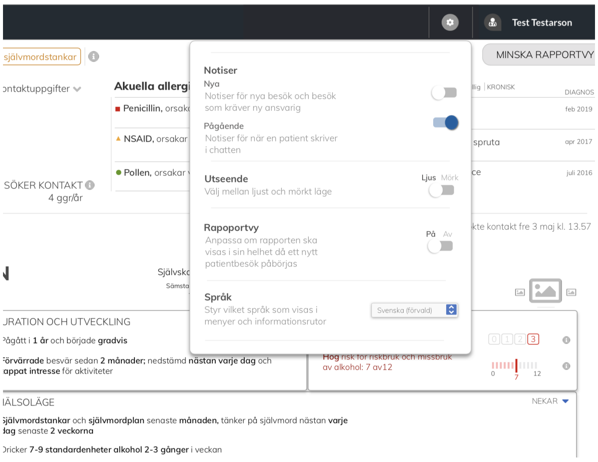

Figure 24: General settings.

Since it was important for the nurses to look at the report while chatting with the patient, the report is presented next to the chat as seen in Figure 25. The nurse is given the option to cancel or pause the visit, copy the report or choose settings specific to the patient. One such example could be wanting to turn on notifications when the patient answers, even though the nurse has disabled the function in the general settings. Other features supported by the platform is to view what questions the patient has not answered, or statements that the patient has answered not to be true. Furthermore, an idea is to make it possible for the nurses to take notes when reading the report since they tended to treat a big number of patients simultaneously. The notes could help the nurses remember who the patient was when navigating between many ongoing patient visits. Another idea is to make it possible to 'pin' information presented in the report and to summarize such information next to the chat, resulting in a reduced amount of information presented to the nurses.

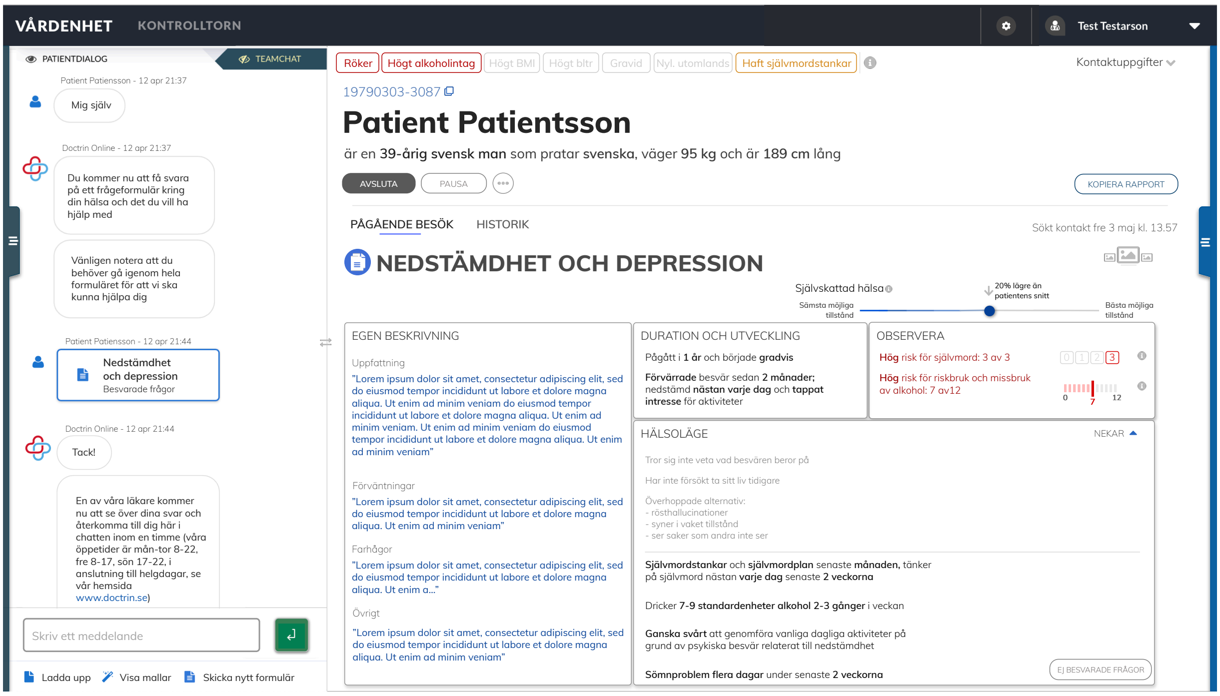

Figure 25: The 'standard view' presenting the report together with the chat.

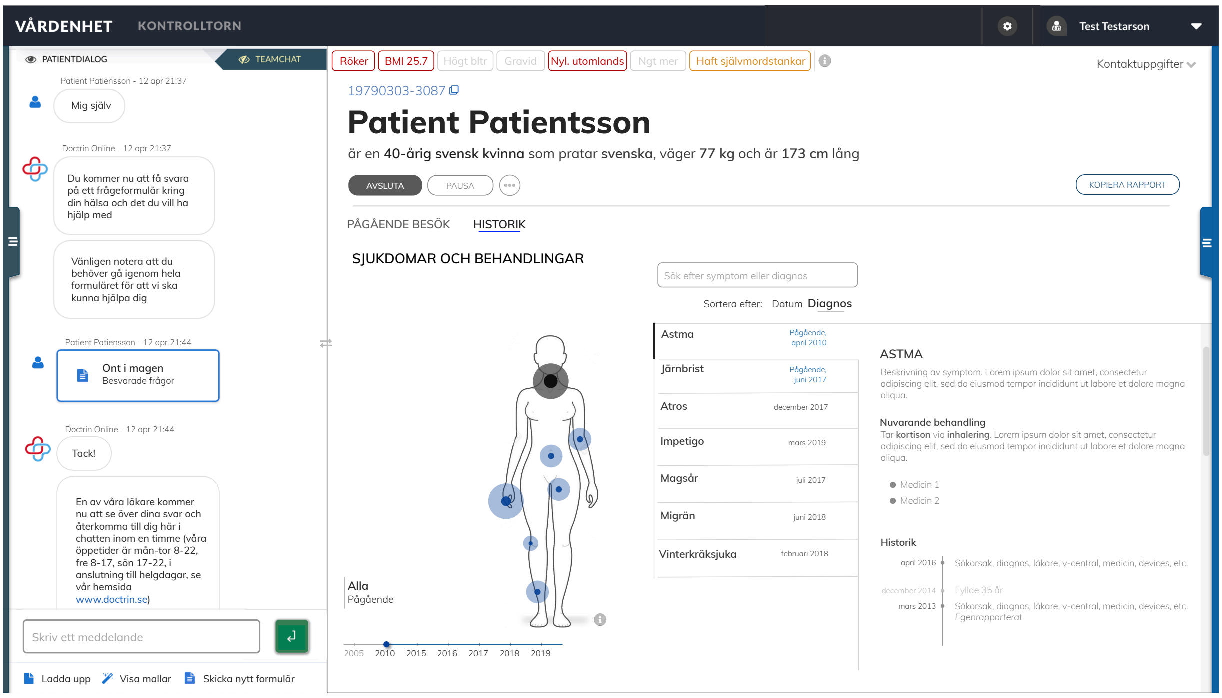

Figure 26: The patient's medical history.

Another function that could help the nurses in their triaging process is to include the patient's medical records and history in the platform. Since there are many limitations relating to the access and usage of patient data today, this feature cannot be realized at the time of writing. However, it is interesting to investigate what such an interface could look like in the future and one suggestion can be seen in Figure 26. A figure displaying the patient's previous and ongoing diseases can be a great tool for enabling a quick comprehension of the patient's current status. For example, the size of the circles can indicate the severity of the disease or the number of times that the patient has initiated contact with the healthcare center. It is however accompanied with issues that need to be further analyzed, such as how a disease that is not related to a specific body part, e.g. 'depression', should be visualized?

9.2 Validation

The prototypes have been presented to both nurses and employees of *the Company*, who have given their input throughout the design process. In general, the nurses were positive towards the prototypes and claimed them to be an improvement compared to the current platform. The reason for this was that the prototypes enabled a more intuitive workflow with fewer 'clicks' and 'scrolls' needed by the user to get where he/she wanted. However, thorough testing is needed to confirm that the design fits the nurses' initial needs and to identify possible flaws. More specifically, the next step would be to let the nurses navigate through the interface themselves and test what works well and not. At a later stage, attention would be put to the details and the design choices of the platform.

CONCLUSION

The last chapter aims to answer the research question stated in the first chapter. This is followed by analyzing the limitations of the study along with suggestions for future work. Lastly, new insights that the project has contributed to is being described.

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10 Conclusion

This thesis aimed to investigate the information needed in the triage process done by nurses. The initial aim and research question were addressed by combining deeper data analyses, more specifically using machine learning concepts, with broader understandings originating from a user research approach. The results from the two fields served as a basis for design choices to better visualize the data, leading to a number of prototypes presented in the previous chapter. The results gained from the random forest classifier and the user research were shown to align, indicating the same type of information to be important in the medical report.

The three classification algorithms tested showed to have similar accuracies. However, the random forest model resulted in marginally higher accuracy, 69.46%, also having the shortest execution time. The personal patient information such as age, gender, social security number and reason for contact were stated to be of very high importance. Except for this, the most important features were stated to be the duration and progress of the symptoms, allergies to medicine, chronic diseases and the patient's own estimate of his/her health. These factors could all be confirmed to be important by the user research approach. However, the user research approach generated valuable insights that the data analysis could not consider. The second most important information, after the patients' personal information, was stated by the nurses to be the patients' own description of their symptoms and issues. It could also be stated that the report, containing the hard data, together with the chat, i.e. the interaction with the patient, was equally important. Due to the limited scope of this thesis, the data analysis could not include free text in the analysis. Furthermore, the user research approach stated that there are factors not only involving the patient-generated information that are important. For example, the visualization and placement of the data can be of equal importance to enable an efficient triaging process. Referring back to the suggestions stating that nurses look for information differently depending on the patients and their symptoms, one can conclude that this is not the case. Instead, the nurses taking part in the data collection used the report in surprisingly similar ways.

10.1 Future work

As previously mentioned, this project analyzes the functionality of the report presented to nurses when triaging patients. Thus, patients perspectives, motives and usage of the platform have not been considered, nor have other healthcare professions such as physicians or specialists. A relatively small sample of nurses has been considered when collecting the data which is not a representative selection. When investigating what data is important to present to nurses when triaging patients, the focus has lied on understanding the reasoning processes and knowledge structures used during patient encounters, such as comprehension and decision-making. Even though such processes might vary greatly depending on the nurse, certain regularities of the human information processing system can be capitalized and enables for generalization, as in the case of this project.

Some nurses participating in the data collection have been relatively unfamiliar with using the platform which, in relation to the ones that are more experienced, gives the study relevance. The nurses' perception of the service is not static and is likely to change as time passes, to the better or worse. Given the time frames of the project, this study has not aimed at analyzing past attitudes or to observe any long term effects in the future, but instead to conduct an analysis on nurses' attitudes as they are now. Since it has been observed that healthcare professionals tend to be more positive as they are becoming more familiar with the tools and works structures of new technology,[57] an effect of this study's scope might be that nurses are framed to be more negative than they will be in the near future. An idea for future work is therefore to observe more nurses during a longer period of time.

It is possible that individual and collective views presented in the project are heavily influenced by local contexts, such as working structures and patients' attitudes and usage of the technology. When collecting data, only one healthcare center has been participating which can be a limiting factor for the study. No distinction has been made between nurses working in different regions in Sweden which is important to acknowledge since they differ in the number of patients and nurses, affecting the workload, working environment and roles among the nurses. Although the data collection have been relatively time consuming and thorough, they have been single visits which could be troublesome since more visits could have established a better relationship between nurse and interviewer. It could have resulted in nurses being more relaxed during the observations which could have lead to a more in-depth understanding of their usage of the platform. One additional limitation relating to the data collection is that only one nurse has been observed at a time and less focus has been given to social processes in the team such as communication, coordination and distribution of knowledge. The interviewer must therefore rely on information that the nurses choose to share themselves during the data collection. The aim of the study is not to analyze such processes but they do, nevertheless, play a big part in how healthcare technology is being received and used. In terms of future work, more data collection sessions should be conducted to establish a better relationship and get a more in-depth understanding of the nurses' needs.

Qualitative research has been criticized to be too subjective and dependent on what the interviewers find important for the study. The data collected therefore risk being biased since the researcher decides what is valuable or not.[58] By using different methods for gathering data and having multiple sources pointing in the same direction, the risk can be reduced. As for the data analysis, only a fixed number of classifiers were tested due to the scope of the project and the limited time frame. Ideally, more classifiers would have been developed and tested. Furthermore, only a limited amount of variations of parameters were tested. As described previously in the report, a patient being faced with *the Company's* platform is asked to answer both free-text questions as well as multiple choice questions, where the patient can choose from a fixed number of predetermined answers. In this project, the machine learning algorithms have only been using those multiple choice questions, since analyzing free-text would go beyond the scope of this project. It is, however, interesting to continue to develop the analyzes so that the free-text questions are taken into account alongside the multiple choice questions. There are a number of other factors that possibly could have affected the results. For example, all data used in this project originate from one single healthcare center. The data has been gathered during the first 6 months that the platform has been live at the healthcare center, generating a limited amount of data. It is likely that better results could be achieved if continuing gathering data, thus enabling the models to train on larger data sets and possibly generating better performance accuracies. Gathering data from several different healthcare centers could also entail more representative data.

Another aspect of the gathering of data that started simultaneously to when the platform went live, is that both the nurses and patients weren't used to using it and this could have had misleading impacts on the data. Furthermore, it can be argued that the data set is somewhat imbalanced. The number of features is approximately 2700, while for each case there are only between 15-20 of these features that contain values. A different approach for future investigations could be to not handle the reasons for contact as any other input feature, but instead analyze each specific reason for contact and its corresponding features. This would of course require large amounts of data, which is the reason why this approach was not feasible in this project since there were very sparse amounts of cases for each reason for contact. However, using this approach in the future would reduce the risk of getting imbalanced data coming from many patients applying for the same issue, e.g. pinworm, leading to an over-representation of those issues in the data set.

10.2 Final words

In this project, we have investigated what, and how, medical information should be presented to better facilitate nurses in their triaging process. The reasons to why this task was chosen are many. Most importantly is the fact that none or very little research has, to our knowledge, been done focusing on digital triaging or nurses working in a digital context. Yet, the triaging process is directly related to nurses' daily work as well as the quality of patient care; metrics for which healthcare professionals are held accountable for. The study has consequently contributed with new insights relating to areas previously unexplored, which can be said to be the most important result of the study. Not only is previous research regarding digital triaging remarkably sparse, the area is also relatively unexplored in terms of putting research into practice. Digitalized healthcare is a fast-paced field with no rights and wrongs in terms of visualization of patient information, which enables for our results to have an impact on how *the Company's* platform should be structured and designed.

The combination of the two fields user experience and machine learning is not commonly combined, but has in this project proven to be valuable and enabled for a more nuanced and thorough investigation. Prior to this study, one field has often been chosen over the other, resulting in a loss of either qualitative or quantitative data. Another important result is therefore that the results from the two fields were comparable and showed to align. However, if another machine learning model would have been chosen, the results would have differed in many ways. If more time would have been given, it would therefore have been interesting to analyze larger data sets originating from more than one healthcare center and spanning across a longer period of time. By doing so, the findings from the study could have enabled for generalization and possibly resulted in a more effective triaging process.

References

[1] McKinsey&Company, "Värdet av digital teknik i den svenska vården." Available at `https://www.mckinsey.com/~/media/McKinsey/Industries/Healthcare%20Systems%20and%20Services/Our%20Insights/Digitizing%20healthcare%20in%20Sweden/Digitizing-healthcare-in-Sweden.ashx` (2016).

[2] G. Fitzpatrick and G. Ellingsen, "A review of 25 years of cscw research in healthcare: Contributions, challenges and future agendas," *Computer Supported Cooperative Work (CSCW)*, vol. 22, no. 4, pp. 609–665, 2013.

[3] S. Nundy, C.-Y. E. Lu, P. Hogan, A. Mishra, and M. E. Peek, "Using patient-generated health data from mobile technologies for diabetes self-management support: provider perspectives from an academic medical center," *Journal of Diabetes Science and Technology*, vol. 8, no. 1, pp. 74–82, 2014.

[4] K. Sjögren, M. Lindkvist, P.-O. Sandman, K. Zingmark, and D. Edvardsson, "To what extent is the work environment of staff related to person-centred care? a cross-sectional study of residential aged care," *Journal of Clinical Nursing*, vol. 24, no. 9–10, pp. 1310–1319, 2015.

[5] C. Grünloh, Åsa Cajander, and G. Myreteg, ""the record is our work tool!"—physicians' framing of a patient portal in sweden," *Journal of Medical Internet Research*, vol. 18, no. 6, pp. 1–14, 2016.

[6] Åsa Cajander, J. Moll, S. Englund, and A. Hansman, "Medical records online for patients and effects on the work environment of nurses," *Studies in Health Technology and Informatics*, vol. 30, no. 3, pp. 271–275, 2018.

[7] C. Allard and A. Ögnelod, "Triage at the emergency department from the nurse's perspective," Master's thesis, Högskolan i Skövde, 2017.

[8] M. Gerdtz and T. Bucknall, "Australian nurses' decision- making and scope of practice," *Australian Emergency Nursing Journal*, vol. 4, no. 1, pp. 19–26, 2001.

[9] A. Kushniruk, "Analysis of complex decision-making processes in health care: cognitive approaches to health informatics," *Journal of Biomedical Informatics*, vol. 34, no. 5, pp. 365–376, 2001.

[10] V. M. Vaughn and J. A. Linder, "Thoughtless design of the electronic health record drives overuse, but purposeful design can nudge improved patient care," *BMJ Quality and Safety*, vol. 27, no. 8, pp. 583–586, 2018.

[11] J. S. Ash, M. Berg, and E. Coiera, "Some unintended consequences of information technology in health care: The nature of patient care information system-related errors,"

Journal of the American Medical Informatics Association, vol. 11, no. 2, pp. 104–112, 2011.

[12] T. P. Thyvalikakath, M. P. Dziabiak, R. Johnson, M. H. Torres-Urquidy, A. Acharya, J. Yabes, and T. K. Schleyer, "Advancing cognitive engineering methods to support user interface design for electronic health records," *International Journal of Medical Informatics*, vol. 83, no. 4, pp. 292–302, 2014.

[13] D. Mechanic and S. Meyer, "Concepts of trust among patients with serious illness," *Social Science Medicine*, vol. 51, no. 5, pp. 657–668, 2000.

[14] T. O. Staiger, J. G. Jarvik, R. A. Deyo, B. Martin, and C. H. B. III, "Brief report: Patient-physician agreement as a predictor of outcomes: In patients with back pain," *Journal of General Internal Medicine*, vol. 20, no. 10, pp. 935–937, 2005.

[15] R. M. Epstein and E. Peters, "Beyond information: Exploring patients' preferences," *American Medical Association*, vol. 302, no. 2, pp. 195–197, 2009.

[16] P. C. Tang and D. Lansky, "The missing link: Bridging the patient-provider health information gap," *Health Affairs*, vol. 24, no. 5, pp. 1290–1295, 2005.

[17] J. S. Ash, M. Berg, and E. Coiera, "Some unintended consequences of information technology in health care: The nature of patient care information system-related errors," *Journal of the American Medical Informatics Association*, vol. 11, no. 2, pp. 104–112, 2004.

[18] J. S. Evans, J. L. Barston, and P. Pollard, "On the conflict between logic and belief in syllogistic reasoning," *Memory and cognition*, vol. 11, no. 3, pp. 295–306, 1983.

[19] T. O. Andersen, J. P. Bansler, F. Kensing, J. Moll, T. Mønsted, K. D. Nielsen, O. W. Nielsen, H. H. Petersen, and J. H. Svendsen, "Aligning concerns in telecare: Three concepts to guide the design of patient-centred e-health," *Computer Supported Cooperative Work (CSCW)*, vol. 27, no. 3, pp. 1181–1214, 2018.

[20] K. T. Unruh and W. Pratt, "Patients as actors: The patient's role in detecting, preventing, and recovering from medical errors," *International Journal of Medical Informatics*, vol. 76, pp. 236–244, 2006.

[21] J. Wang, Y. Wang, C. Wei, N. A. Yao, A. Yuan, Y. Shan, and C. Yuan, "Smartphone interventions for long-term health management of chronic diseases: An integrative review," *Telemedicine and e-Health*, vol. 20, no. 6, pp. 57–583, 2014.

[22] R. van der Vaart, C. H. Ssaert, E. Taal, and M. A. F. J. van de Laar, "Giving rheumatology patients online home access to their electronic medical record (emr): advantages, drawbacks and preconditions according to care providers," *Rheumatology international*, vol. 33, no. 9, pp. 2405–2410, 2013.

[23] J. B. Fowles, A. C. Kind, C. Craft, E. A. Kind, J. L. Mandel, and S. Adlis, "Patients' interest in reading their medical record: Relation with clinical and sociodemographic characteristics and patients' approach to health care," *Archives of Internal Medicine*, vol. 164, no. 7, pp. 793–800, 2004.

[24] L. Bouayad, A. Ialynytchev, and B. Padmanabhan, "Patient health record systems scope and functionalities: Literature review and future directions," *Journal of medical Internet research*, vol. 19, no. 11, p. 388, 2017.

[25] G. Szarvas, R. Farkas, and R. Busa-Fekete, "State-of-the-art anonymization of medical records using an iterative machine learning framework," *ournal of the American Medical Informatics Association*, vol. 14, no. 5, p. 574–580, 2007.

[26] K. J. Vicente, *The human factor: revolutionizing the way people live with technology.* Routledge, 1 ed., 2006.

[27] P. Rasmussen, A. Henderson, N. Andrew, and T. Conroy, "Factors influencing registered nurses' perceptions of their professional identity: An integrative literature review," *Journal of continuing education in nursing*, vol. 49, no. 5, pp. 225–232, 2018.

[28] J. Keogh, "Professionalization of nursing: development, difficulties and solutions," *Journal of advanced nursing*, vol. 25, no. 2, pp. 302–308, 1997.

[29] K. Miller, S. Reeves, M. Zwarenstein, J. D. Beales, C. Kenaszchuk, and L. G. Conn, "Nursing emotion work and interprofessional collaboration in general internal medicine wards: a qualitative study," *Journal of advanced nursing*, vol. 64, no. 4, pp. 332–343, 2008.

[30] V. Patel, E. Shortliffe, M. Stefanelli, M. B. Peter Szolovits, R. Bellazi, and A. Abu-Hanna, "The coming of age of artificial intelligence in medicine," *Artificial Intelligence in Medicine*, vol. 46, no. 1, pp. 5–17, 2009.

[31] C. Bennett and K. Hauser, "Artificial intelligence framework for simulating clinical decision-making: A markov decision process approach," *Artificial Intelligence in Medicine*, no. 57, pp. 9–19, 2013.

[32] A. Reich, M. Heisig, N. Q. Phan, K. Taneda, K. Takamori, S. Takeuchi, M. Furue, C. Blome, M. Augustin, S. Ständer, and J. C. Szepietowski, "Visual analogue scale: evaluation of the instrument for the assessment of pruritus," *Acta dermato-venereologica*, vol. 92, no. 5, p. 497, 2012.

[33] K. Holtzblatt and H. Beyer, *Contextual design: evolved.* Morgan Claypool Publishers, 2015.

[34] T. R. Johnson, C. M. Johnson, and J. Zhang, "A user-centered framework for redesigning health care interfaces," *Journal of Biomedical Informatics*, vol. 38, no. 1, pp. 75–87, 2005.

[35] M. W. Jaspers, T. Steen, C. van den Bos, and M. Geenen, "The think aloud method-a guide to user interface design," *International Journal of Medical Informatics*, vol. 73, no. 11, pp. 781–795, 2004.

[36] T. R. Johnson, C. M. Johnson, and J. Zhang, "A user-centered framework for redesigning health care interfaces," *Journal of Biomedical Informatics*, vol. 38, no. 1, pp. 75–87, 2005.

[37] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning with Applications in R.* New York: Springer Publishing Company, 2 ed., 2013.

[38] P.-N. Tan, M. Steinbach, and V. Kumar, *Introduction to Data Mining.* Boston: Pearson Addison-Wesley, 2006.

[39] T. Hastie, R. Tihshirani, and J. Friedman, *The Elements of Statistical Learning - Data Mining, Inference and Prediction.* California: Springer Publishing Company, 2 ed., 2009.

[40] S. Russell and P. Norvig, *Artificial Intelligence - A Modern Approach.* New Jersey: Pearson, 3 ed., 2010.

[41] Scikit-learn, "Generalized linear models." Available at `https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression` (2019/05/27).

[42] A. Lindholm, N. Wahlström, F. Lindsten, and T. B. Schön, "Supervised machine learning - lecture notes for the statistical machine learning course." Available at `http://www.it.uu.se/edu/course/homepage/sml/literature/lecture_notes.pdf` (2019/05/27).

[43] X. boost developers, "Ensemble methods." Available at `https://scikit-learn.org/stable/modules/ensemble.html#random-forests` (2019/05/27).

[44] Scikit-learn, "Introduction to boosted trees." Available at `https://xgboost.readthedocs.io/en/latest/tutorials/model.html` (2019/05/27).

[45] T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," *ACM*, vol. 13-17, pp. 785–794, 2016.

[46] G. Tseng, "Gradient boosting and xgboost." Available at `https://medium.com/@gabrieltseng/gradient-boosting-and-xgboost-c306c1bcfaf5` (2019/05/27).

[47] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing and Management*, no. 45, pp. 427–437, 2009.

[48] Google, "Classification." Available at `https://developers.google.com/machine-learning/crash-course/classification/video-lecture` (2019/05/27).

[49] N. developers, "Numpy." Available at `https://www.numpy.org/` (2019/05/27).

[50] Pandas, "Python data analysis library." Available at `https://pandas.pydata.org/` (2019/05/27).

[51] Scikit-learn, "Machine learning in python." Available at `https://scikit-learn.org/stable/#` (2019/05/27).

[52] L. Cai and Y. Zhu, "The challenges of data quality and data quality assessment in the big data era," *Data Science Journal*, no. 14, 2015.

[53] L. Yu and H. Liu, "Feature selection for high-dimensional data: A fast correlation-based filter solution," in *Machine Learning, Proceedings of the Twentieth International Conference (ICML 2003), August 21-24, 2003, Washington, DC, USA*, pp. 856–863, 2003.

[54] Scikit-learn, "Recursive feature elimination." Available at `https://scikit-learn.org/stable/modules/feature_selection.html#recursive-feature-elimination` (2019/05/27).

[55] L. Breiman, J. Friedman, C. Stone, and R. Olshen, *Classification and Regression Trees*. U.S.: Chapman Hall, 1984.

[56] G. Louppe, "How are feature importances in randomforestclassifier determined?." Available at `https://stackoverflow.com/questions/15810339/how-are-feature-importances-in-randomforestclassifier-determined` (2019/05/29).

[57] G. G. Macdonald, A. F. Townsend, P. Adam, L. C. Li, S. Kerr, M. McDonald, and C. L. Backman, "ehealth technologies, multimorbidity, and the office visit: Qualitative interview study on the perspectives of physicians and nurses," *Journal of medical Internet research*, vol. 20, no. 1, p. 31, 2018.

[58] A. Bryman and E. Bell, *Business Research Methods*. Oxford: Oxford University Press, 4 ed., 2015.

Appendix

Appendix A

Project focus: data collection part 1

Method and aim
The nurse is asked to triage a number of test cases while thinking out loud. There are 20 test cases in total, all formulated differently to reflect a real-life scenario. Only five reasons for contacts have been chosen when creating test cases. The data collection can take place either on distance (using screen recordings and Skype) or in person.

The goal is to identify what information a nurse is looking for, and in what order, given a specific reason for contact and patient. Do nurses look for different information depending on the patient, or do they follow the same navigation pattern no matter the patients' symptoms? Additionally, it would be interesting to hear the nurses' attitudes towards the design and structure of the report and platform.

Target Group
Nurses with different roles and experiences working with *the Company's* platform and using the medical report in combination with the online chat.

Suggestions
It is likely that nurses look for different information, in a different order, depending on the severity of the patients' symptoms and their reason for contact. However, it is also likely that some information always is of high interest for the nurse, independent of what information is included in the report. Additionally, it is likely that the report can be made more user-friendly, which in the long run could enable a more efficient triaging process.

Project focus: data collection part 2

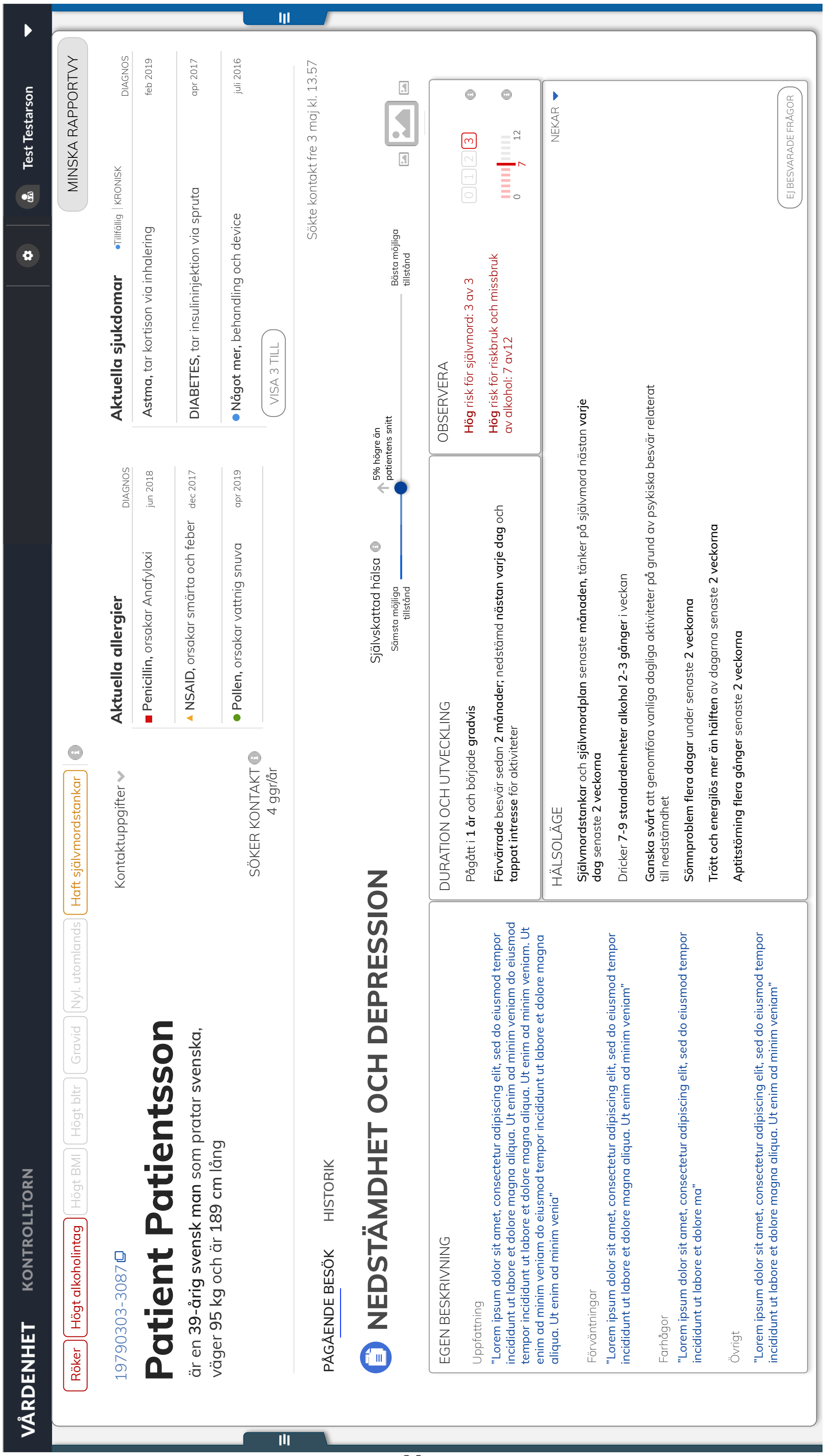
Method and aim
The nurse is asked to interact with the platform as usual, i.e. triage patients. A master/apprentice model is taken to enable the observer to ask questions and get a more thorough understanding of how the platform is used in real-life.

By combining the first part of the data collection with this second part, the hopes are to cover a wider range of usage and to obtain an in-depth understanding for how the report is being used in the nurses' daily life. Additionally, the hopes are to gather aspects that the user is unaware of or doesn't know how to articulate.

Target Group
Nurses with different roles and experiences working with *the Company's* platform and using the medical report in combination with the online chat.

Suggestions
It is likely that nurses interact with the platform differently than what they claim/think that they do. Additionally, their attitudes and usage of the platform are likely to change when they are being observed in their natural working environment, compared to testing settings.

Appendix B



VÅRDENHET
KONTROLLTORN
Test Testarson
Röker
Högt alkoholintag
Högt BMI
Högt bltr
Gravid
Nyl. utomlands
Haft självmordstankar
MINSKA RAPPORTVY
19790303-3087
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
Kontaktuppgifter
Aktuella allergier
DIAGNOS
Penicillin, orsakar Anafylaxi
jun 2018
NSAID, orsakar smärta och feber
dec 2017
Pollen, orsakar vattnig snuva
apr 2019
Aktuella sjukdomar
Tillfällig | KRONISK
Astma, tar kortison via inhalering
feb 2019
DIABETES, tar insulininjektion via spruta
apr 2017
Något mer, behandling och device
juli 2016
VISA 3 TILL
SÖKER KONTAKT
4 ggr/år
Sökte kontakt fre 3 maj kl. 13.57
PÅGÅENDE BESÖK
HISTORIK
NEDSTÄMDHET OCH DEPRESSION
Självskattad hälsa
Sämsta möjliga tillstånd
5% högre än patientens snitt
Bästa möjliga tillstånd
EGEN BESKRIVNING
Uppfattning
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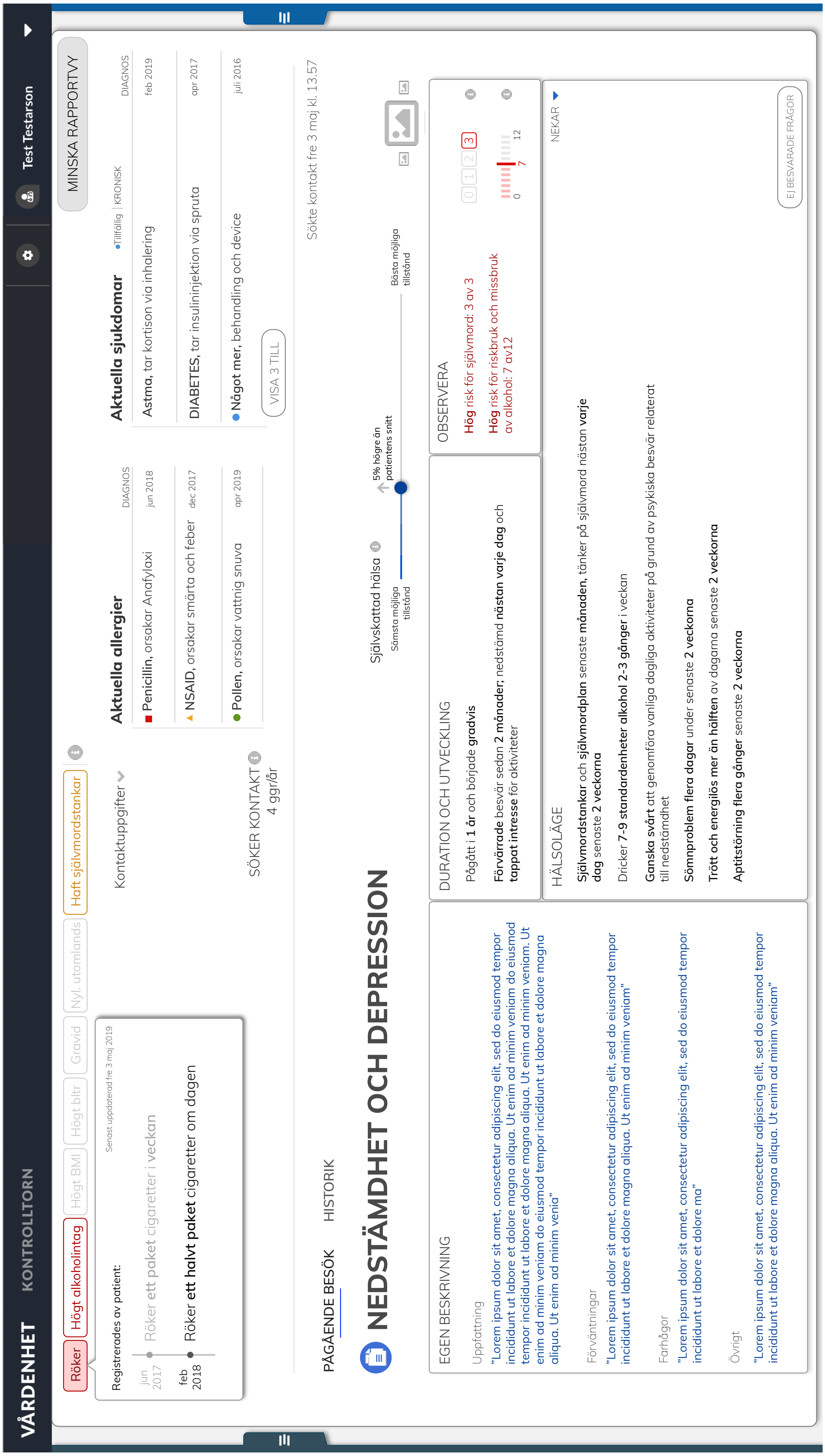
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader; nedstämd nästan varje dag och tappat intresse för aktiviteter
OBSERVERA
Hög risk för självmord: 3 av 3
Hög risk för riskbruk och missbruk av alkohol: 7 av12
0 1 2 3
0 7 12
HÄLSOLÄGE
NEKAR
Självmordstankar och självmordplan senaste månaden, tänker på självmord nästan varje dag senaste 2 veckorna
Dricker 7-9 standardenheter alkohol 2-3 gånger i veckan
Ganska svårt att genomföra vanliga dagliga aktiviteter på grund av psykiska besvär relaterat till nedstämdhet
Sömnproblem flera dagar under senaste 2 veckorna
Trött och energilös mer än hälften av dagarna senaste 2 veckorna
Aptitstörning flera gånger senaste 2 veckorna
EJ BESVARADE FRÅGOR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Haft självmordstankar
MINSKA RAPPORTVY
Registrerades av patient:
Senast uppdaterad fre 3 maj 2019
jun 2017
Röker ett paket cigaretter i veckan
feb 2018
Röker ett halvt paket cigaretter om dagen
Kontaktuppgifter
Aktuella allergier
DIAGNOS
Penicillin, orsakar Anafylaxi
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Förvärrade besvär sedan 2 månader, nedstämd nästan varje dag och tappat intresse för aktiviteter
OBSERVERA
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0 1 2 3
0 7 12
HÄLSOLÄGE
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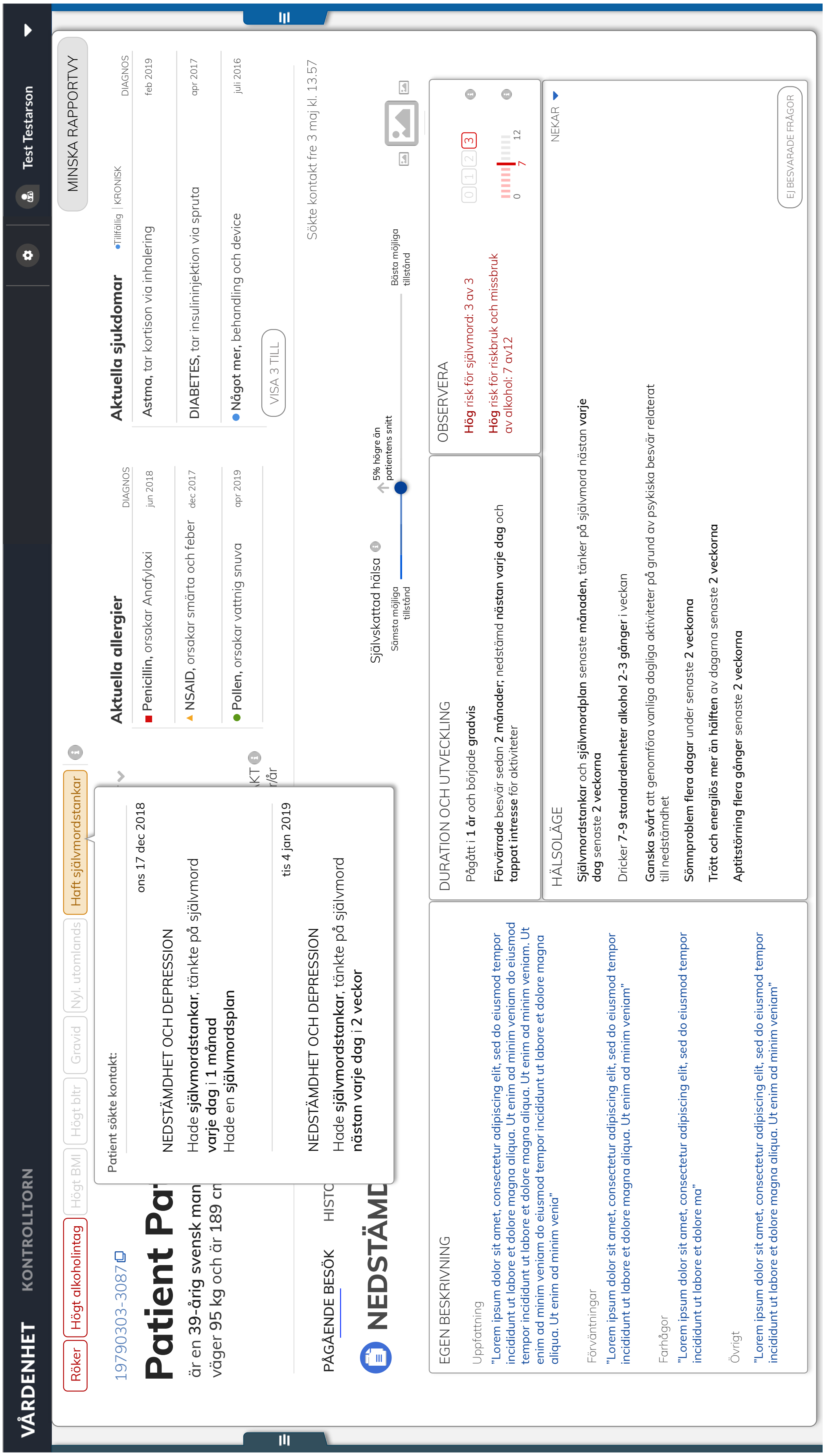
EJ BESVARADE FRÅGOR



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MINSKA RAPPORTVY
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Patient Pa
är en 39-årig svensk man
väger 95 kg och är 189 cm
PÅGÅENDE BESÖK
HISTO
NEDSTÄMD
Patient sökte kontakt:
ons 17 dec 2018
NEDSTÄMDHET OCH DEPRESSION
Hade självmordstankar, tänkte på självmord varje dag i 1 månad
Hade en självmordsplan
tis 4 jan 2019
NEDSTÄMDHET OCH DEPRESSION
Hade självmordstankar, tänkte på självmord nästan varje dag i 2 veckor
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EGEN BESKRIVNING
Uppfattning
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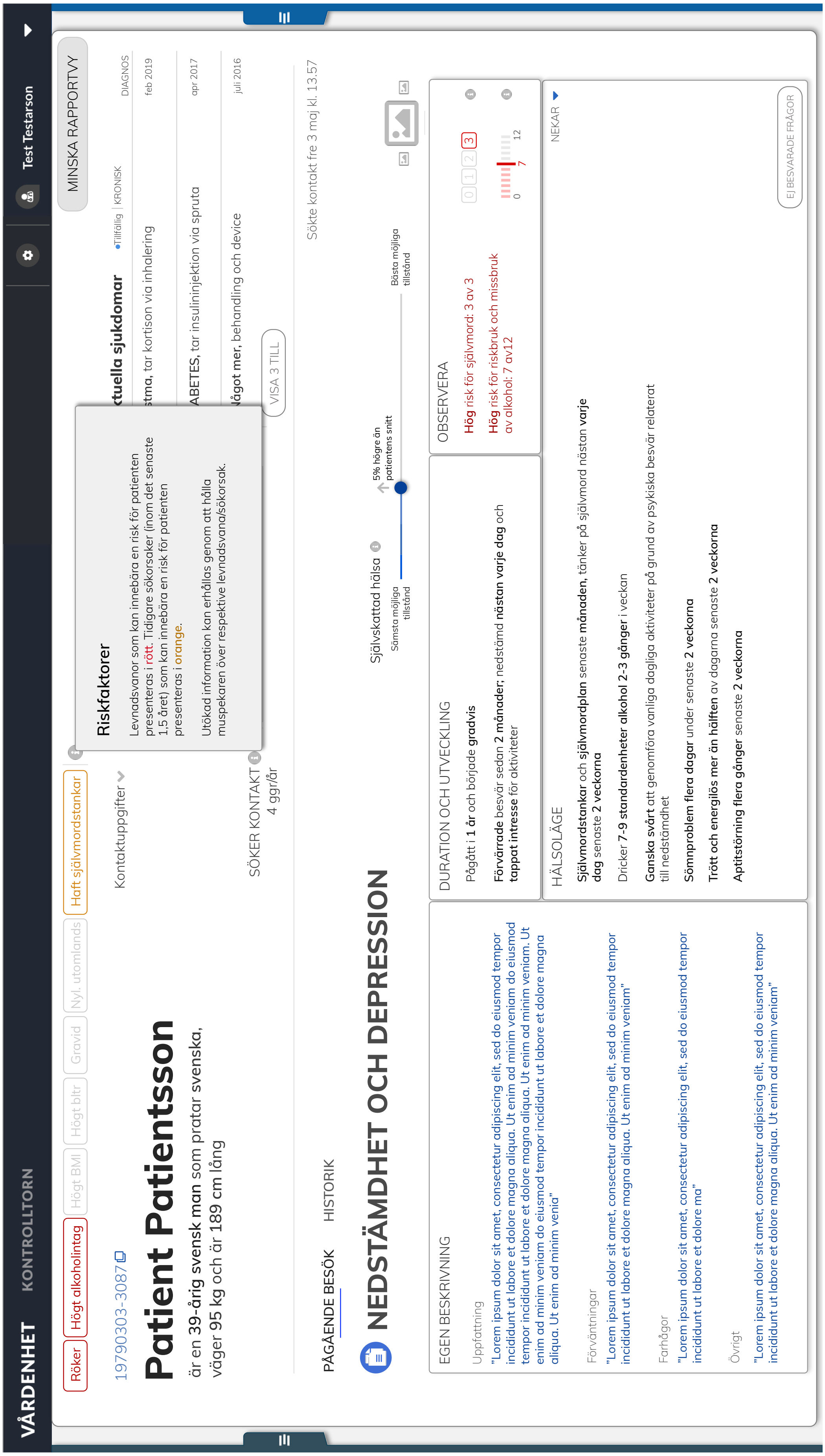
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19790303-3087
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
Kontaktuppgifter
Riskfaktorer
Levnadsvanor som kan innebära en risk för patienten presenteras i rött. Tidigare sökorsaker (inom det senaste 1.5 året) som kan innebära en risk för patienten presenteras i orange.
Utökad information kan erhållas genom att hålla muspekaren över respektive levnadsvana/sökorsak.
ktuella sjukdomar
Tillfällig | KRONISK
DIAGNOS
stma, tar kortison via inhalering
feb 2019
ABETES, tar insulininjektion via spruta
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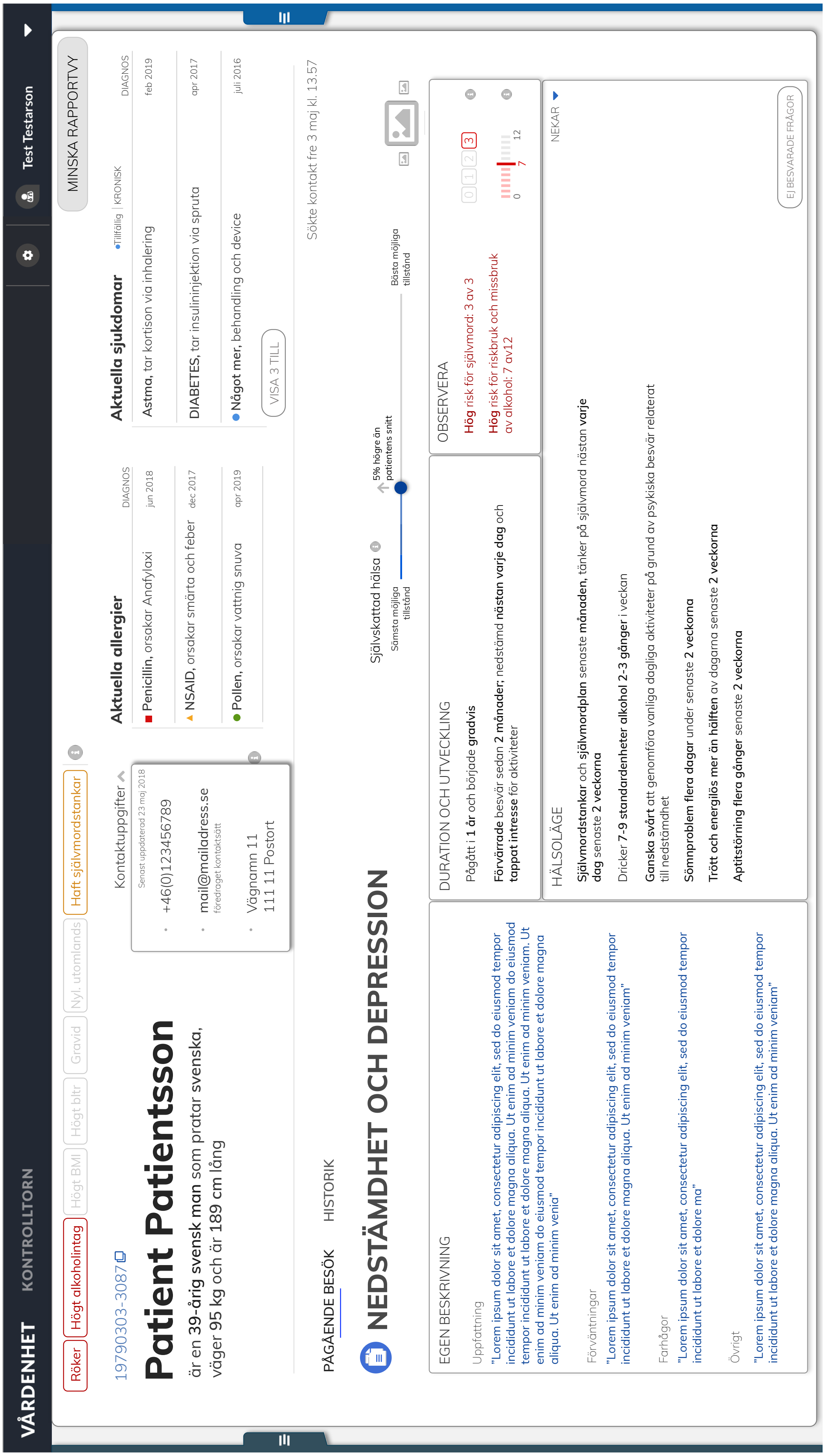
NEKAR
EJ BESVARADE FRÅGOR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är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
Kontaktuppgifter
Senast uppdaterad 23 maj 2018
+46(0)123456789
mail@mailadress.se
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Vägnamn 11
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Aktuella allergier
DIAGNOS
Penicillin, orsakar Anafylaxi
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Tillfällig | KRONISK
DIAGNOS
Astma, tar kortison via inhalering
feb 2019
DIABETES, tar insulininjektion via spruta
apr 2017
Något mer, behandling och device
juli 2016
VISA 3 TILL
Sökte kontakt fre 3 maj kl. 13.57
PÅGÅENDE BESÖK
HISTORIK
NEDSTÄMDHET OCH DEPRESSION
Självskattad hälsa
Sämsta möjliga tillstånd
5% högre än patientens snitt
Bästa möjliga tillstånd
EGEN BESKRIVNING
Uppfattning
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim venia"
Förväntningar
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Farhågor
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Övrigt
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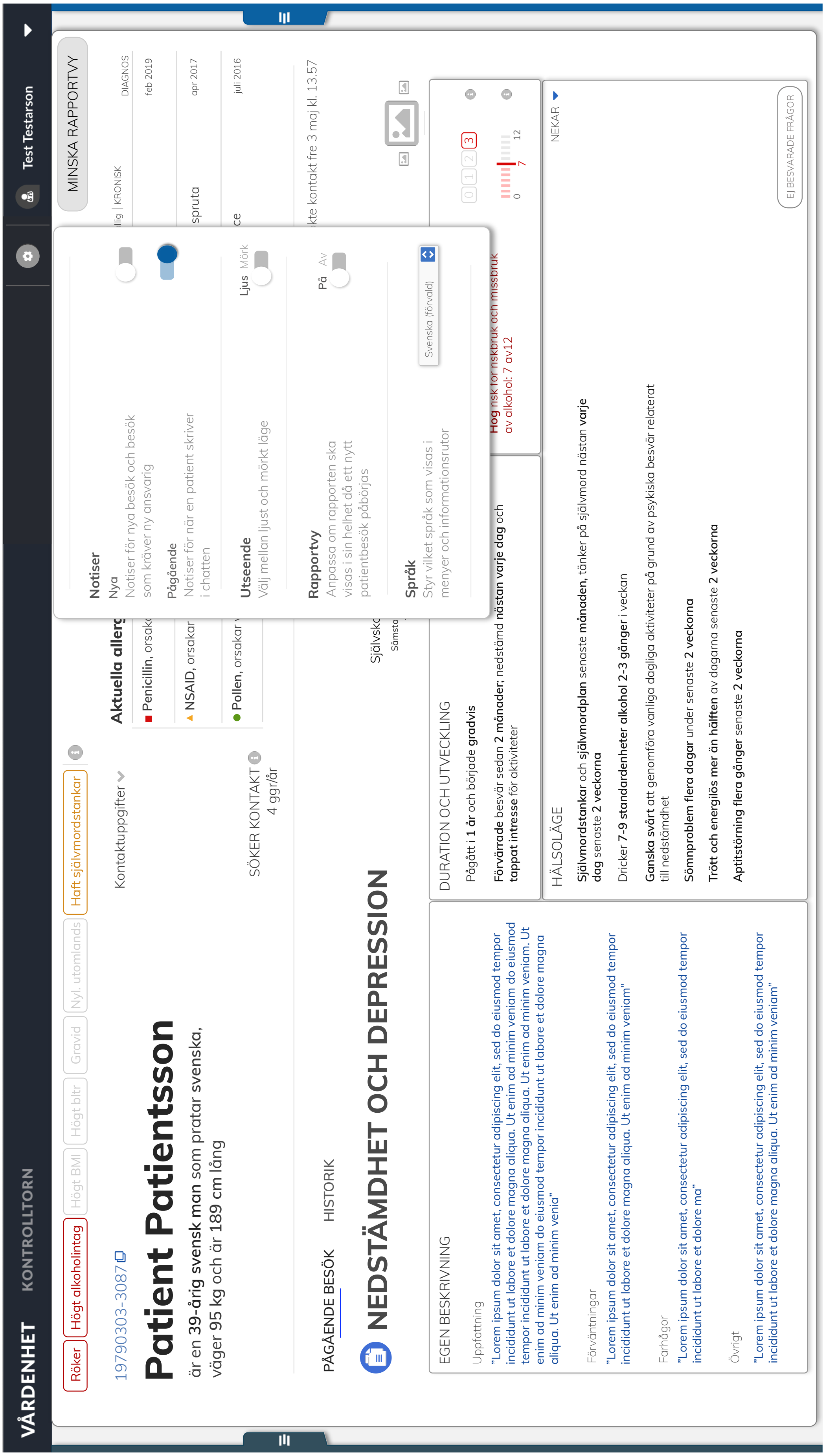
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader, nedstämd nästan varje dag och tappat intresse för aktiviteter
OBSERVERA
Hög risk för självmord: 3 av 3
Hög risk för riskbruk och missbruk av alkohol: 7 av12
0 1 2 3
0 7 12
HÄLSOLÄGE
NEKAR
Självmordstankar och självmordplan senaste månaden, tänker på självmord nästan varje dag senaste 2 veckorna
Dricker 7-9 standardenheter alkohol 2-3 gånger i veckan
Ganska svårt att genomföra vanliga dagliga aktiviteter på grund av psykiska besvär relaterat till nedstämdhet
Sömnproblem flera dagar under senaste 2 veckorna
Trött och energilös mer än hälften av dagarna senaste 2 veckorna
Aptitstörning flera gånger senaste 2 veckorna
EJ BESVARADE FRÅGOR


VÅRDENHET
KONTROLLTORN
Test Testarson
MINSKA RAPPORTVY
Röker
Högt alkoholintag
Högt BMI
Högt bltr
Gravid
Nyl. utomlands
Haft självmordstankar
19790303-3087
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
Kontaktuppgifter
SÖKER KONTAKT
4 ggr/år
Aktuella allerg
Penicillin, orsak
NSAID, orsakar
Pollen, orsakar
KRONISK
DIAGNOS
feb 2019
spruta
apr 2017
juli 2016
kte kontakt fre 3 maj kl. 13.57
Notiser
Nya
Notiser för nya besök och besök som kräver ny ansvarig
Pågående
Notiser för när en patient skriver i chatten
Utseende
Välj mellan ljust och mörkt läge
Ljus
Mörk
Rapportvy
Anpassa om rapporten ska visas i sin helhet då ett nytt patientbesök påbörjas
På
Av
Språk
Styr vilket språk som visas i menyer och informationsrutor
Svenska (förvald)
PÅGÅENDE BESÖK
HISTORIK
NEDSTÄMDHET OCH DEPRESSION
EGEN BESKRIVNING
Uppfattning
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim venia"
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Övrigt
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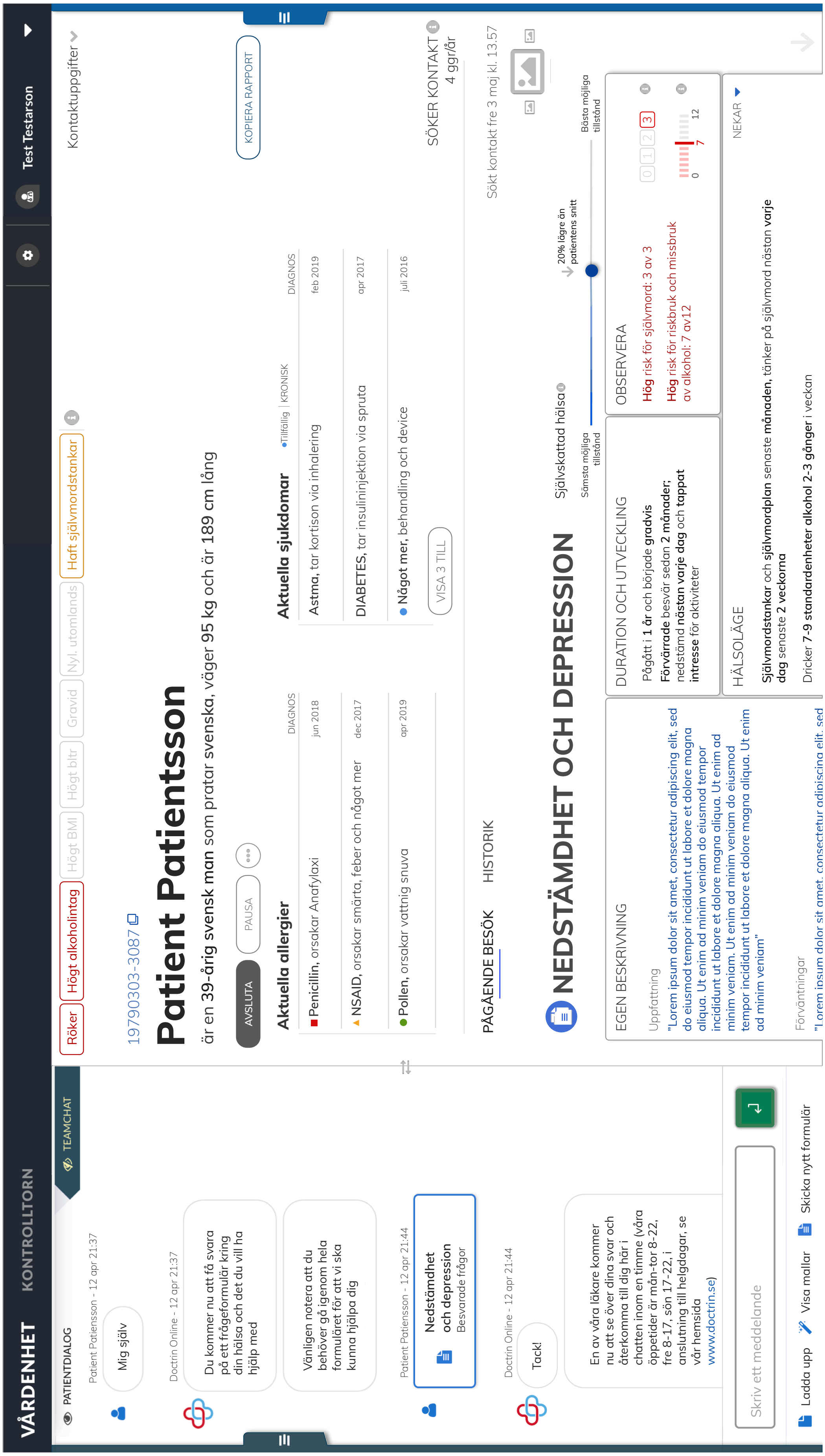
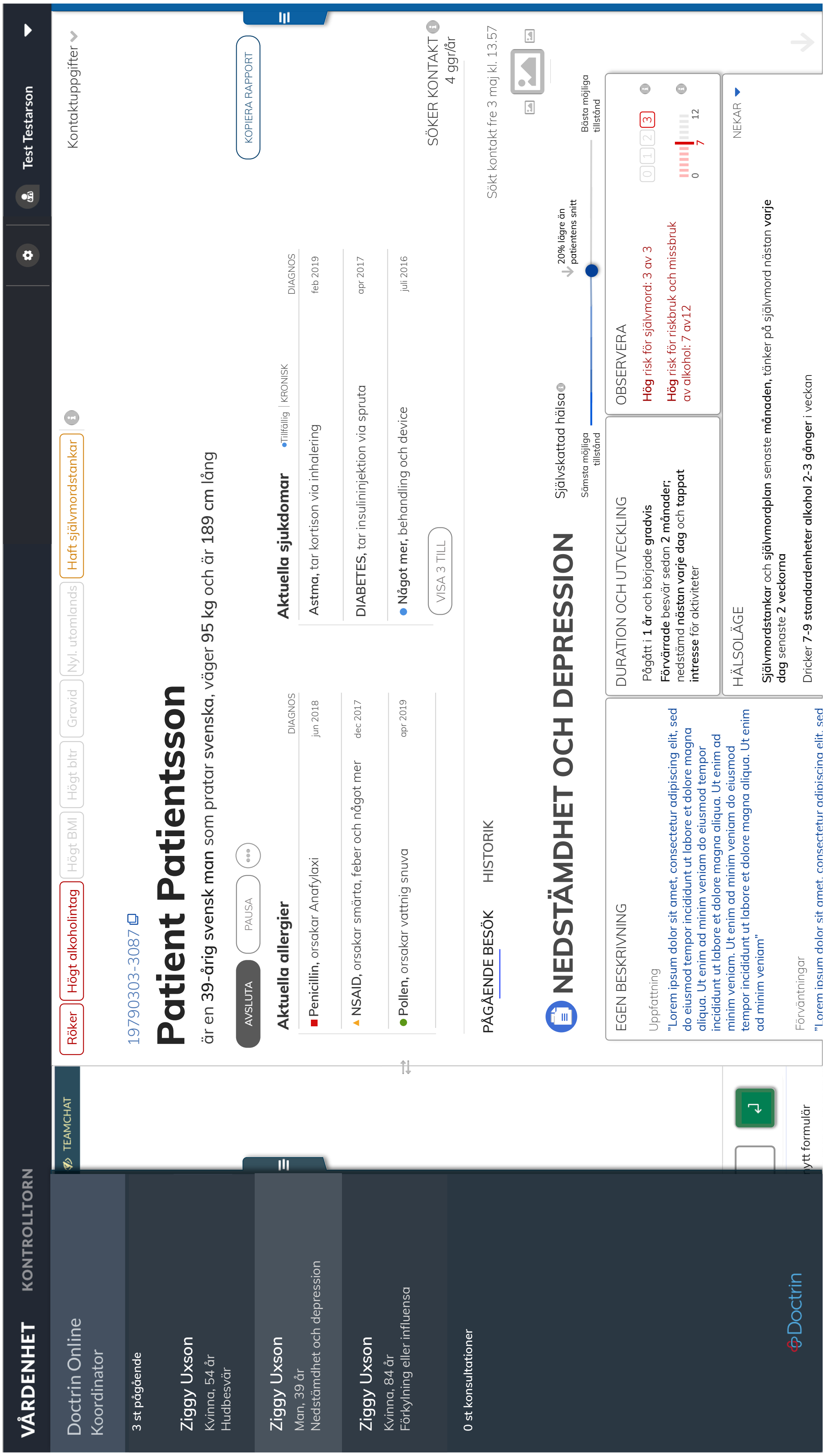
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader, nedstämd nästan varje dag och tappat intresse för aktiviteter
Hög risk för riskbruk och missbruk av alkohol: 7 av12
0 1 2 3
0 7 12
HÄLSOLÄGE
NEKAR
Självmordstankar och självmordplan senaste månaden, tänker på självmord nästan varje dag senaste 2 veckorna
Dricker 7-9 standardenheter alkohol 2-3 gånger i veckan
Ganska svårt att genomföra vanliga dagliga aktiviteter på grund av psykiska besvär relaterat till nedstämdhet
Sömnproblem flera dagar under senaste 2 veckorna
Trött och energilös mer än hälften av dagarna senaste 2 veckorna
Aptitstörning flera gånger senaste 2 veckorna
EJ BESVARADE FRÅGOR


VÅRDENHET
KONTROLLTORN
Test Testarson
PATIENTDIALOG
TEAMCHAT
Patient Patiensson - 12 apr 21:37
Mig själv
Doctrin Online - 12 apr 21:37
Du kommer nu att få svara på ett frågeformulär kring din hälsa och det du vill ha hjälp med
Vänligen notera att du behöver gå igenom hela formuläret för att vi ska kunna hjälpa dig
Patient Patiensson - 12 apr 21:44
Nedstämdhet och depression
Besvarade frågor
Doctrin Online - 12 apr 21:44
Tack!
En av våra läkare kommer nu att se över dina svar och återkomma till dig här i chatten inom en timme (våra öppetider är mån-tor 8-22, fre 8-17, sön 17-22, i anslutning till helgdagar, se vår hemsida www.doctrin.se)
Skriv ett meddelande
Ladda upp
Visa mallar
Skicka nytt formulär
Röker
Högt alkoholintag
Högt BMI
Högt bltr
Gravid
Nyl. utomlands
Haft självmordstankar
Kontaktuppgifter
19790303-3087
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
AVSLUTA
PAUSA
KOPIERA RAPPORT
Aktuella allergier
DIAGNOS
Penicillin, orsakar Anafylaxi
jun 2018
NSAID, orsakar smärta, feber och något mer
dec 2017
Pollen, orsakar vattnig snuva
apr 2019
Aktuella sjukdomar
Tillfällig | KRONISK
DIAGNOS
Astma, tar kortison via inhalering
feb 2019
DIABETES, tar insulininjektion via spruta
apr 2017
Något mer, behandling och device
juli 2016
VISA 3 TILL
SÖKER KONTAKT
4 ggr/år
PÅGÅENDE BESÖK
HISTORIK
Sökt kontakt fre 3 maj kl. 13.57
NEDSTÄMDHET OCH DEPRESSION
Självskattad hälsa
20% lägre än patientens snitt
Sämsta möjliga tillstånd
Bästa möjliga tillstånd
EGEN BESKRIVNING
Uppfattning
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
Förväntningar
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader; nedstämd nästan varje dag och tappat intresse för aktiviteter
OBSERVERA
Hög risk för självmord: 3 av 3
0 1 2 3
Hög risk för riskbruk och missbruk av alkohol: 7 av12
0 7 12
HÄLSOLÄGE
NEKAR
Självmordstankar och självmordplan senaste månaden, tänker på självmord nästan varje dag senaste 2 veckorna
Dricker 7-9 standardenheter alkohol 2-3 gånger i veckan


VÅRDENHET
KONTROLLTORN
Doctrin Online Koordinator
3 st pågående
Ziggy Uxson
Kvinna, 54 år
Hudbesvär
Ziggy Uxson
Man, 39 år
Nedstämdhet och depression
Ziggy Uxson
Kvinna, 84 år
Förkylning eller influensa
0 st konsultationer
Doctrin
Test Testarson
TEAMCHAT
Kontaktuppgifter
Röker
Högt alkoholintag
Högt BMI
Högt bltr
Gravid
Nyl. utomlands
Haft självmordstankar
19790303-3087
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
AVSLUTA
PAUSA
KOPIERA RAPPORT
Aktuella allergier
DIAGNOS
Penicillin, orsakar Anafylaxi
jun 2018
NSAID, orsakar smärta, feber och något mer
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Pollen, orsakar vattnig snuva
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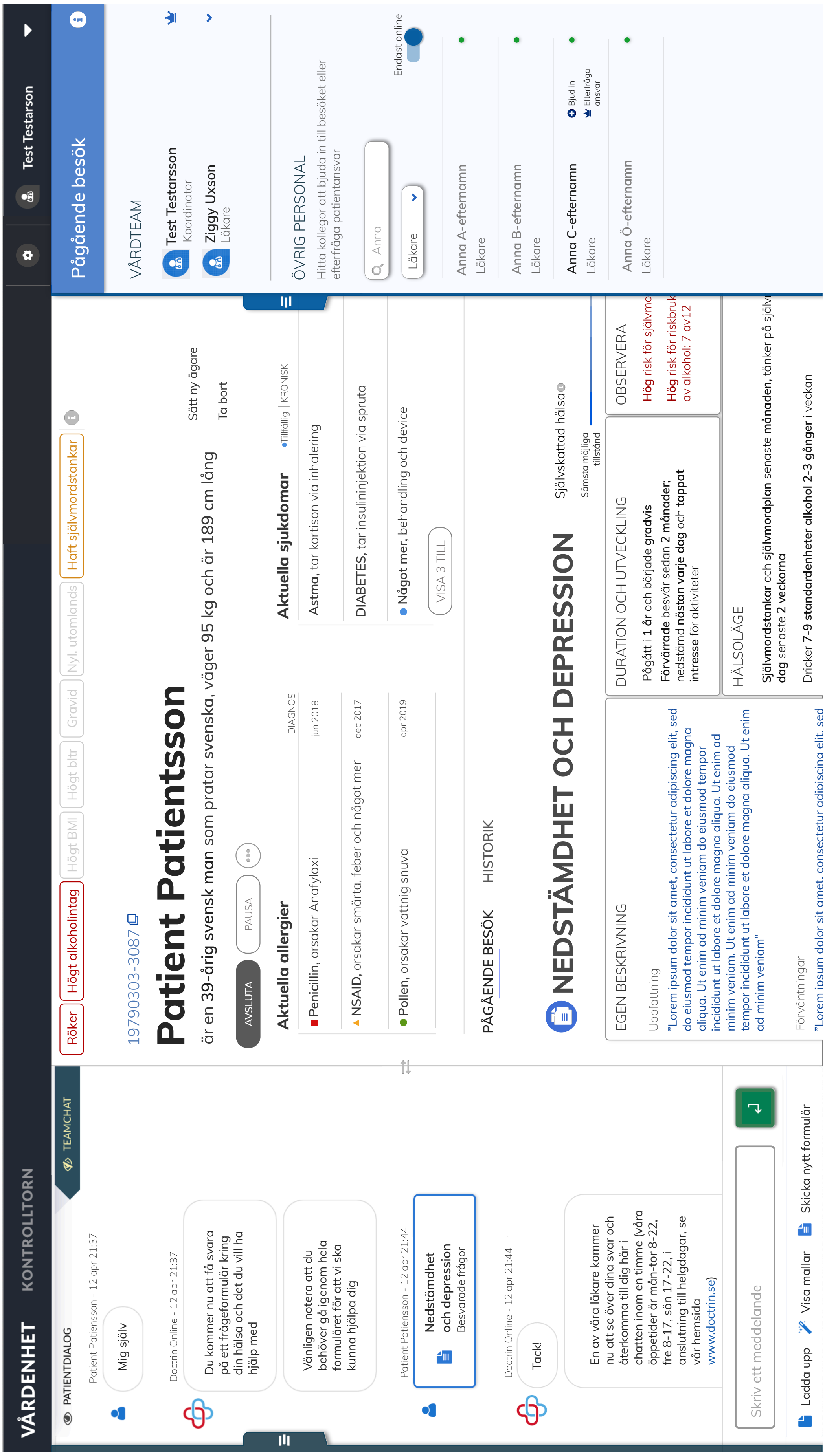
apr 2017
Något mer, behandling och device
juli 2016
VISA 3 TILL
SÖKER KONTAKT
4 ggr/år
Sökt kontakt fre 3 maj kl. 13.57
PÅGÅENDE BESÖK
HISTORIK
NEDSTÄMDHET OCH DEPRESSION
Självskattad hälsa
Sämsta möjliga tillstånd
20% lägre än patientens snitt
Bästa möjliga tillstånd
EGEN BESKRIVNING
Uppfattning
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
Förväntningar
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader; nedstämd nästan varje dag och tappat intresse för aktiviteter
OBSERVERA
Hög risk för självmord: 3 av 3
Hög risk för riskbruk och missbruk av alkohol: 7 av12
HÄLSOLÄGE
Självmordstankar och självmordplan senaste månaden, tänker på självmord nästan varje dag senaste 2 veckorna
Dricker 7-9 standardenheter alkohol 2-3 gånger i veckan
NEKAR
nytt formulär



VÅRDENHET
KONTROLLTORN
Test Testarson
PATIENTDIALOG
TEAMCHAT
Patient Patiensson - 12 apr 21:37
Mig själv
Doctrin Online - 12 apr 21:37
Du kommer nu att få svara på ett frågeformulär kring din hälsa och det du vill ha hjälp med
Vänligen notera att du behöver gå igenom hela formuläret för att vi ska kunna hjälpa dig
Patient Patiensson - 12 apr 21:44
Nedstämdhet och depression
Besvarade frågor
Doctrin Online - 12 apr 21:44
Tack!
En av våra läkare kommer nu att se över dina svar och återkomma till dig här i chatten inom en timme (våra öppetider är mån-tor 8-22, fre 8-17, sön 17-22, i anslutning till helgdagar, se vår hemsida www.doctrin.se)
Skriv ett meddelande
Ladda upp
Visa mallar
Skicka nytt formulär
Röker
Högt alkoholintag
Högt BMI
Högt bltr
Gravid
Nyl. utomlands
Haft självmordstankar
19790303-3087
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
Sätt ny ägare
Ta bort
AVSLUTA
PAUSA
Aktuella allergier
DIAGNOS
Penicillin, orsakar Anafylaxi
jun 2018
NSAID, orsakar smärta, feber och något mer
dec 2017
Pollen, orsakar vattnig snuva
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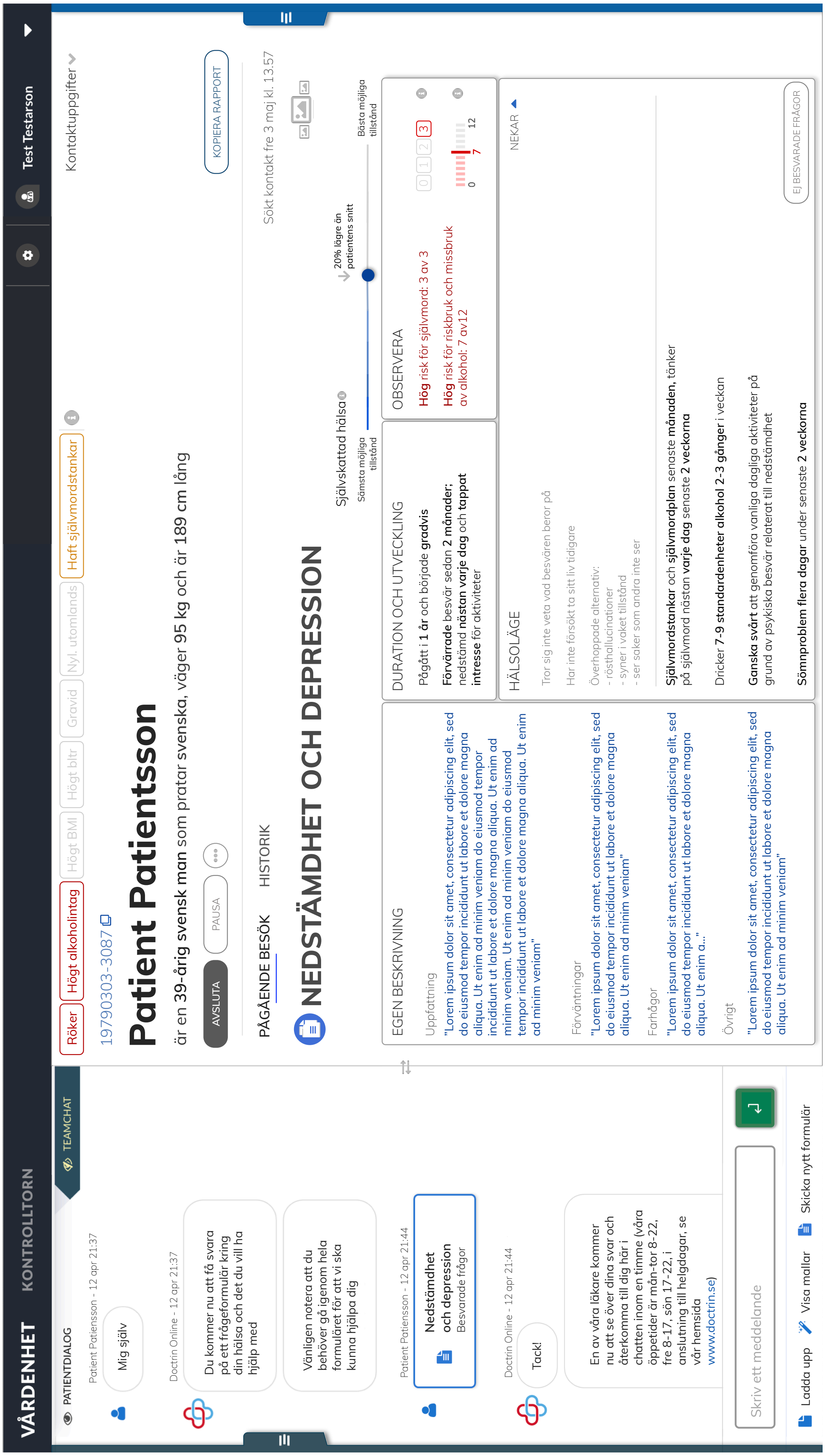
Aktuella sjukdomar
Tillfällig | KRONISK
Astma, tar kortison via inhalering
DIABETES, tar insulininjektion via spruta
Något mer, behandling och device
VISA 3 TILL
PÅGÅENDE BESÖK
HISTORIK
NEDSTÄMDHET OCH DEPRESSION
Självskattad hälsa
Sämsta möjliga tillstånd
EGEN BESKRIVNING
Uppfattning
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
Förväntningar
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader; nedstämd nästan varje dag och tappat intresse för aktiviteter
OBSERVERA
Hög risk för självmo
Hög risk för riskbruk av alkohol: 7 av12
HÄLSOLÄGE
Självmordstankar och självmordplan senaste månaden, tänker på själv dag senaste 2 veckorna
Dricker 7-9 standardenheter alkohol 2-3 gånger i veckan
Pågående besök
VÅRDTEAM
Test Testarsson
Koordinator
Ziggy Uxson
Läkare
ÖVRIG PERSONAL
Hitta kollegor att bjuda in till besöket eller efterfråga patientansvar
Endast online
Anna
Läkare
Anna A-efternamn
Läkare
Anna B-efternamn
Läkare
Anna C-efternamn
Läkare
Bjud in
Efterfråga ansvar
Anna Ö-efternamn
Läkare

REFERENCES


VÅRDENHET
KONTROLLTORN
Test Testarson
PATIENTDIALOG
TEAMCHAT
Patient Patiensson - 12 apr 21:37
Mig själv
Doctrin Online - 12 apr 21:37
Du kommer nu att få svara på ett frågeformulär kring din hälsa och det du vill ha hjälp med
Vänligen notera att du behöver gå igenom hela formuläret för att vi ska kunna hjälpa dig
Patient Patiensson - 12 apr 21:44
Nedstämdhet och depression
Besvarade frågor
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Skriv ett meddelande
Ladda upp
Visa mallar
Skicka nytt formulär
Röker
Högt alkoholintag
Högt BMI
Högt bltr
Gravid
Nyl. utomlands
Haft självmordstankar
Kontaktuppgifter
19790303-3087
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
AVSLUTA
PAUSA
KOPIERA RAPPORT
PÅGÅENDE BESÖK
HISTORIK
Sökt kontakt fre 3 maj kl. 13.57
NEDSTÄMDHET OCH DEPRESSION
Självskattad hälsa
20% lägre än patientens snitt
Sämsta möjliga tillstånd
Bästa möjliga tillstånd
EGEN BESKRIVNING
Uppfattning
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
Förväntningar
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Farhågor
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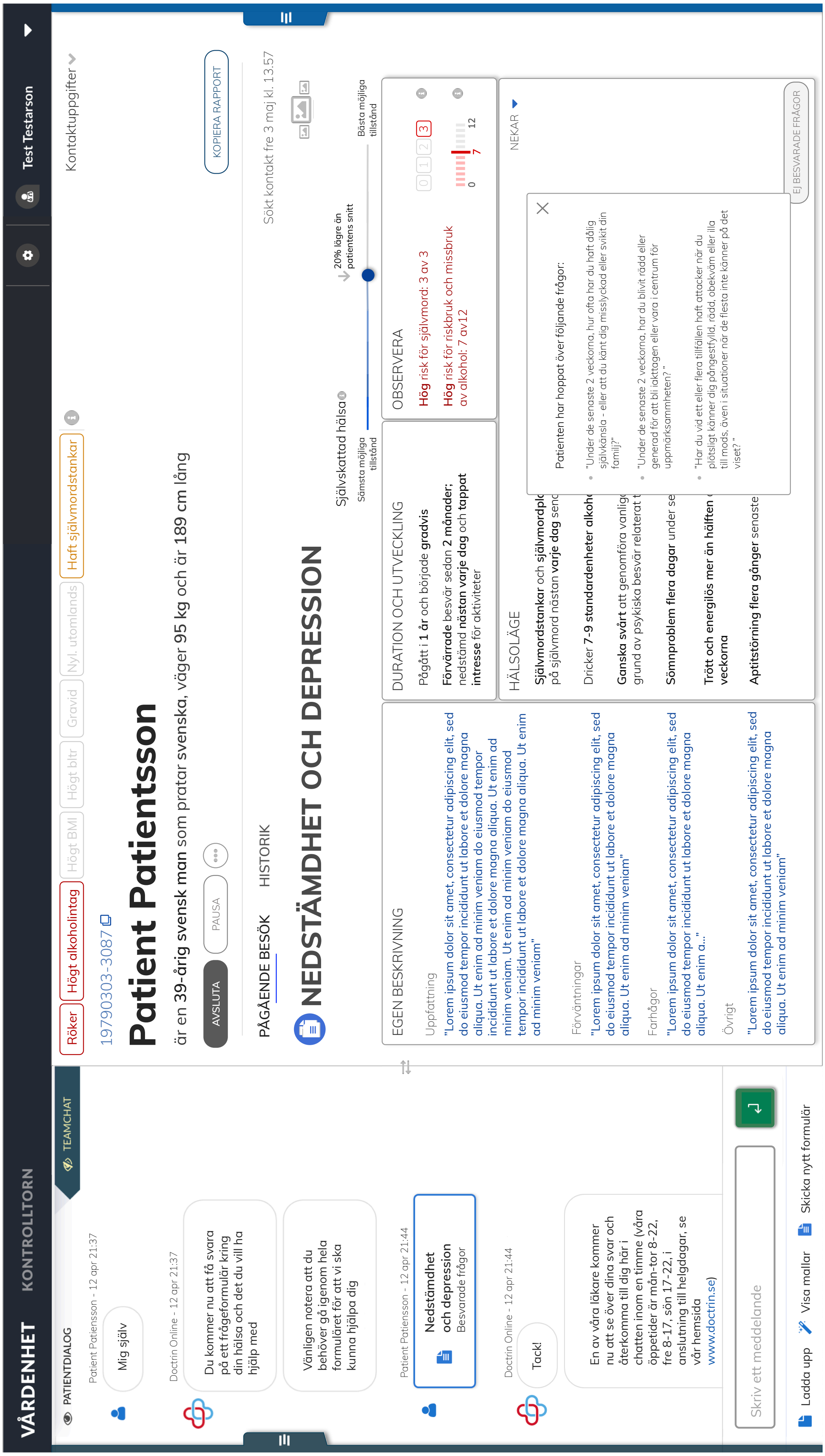
Övrigt
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader; nedstämd nästan varje dag och tappat intresse för aktiviteter
OBSERVERA
Hög risk för självmord: 3 av 3
0 1 2 3
Hög risk för riskbruk och missbruk av alkohol: 7 av12
0 7 12
HÄLSOLÄGE
NEKAR
Tror sig inte veta vad besvären beror på
Har inte försökt ta sitt liv tidigare
Överhoppade alternativ:
- rösthallucinationer
- syner i vaket tillstånd
- ser saker som andra inte ser
Självmordstankar och självmordplan senaste månaden, tänker på självmord nästan varje dag senaste 2 veckorna
Dricker 7-9 standardenheter alkohol 2-3 gånger i veckan
Ganska svårt att genomföra vanliga dagliga aktiviteter på grund av psykiska besvär relaterat till nedstämdhet
Sömnproblem flera dagar under senaste 2 veckorna
EJ BESVARADE FRÅGOR



VÅRDENHET
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Test Testarson
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TEAMCHAT
Patient Patiensson - 12 apr 21:37
Mig själv
Doctrin Online - 12 apr 21:37
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Patient Patiensson - 12 apr 21:44
Nedstämdhet och depression
Besvarade frågor
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PAUSA
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PÅGÅENDE BESÖK
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Farhågor
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim a..."
Övrigt
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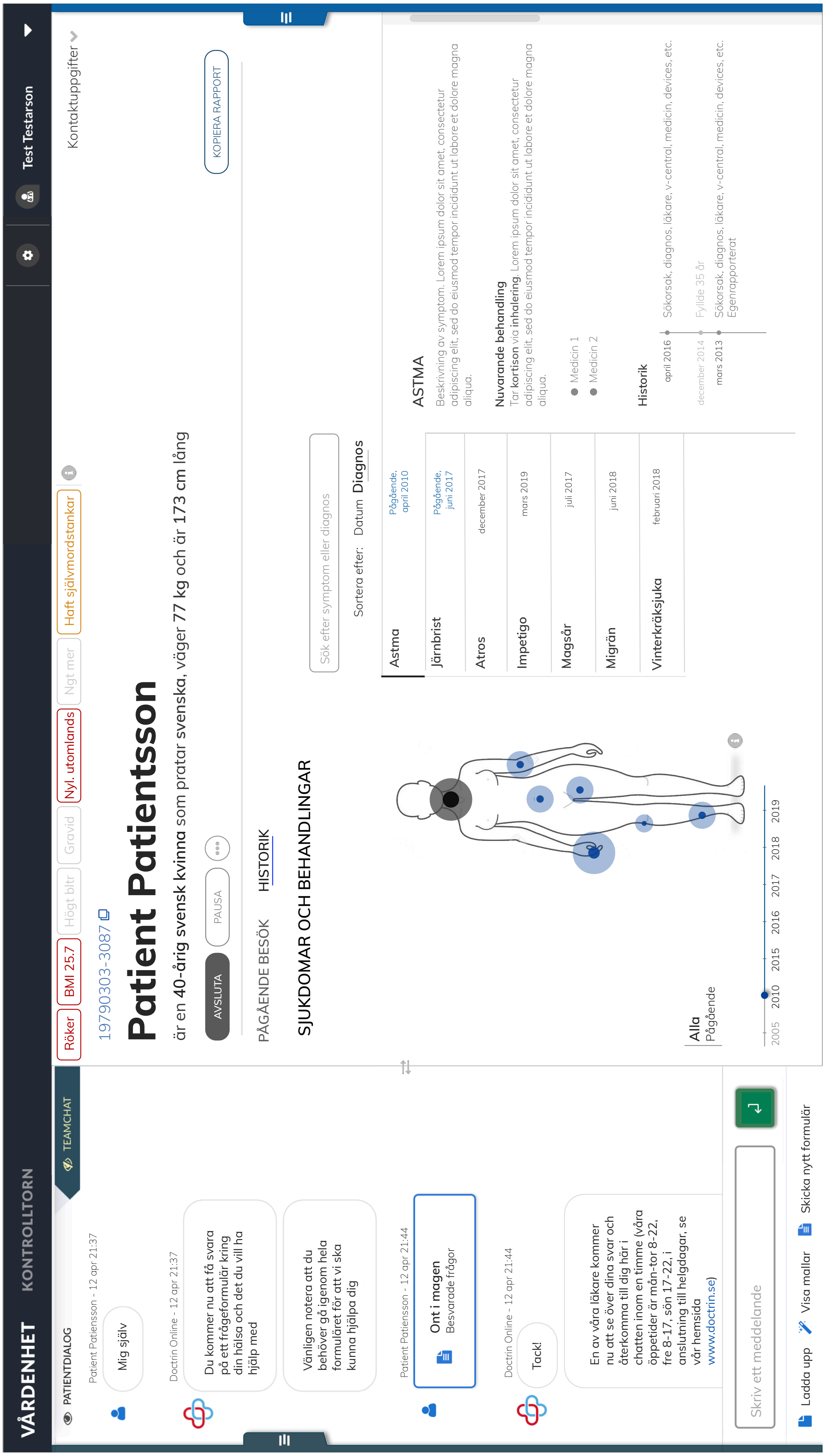
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader; nedstämd nästan varje dag och tappat intresse för aktiviteter
OBSERVERA
Hög risk för självmord: 3 av 3
Hög risk för riskbruk och missbruk av alkohol: 7 av12
HÄLSOLÄGE
NEKAR
Dricker 7-9 standardenheter alkohol
Sömnproblem flera dagar under se
Aptitstörning flera gånger senaste
Patienten har hoppat över följande frågor:
EJ BESVARADE FRÅGOR


VÅRDENHET
KONTROLLTORN
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PATIENTDIALOG
TEAMCHAT
Patient Patiensson - 12 apr 21:37
Mig själv
Doctrin Online - 12 apr 21:37
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Patient Patiensson - 12 apr 21:44
Ont i magen
Besvarade frågor
Doctrin Online - 12 apr 21:44
Tack!
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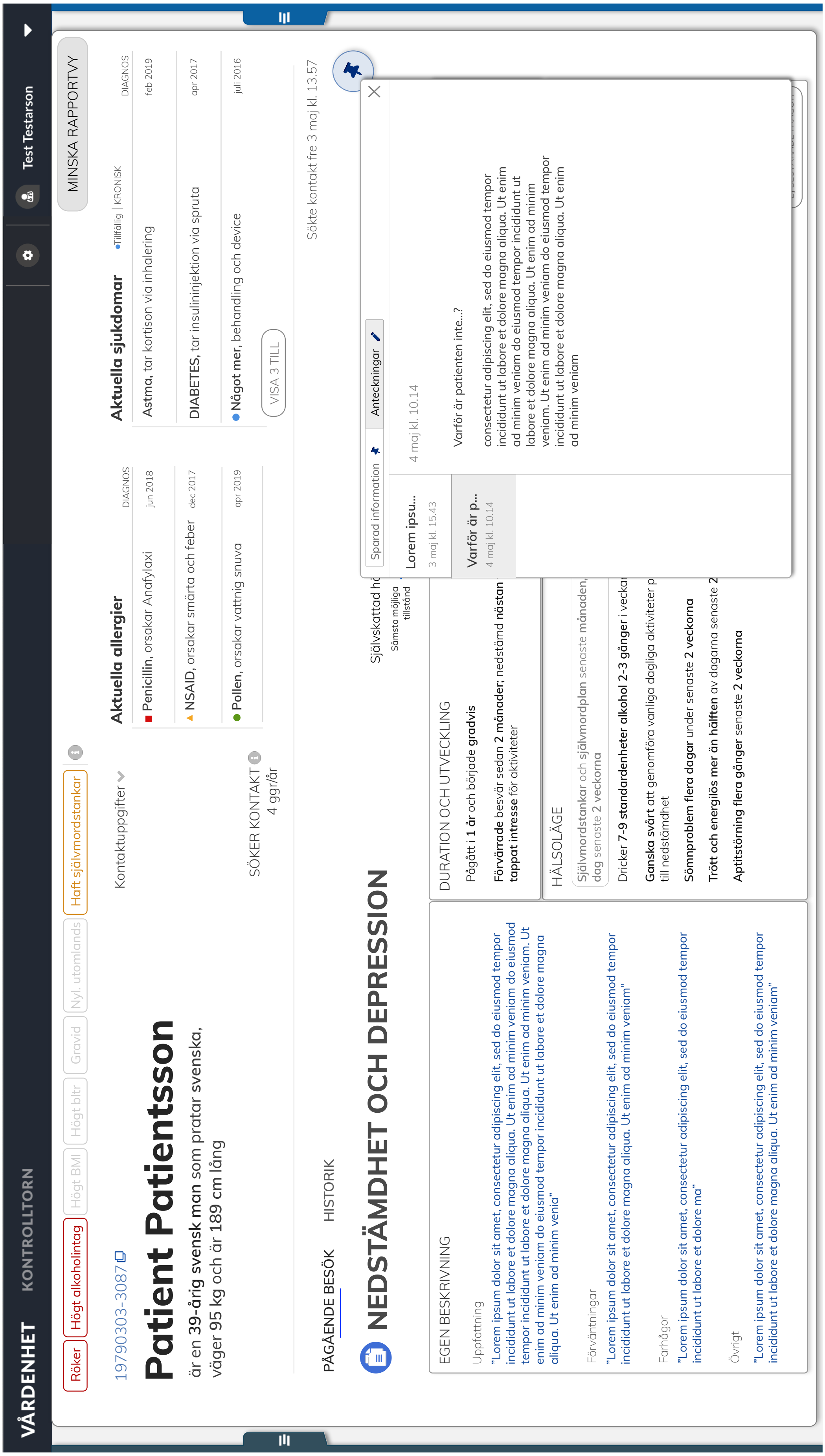
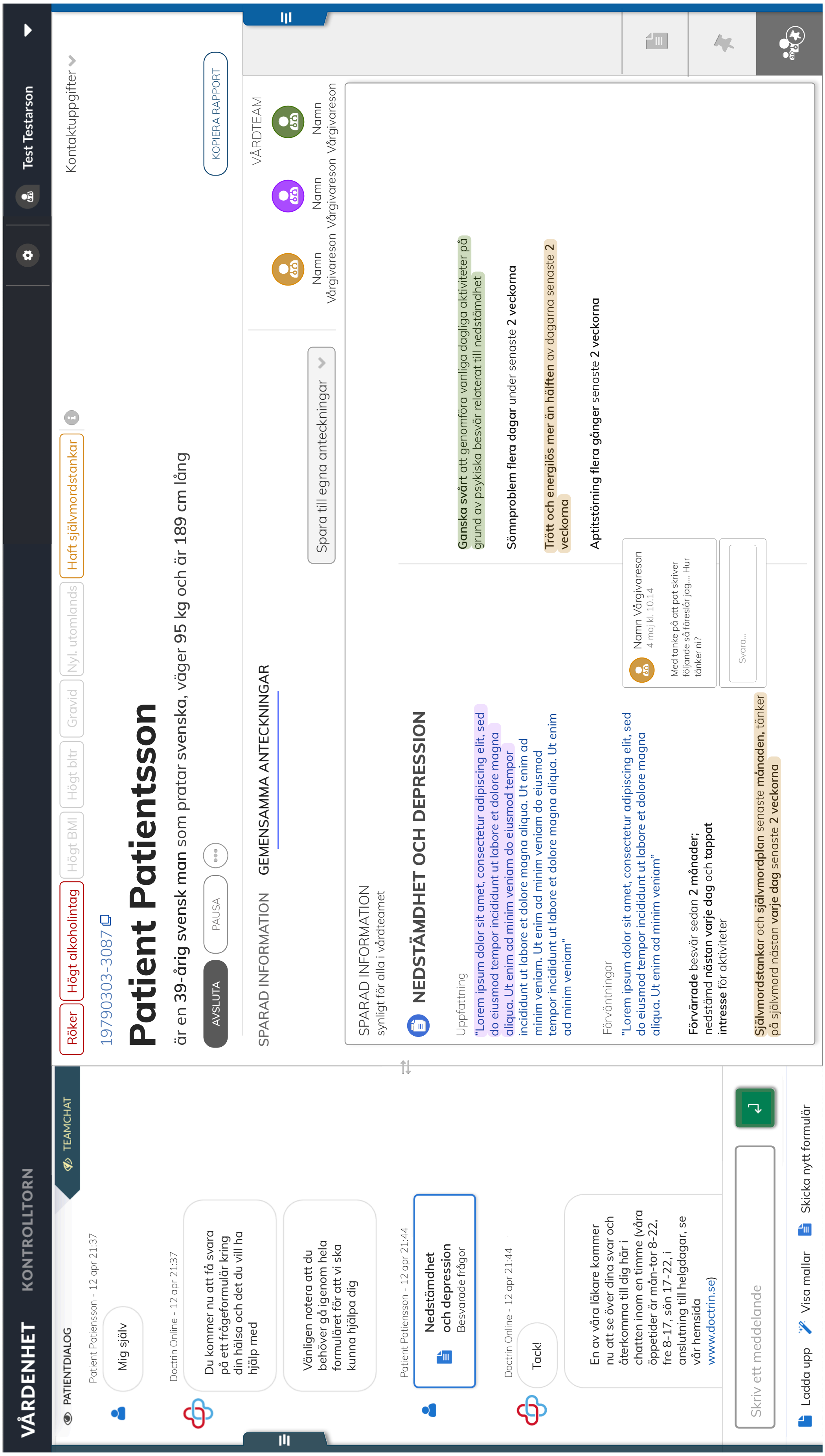
Skriv ett meddelande
Ladda upp
Visa mallar
Skicka nytt formulär
Röker
BMI 25.7
Högt bltr
Gravid
Nyl. utomlands
Ngt mer
Haft självmordstankar
Kontaktuppgifter
19790303-3087
Patient Patientsson
är en 40-årig svensk kvinna som pratar svenska, väger 77 kg och är 173 cm lång
AVSLUTA
PAUSA
KOPIERA RAPPORT
PÅGÅENDE BESÖK
HISTORIK
SJUKDOMAR OCH BEHANDLINGAR
Sök efter symptom eller diagnos
Sortera efter: Datum Diagnos
Astma
Pågående, april 2010
Järnbrist
Pågående, juni 2017
Atros
december 2017
Impetigo
mars 2019
Magsår
juli 2017
Migrän
juni 2018
Vinterkräksjuka
februari 2018
ASTMA
Beskrivning av symptom. Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua.
Nuvarande behandling
Tar kortison via inhalering. Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua.
Medicin 1
Medicin 2
Historik
april 2016
Sökorsak, diagnos, läkare, v-central, medicin, devices, etc.
december 2014
Fyllde 35 år
mars 2013
Sökorsak, diagnos, läkare, v-central, medicin, devices, etc. Egenrapporterat
Alla
Pågående
2005
2010
2015
2016
2017
2018
2019


VÅRDENHET
KONTROLLTORN
Test Testarson
MINSKA RAPPORTVY
Röker
Högt alkoholintag
Högt BMI
Högt bltr
Gravid
Nyl. utomlands
Haft självmordstankar
19790303-3087
Kontaktuppgifter
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
SÖKER KONTAKT
4 ggr/år
Aktuella allergier
DIAGNOS
Penicillin, orsakar Anafylaxi
jun 2018
NSAID, orsakar smärta och feber
dec 2017
Pollen, orsakar vattnig snuva
apr 2019
Aktuella sjukdomar
Tillfällig
KRONISK
DIAGNOS
Astma, tar kortison via inhalering
feb 2019
DIABETES, tar insulininjektion via spruta
apr 2017
Något mer, behandling och device
juli 2016
VISA 3 TILL
Sökte kontakt fre 3 maj kl. 13.57
PÅGÅENDE BESÖK
HISTORIK
NEDSTÄMDHET OCH DEPRESSION
EGEN BESKRIVNING
Uppfattning
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim venia"
Förväntningar
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
Farhågor
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore ma"
Övrigt
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
DURATION OCH UTVECKLING
Pågått i 1 år och började gradvis
Förvärrade besvär sedan 2 månader, nedstämd nästan tappat intresse för aktiviteter
HÄLSOLÄGE
Självmordstankar och självmordplan senaste månaden, dag senaste 2 veckorna
Dricker 7-9 standardenheter alkohol 2-3 gånger i veckan
Ganska svårt att genomföra vanliga dagliga aktiviteter p till nedstämdhet
Sömnproblem flera dagar under senaste 2 veckorna
Trött och energilös mer än hälften av dagarna senaste 2
Aptitstörning flera gånger senaste 2 veckorna
Självskattad hä
Sämsta möjliga tillstånd
Sparad information
Anteckningar
Lorem ipsu...
3 maj kl. 15.43
Varför är p...
4 maj kl. 10.14
4 maj kl. 10.14
Varför är patienten inte...?
consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam


VÅRDENHET
KONTROLLTORN
Test Testarson
PATIENTDIALOG
TEAMCHAT
Patient Patiensson - 12 apr 21:37
Mig själv
Doctrin Online - 12 apr 21:37
Du kommer nu att få svara på ett frågeformulär kring din hälsa och det du vill ha hjälp med
Vänligen notera att du behöver gå igenom hela formuläret för att vi ska kunna hjälpa dig
Patient Patiensson - 12 apr 21:44
Nedstämdhet och depression
Besvarade frågor
Doctrin Online - 12 apr 21:44
Tack!
En av våra läkare kommer nu att se över dina svar och återkomma till dig här i chatten inom en timme (våra öppetider är mån-tor 8-22, fre 8-17, sön 17-22, i anslutning till helgdagar, se vår hemsida www.doctrin.se)
Skriv ett meddelande
Ladda upp
Visa mallar
Skicka nytt formulär
Kontaktuppgifter
Röker
Högt alkoholintag
Högt BMI
Högt bltr
Gravid
Nyl. utomlands
Haft självmordstankar
19790303-3087
Patient Patientsson
är en 39-årig svensk man som pratar svenska, väger 95 kg och är 189 cm lång
AVSLUTA
PAUSA
KOPIERA RAPPORT
SPARAD INFORMATION
GEMENSAMMA ANTECKNINGAR
Spara till egna anteckningar
VÅRDTEAM
Namn Vårgivareson
Namn Vårgivareson
Namn Vårgivareson
SPARAD INFORMATION
synligt för alla i vårdteamet
NEDSTÄMDHET OCH DEPRESSION
Uppfattning
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam. Ut enim ad minim veniam do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
Förväntningar
"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam"
Förvärrade besvär sedan 2 månader; nedstämd nästan varje dag och tappat intresse för aktiviteter
Självmordstankar och självmordplan senaste månaden, tänker på självmord nästan varje dag senaste 2 veckorna
Ganska svårt att genomföra vanliga dagliga aktiviteter på grund av psykiska besvär relaterat till nedstämdhet
Sömnproblem flera dagar under senaste 2 veckorna
Trött och energilös mer än hälften av dagarna senaste 2 veckorna
Aptitstörning flera gånger senaste 2 veckorna
Namn Vårgivareson
4 maj kl. 10.14
Med tanke på att pat skriver följande så föreslår jag... Hur tänker ni?
Svara...