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Personas for Perfectly Tailored eHealth Technologies: Segmenting Heart Failure Patients using the Persona Approach Twente

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Abstract

Background: The full potential of eHealth technologies to support self- and disease-management for patients with chronic diseases, is not being reached. A possible explanation for these lacking results is that during the development process, insufficient attention is paid to the needs, wishes and context of the prospective end-users. To overcome such issues, the User-Centered Design (UCD) practice of creating personas is widely accepted as a means to ensure the fit between a technology and the target group or end-users throughout all phases of development.

Objective: In the current study, we integrate several approaches to persona-development into the Persona Approach Twente (PAT), to attain a structured approach that aligns with the iterative process of eHealth development.

Methods: In three steps, different parts from the dataset were analyzed using the Partitioning Around Medoids clustering method. First, we used health-related EPR data only. Secondly, we added person-related data that was gathered through interviews and questionnaires. Thirdly, we added log data.

Results: In the first step, two clusters were found, with average silhouette widths of 0.12, and 0.27. In the second step, again two clusters were found, with average silhouette widths of 0.08, and 0.12. In the third step, three clusters were identified, with average silhouette widths of 0.09, 0.12, and 0.04.

Conclusions: The Persona Approach Twente is applicable for mixed types of data, and allows alignment of this UCD method to the iterative approach of eHealth development. Challenges lie in data quality and fitness for (quantitative) clustering.

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Original Paper

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Keywords: personas; clustering; heart-failure; eHealth; user-centered design

Introduction

Although eHealth technologies are seen as an opportunity to support self- and disease- management for patients with chronic diseases, their actual use remains low [1]. As a result, the full potential of eHealth technologies is not being reached. A possible explanation for these lacking applications is that during the development process, insufficient attention is paid to the needs, wishes and context of the prospective end-users. To overcome such issues, User-Centered Design (UCD) principles [2] provide tools to keep the intended user in the heart of the eHealth development process. The UCD practice of creating personas is widely accepted as a means to ensure the fit between a technology and the target group or end-users throughout all phases of development [3]. Personas represent fictive members of the target group and consist of a description of these potential users. By engaging with the personas, developers and project team members develop an eye for the characteristics of their target group [4]. One could say, personas are a way to continuously communicate "who we are doing this for" to the team. In addition, the eHealth development team can, for example, anticipate on these personas to tailor educational messages [5], or to support adherence among several types of eHealth users [6]. The approaches that are described for creating personas are using one source of data, ignoring variety and variability in data needed to create groups of end users that have similar characteristics.

Several frameworks advocate to use multiple methods for data collecting during the eHealth development process [7], e.g. through interviews, questionnaires and focus groups. Thus, mixed types of data from several sources are used during eHealth development, while persona-creation often relies on limited data sources. First, health-related attributes form an important part of the personas in eHealth projects [e.g. 8]: the risk of health complications; health related activities that the prospective end-users have to undertake; the variation of symptoms in the target group; tailoring options for medical treatment. These topics reflect factors that can be used to paint the "end-user picture". Thus, health-related factors are major contributors to the construction of eHealth personas. However, as research and experience in eHealth development progresses and matures, it has become obvious that an eHealth user should be characterized by more than just health status and zooming in on health-related factors only tells part of the users' story. Rather, a person, who may be ill, has a chronic disease, aims to recover after surgery or disease, or simply looks to preserve his/her health, still has many more personal characteristics, likes, dislikes, or habits that are also relevant for understanding this person [9].

Therefore, secondly, personas are created focusing on how a person wants, likes, or prefers to live life. LeRouge and colleagues developed a conceptual model for identifying a broad range of user profile and persona attributes from qualitative data [10]. A related approach which considers characteristics beyond health factors is described by Vosbergen et al. [5]. They have demonstrated how a variation in information needs can lead to personas (and consequently, technology design) that represent different ways in which people value and consume information. Similarly, there are many preferences, habits, and other variables beyond health/disease status and demographics that may be worthwhile to include in eHealth personas [11, 12]. In these approaches, the personas result from a selection of relevant factors depending on more subjective experiences and tacit knowledge from experts. This can easily result in somewhat arbitrary decisions made on what to include in the persona. An approach that addresses this issue is proposed by Holden et al, using a quantitative cluster analysis on biopsychosocial survey data. In their approach, Holden et al. use qualitative data such as subjective eHealth literacy to describe the target group and distill personas that represent this group [13].

In addition to the use of health-related data and person-related data, we have also noticed approaches in which server log data are used for identifying and describing user groups. Server log data are an automatic registration of, among others, the time, date, and activity that is carried out by the eHealth user within the system. An example is the identification of user groups on the basis of activities within the eHealth system, resulting in personas characterized by the activities that are most prominent within the clusters [14]. A more comprehensive approach is described in the study by Jones et al. [15], in which activities within the system are expanded with information about the frequency, intensity, consistency and demographics of the users. Using such data results in personas that include demographics of the users, as well as users' engagement with an eHealth system. When this method is applied for identifying groups of eHealth users with chronic conditions, this approach itself can be expanded even further with log data related to monitored health values.

Overall, we see that there are several frameworks describing the steps very structured or less structured through which eHealth technologies can be developed. These frameworks are similar in that we see several data collection methods during the phases, that are iteratively walked through to come to a technology that fits with the end users. Yet, the approaches for developing personas, as described above, only focus on one method for collecting data (e.g. interviews, questionnaire data, log data), ignoring the variety of data collected during UCD development processes. Therefore, we have studied how to develop a structured iterative approach for personas within the eHealth development process. Data from a previous study were used in which the phases of the CeHRes roadmap were completed, resulting in data that was collected through various methods (e.g. interviews, questionnaires, log data).

Methods

In the current study, we have used a three-step iterative approach to personas. As a first step, health-related data were used to develop the personas, using data from an electronic patient record (EPR). In the second step, these EPR data were enriched with person-related data that was gathered through interviews and questionnaires. In the third step, log data were added to the model, to illustrate how personas can be further developed after log data is collected through a pilot study, or after the eHealth technology is launched and actually used by the end user. From now on, we refer to this iterative approach to eHealth development as the Persona Approach Twente (PAT).

During this illustration of PAT, the focus is also on (1) how the approaches as described by Holden [13] and LeRouge [10] can be combined enabling the use of several data collection methods (quantitative and qualitative) for describing user groups, and on (2) the use of semi- automated methods for grouping the end-users so that the arbitrarily approach applied in previous studies for developing person-related personas is replaced by a more systematic approach. Thereby, we have aimed to contribute to achieving the full potential of eHealth technologies for chronic diseases.

Data Collection

Data collected in a previous study for the development of a telemonitoring application for people with heart failure (HF) were used, guided by the steps described in the CeHRes roadmap [7]. These data were gathered among 25 patients with mild to moderate chronic HF from the out-patient clinic of the Hospital Group Twente (ZGT), Almelo and Hengelo, The Netherlands, of whom 13 were females (56%). Their mean age was 68 years (sd = 9), ranged 46 to 82. Patients with a New York Heart Association (NYHA) functional classification 2 or 3 [17], with stable symptoms and stable medication were included in this study. All participants gave permission for the use of these data, and signed an informed consent form. Persons admitted to the hospital within one month after data collection were excluded.
Firstly, data from electronic patient records of the participants were used to collect health- related data, such as NYHA classification and CVA or TIA comorbidity. Secondly, quantitative data were collected through the 8-item EHEALs questionnaire [18] to gain insight into the eHealth literacy status of the participants. Thirdly, the EQ5D5L questionnaire was used to gain insight into participants’ quality of life, consisting of mobility, self-care, usual activities, pain/discomfort and anxiety/depression [19]. Moreover, qualitative data regarding experiences in living with heart failure, technology use and trust, and motivation were collected through interviews with the participants.

Based on these data, the iMediSense™ telemonitoring system (2016, Thales, Hengelo, The Netherlands) was developed in another study [16]. A pilot study was conducted that was clinically supervised by cardiologists and nurse practitioners (NPs). In this pilot, patients were instructed to conduct measurements at least once daily for 60 days: diastolic blood pressure, systolic blood pressure, heart rate and body weight. Also, they filled out a HF-symptoms- questionnaire. When measurements exceeded predefined ranges, alarms were generated. NPs were instructed to view the generated alarms and react accordingly. The log data regarding the appointed symptoms, the alarms during the pilot-study, and usage log data were used for the secondary analysis in the current study.

In Table 1, the aforementioned data collection methods are coupled with the variables that were collected through these methods. The variables also display the number of participants for whom a variable is known. Due to the secondary analysis of this data set, not all variables were present or assessed among all participants.

Table 1. Data collection methods used in this study coupled with the variables that were collected through these methods

Data collection method	Variables (n)
Interviews	Education type (7), Smartphone ownership (23), PC ownership (22), Tablet ownership (23), Use of technology for entertainment (13), Use of technology for social purposes (14), Use of technology for gaining information (14), Children (13), Grandchildren (5), Divorcement (13), Marital status (16), Employment (22), Positive coping (25), Negative coping (25), Health-related goals (25), Years ago diagnosed with heart failure (24)
Log data	Appointed symptoms during pilot-study (25), Alarms during pilot-study (24), Usage of telemonitoring technology (25)
Electronic patients record	Gender (25), Age (25), CVA or TIA comorbidity (25), COPD comorbidity (25), Diabetes comorbidity (25), LVEF (25), HFrEF (LVEF<40%) (25), Ischemic Heart Disease (25), Hypertension (25), Atrial fibrillation (25), NYHA 2 or NYHA 3 (25), Heart Failure Hospitalization (25), Cardiac Resynchronization Therapy Defibrillator (25), estimated Glomerular Filtration Rate (25), Implantable Cardioverter Defibrillator (25)
EHEALs questionnaire	Capacity for engaging in eHealth (22)
EQ5D5L	Quality of life before using the telemonitoring technology (25), Quality of life after using the telemonitoring technology (25)

Before analyzing the data, the qualitative data collected through the semi-structured interviews, were coded by two independent coders (FS, JW). The scheme of LeRouge for coding and identifying user profile and persona attributes of significance was used as a basis [10], and complemented with additional themes that emerged from the data. After qualitative analysis, all resulting themes and variations were categorized into binary variables to enable cluster analysis.

This means that if a theme consisted of a number of variations, multiple binary variables were created: one for every variation. For example, marital status was divided in two variables, namely marriage (married or not married), and divorcement (divorced or not divorced). Moreover, when a code was assigned to less than 5 quotes, then these were deleted from further analysis to reduce the influence of missing values on the cluster results. Secondly, Shapiro-Wilk tests were performed to check whether variables were normally distributed. We found that the variables age, capacity for engaging in eHealth, and eGFR were normally distributed ($p > 0.05$). The remaining variables were not normally distributed ($p < 0.05$; see appendix B), and therefore log transformed before carrying out the cluster analyses.

Data Analysis

Since data were both numerical and binary, distance matrices were created using Gower distances. Gower distances can handle these types of mixed data, using range-normalized Manhattan distances for quantitative data, and Dice coefficient for nominal variables [20]. Subsequently, three Partitioning Around Medoids (PAM) cluster analyses were carried out to develop personas related to one of the three steps in the Persona Approach Twente. A cluster analysis is a form of exploratory data analysis, where observations are divided into meaningful groups that share common characteristics. The PAM was chosen since it fits with Gower distances, and the medoids can be used as ‘representatives’ for the translation of clusters to personas. Medoids refer to observations that fall within in a cluster for which the average dissimilarity between it and all the other members of the cluster is minimal. By using these representatives, we limit the influence of extreme values among the participants. The analyses were conducted on three distinct parts of the same dataset: on the (1) health related data, (2) the qualitative and quantitative health- and person related data, and (3) the qualitative and quantitative health- and person related data, enriched with log data collected during the pilot study. All analyses were carried out using RStudio [21], the R Cluster package [22], and results were visualized using the Ggplot2 package [23]. To estimate the optimal number of clusters, the average silhouette method was used. After conducting the cluster analyses, the medoids of the resulting clusters were used to describe personas. Table 2 summarizes the cluster analyses that were carried out, coupled with the included variables.

Table 2. Cluster analyses carried out in this study coupled with variables used

Step	Variables
Step 1: Health-related data	CVA or TIA comorbidity (25), COPD comorbidity (25), Diabetes comorbidity (25), LVEF (25), HFrEF (LVEF<40%) (25), Ischemic Heart Disease (25), Hypertension (25), Atrial fibrillation (25), NYHA 2 or NYHA 3 (25), Heart Failure Hospitalization (25), Cardiac Resynchronization Therapy Defibrillator (25), estimated Glomerular Filtration Rate (25), Implantable Cardioverter Defibrillator (25)
	Appointed symptoms during pilot-study (25), Alarms during pilot-study (24), Usage of telemonitoring technology (25)
Step 2: Health-related data enriched with person-related data	Aforementioned health-related data, enriched with Education type (7), Smartphone ownership (23), PC ownership (22), Tablet ownership (23), Use of technology for entertainment (13), Use of technology for social purposes (14), Use of technology for gaining information (14), Children (13), Grandchildren (5), Divorcement (13), Marital status (16), Employment (22), Positive coping (25), Negative coping (25), Health-related goals (25), Gender (25), Age (25), Capacity for engaging in eHealth (22), Quality of life before using the telemonitoring technology (25), Years ago diagnosed with heart failure (24)

Step 3: Disease-related data, person-related data, and log data of eHealth usage	Aforementioned disease- and person-related data, enriched with usage of distinct parts of telemonitoring technology: Start new measurement (25), Send symptoms-measurement (25), Send physical measurements (25), Open History of measurements (25), Contact Care provider (25), Open Profile-page (25), Open User Manual (25), Appointed symptoms during pilot-study (25), Alarms during pilot-study (24), Quality of life after using the telemonitoring technology (25)

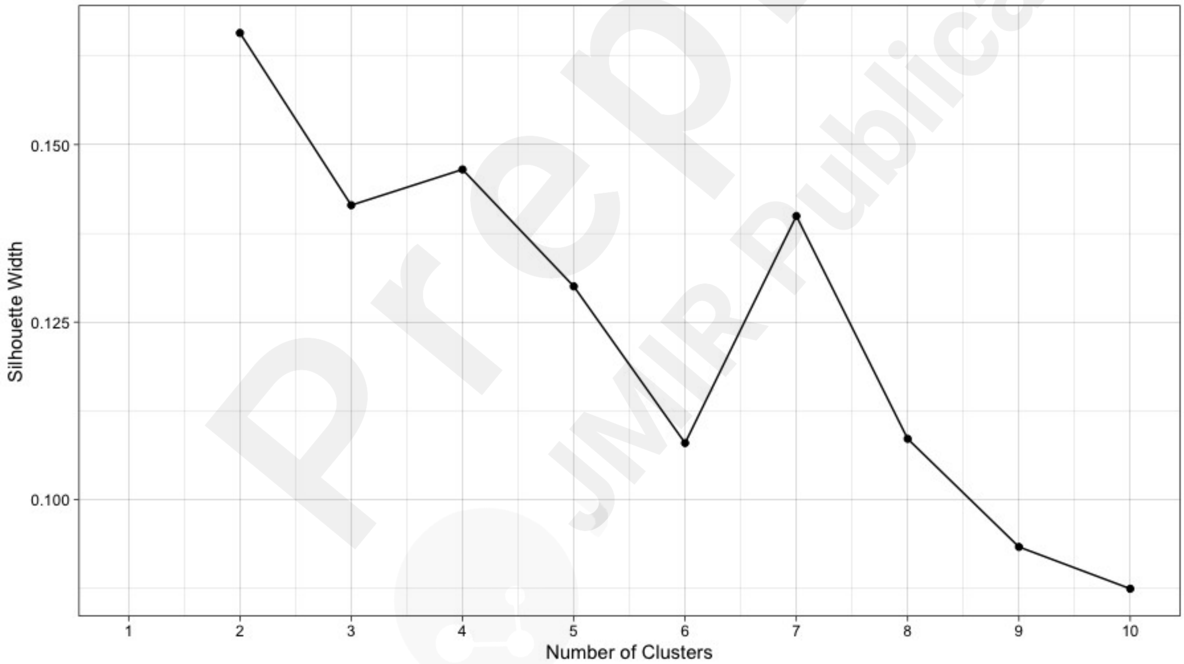
Results

Three cluster analyses were carried out that align with data collected through the (1) EPR (2) these data enriched with interview and questionnaire data, and (3) the aforementioned data enriched with log data.

Clustering Health-Related Data

In figure 1 below, average silhouette widths for the number of clusters ranging from 2 to 10 can be found. Based on this figure, it was decided that the optimal number of clusters was 2, yielding an average silhouette width of 0.17.

Figure 1. Average silhouette plot for the cluster analysis on the health-related data[a].



[a] The x-axis shows the number of clusters ranging from 2 to 10, and the y-axis shows the corresponding average silhouette width, where a value of -1 indicates that the sample is close to its neighboring cluster, and a value of 1 indicates that the sample is far away from its neighboring cluster.

In total 25 persons were divided into two clusters. The first cluster has an average silhouette width of 0.12, and consists of 17 persons, which is 68% of the total number of persons. The second cluster has an average silhouette width of 0.27, and consists of 8 persons, which is 32% of the total number of persons. A description of these clusters can be found in Appendix F. The medoids of these clusters were used to translate these clusters in personas. For cluster 1 the medoid is participant 306, and for cluster 2 participant 295. The variable values for these participants were used for the persona-description, which can be found below:

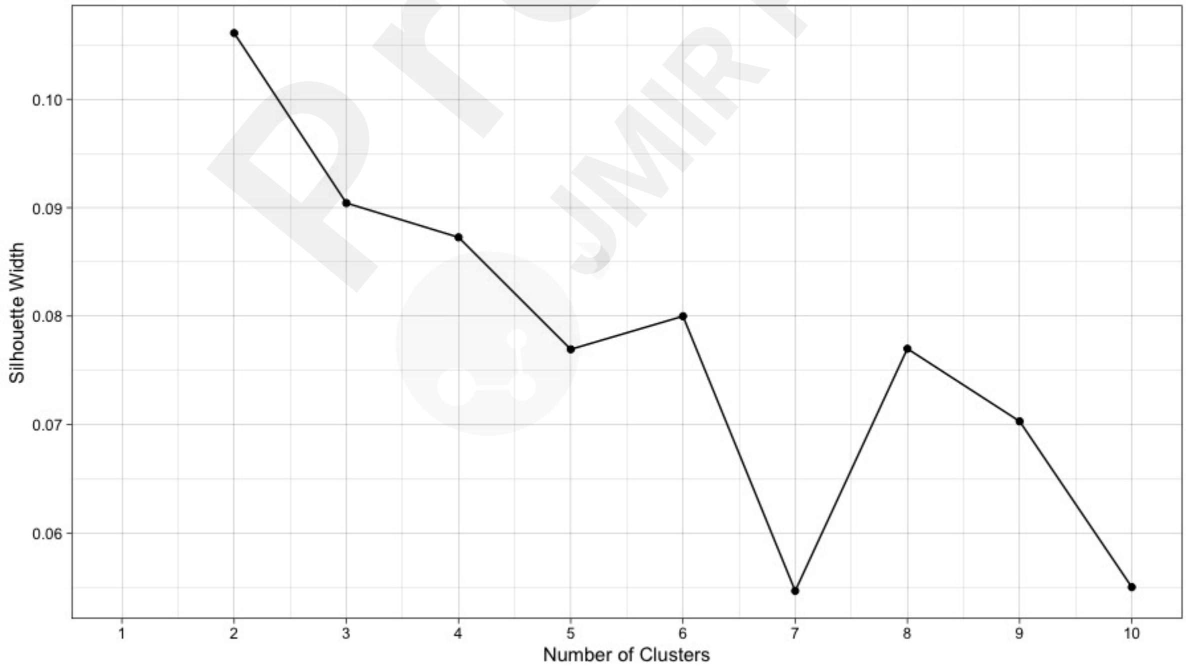
Table 3. Persona-descriptions on the basis of the medoids within the 2 clusters of health-related data

Cluster 1 (n = 17) Senior male	Cluster 2 (n = 8) Middle aged female
Demographic Peter is a 75 years old male.	Demographic Barbara is a 63 years old female.
Health related Peter has a reduced left ventricular ejection fraction of 37 (HrEF). Moreover, he has an ischemic etiology of his heart failure, and an estimated Glomerular Filtration Rate of 60. Furthermore, he doesn't have other comorbidities such as diabetes or COPD.	Health related Barbara has a reduced left ventricular ejection fraction of 35 (HrEF). She has no ischemic heart disease, but hypertension and atrial fibrillation, and an estimated Glomerular Filtration Rate was reduced (43). Barbara has had a prior hospitalization for heart failure. Furthermore, she doesn't have other comorbidities such as diabetes or COPD.

Clustering health-related data enriched with person-related data

In the second step, we clustered the dataset with health-related data, interview data, and the EHEALs questionnaire [18]. After the cluster analysis, an average silhouette plot was created yielding 2 clusters, and this can be found in figure 2 below. The corresponding average silhouette width for 2 clusters is 0.11.

Figure 2. Average silhouette plot for the cluster analysis on the health- and person-related data[a].



[a] The x-axis shows the number of clusters ranging from 2 to 10, and the y-axis shows the corresponding average silhouette width, where a value of -1 indicates that the sample is close to its neighboring cluster, and a value of 1 indicates that the sample is far away from its neighboring

cluster.

The first cluster consists of 10 persons (40%) with an average silhouette width of 0.08. The second cluster consists of 15 persons (60%) with an average silhouette width of 0.12. A description of the variable values within this cluster can be found in Appendix G. Persona- descriptions were made based on the medoids within the two clusters. The medoid for cluster 1 is participant 305, and for cluster 2 participant 306.

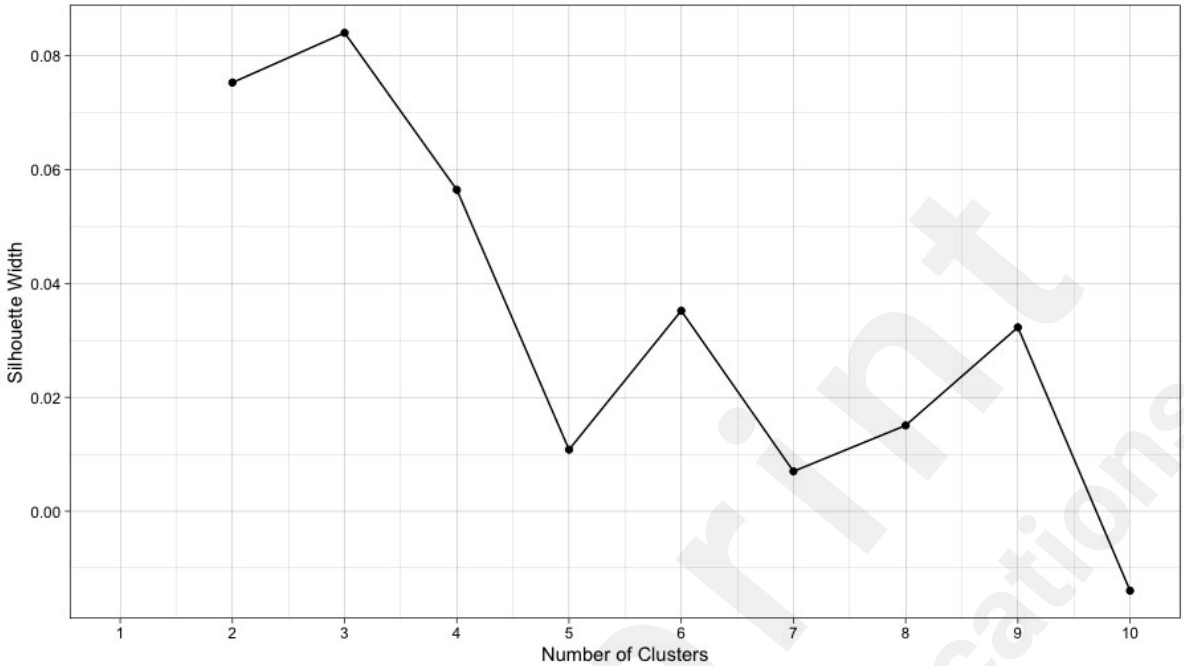
Table 4. Persona-descriptions on the basis of the medoids within the two clusters of health- and person-related data

Cluster 1 (n = 10) Middle aged female	Cluster 2 (n = 15) Senior male
Demographic Eva is a 66 years old married female. She has 1 child, and is currently unemployed.	Demographic Christoph is a 75 years old married male who had vocational education. He has two children and is currently unemployed.
Health related Eva was two years ago diagnosed with heart failure with reduced ejection fraction of 33 (HFrEF). Her eGFR is 66, and she has Atrial Fibrillation. Eva has no CRT-D or ICD to support her heart function. Besides, she has a New York Heart Association (NYHA) classification 2. Before the current hospital visit, she was not hospitalized for heart failure before.	Health related Christoph was two years ago diagnosed with heart failure with reduced ejection fraction (HFrEF). Besides, he has a left ventricular ejection fraction of 37, and an eGFR of 60. Christoph has ischemic heart disease, and a New York Heart Association (NYHA) classification 2. Before his current hospital visit, he was not hospitalized for heart failure before, and Christoph has CRT-D or ICD to support his heart function.
Person related Eva has a score of 10 on the EQ5D5L questionnaire on a scale from 5 to 25, indicating a good quality of life with slight problems or health issues. Eva mentioned one way of positive coping, and two ways of negative coping.	Person related Christoph has a score of 5 on the EQ5D5L questionnaire, indicating a good quality of life. He mentioned two ways of negative coping with problems.
Technology preferences Eva owns a smartphone, computer and a tablet. She uses this technology for social purposes (e.g. social media) and for gaining information. Moreover, she has a mean score of 4 on the eHEALs questionnaire, indicating a moderately high capacity for engaging in eHealth. Correspondingly, Eva indicated that she has experience with eHealth technologies.	Technology preferences Christoph owns a computer, but no smartphone or tablet. Moreover, he has a score 3 on the eHeals questionnaire, indicating a moderate capacity for engaging in eHealth. Moreover, Christoph indicated that he has no skills in working with eHealth technologies.

Clustering health- and person-related data combined with log data

In the third step, we enriched the health- and person-related data with usage log data that is typically collected after the Design-phase. After the cluster analysis, an average silhouette plot was created yielding 3 clusters, and this can be found in figure 3 below. The corresponding average silhouette width for 3 clusters is 0.08.

Figure 3. Average silhouette plot for the cluster analysis on the health- and person-related data enriched with usage log data[a].



[a] The x-axis shows the number of clusters ranging from 2 to 10, and the y-axis shows the corresponding average silhouette width, where a value of -1 indicates that the sample is close to its neighboring cluster, and a value of 1 indicates that the sample is far away from its neighboring cluster.

The first cluster consists of 15 persons (60%) with an average silhouette width of 0.09. The second cluster consists of 5 persons (20%) with an average silhouette width of 0.12. The third cluster consists of 5 persons (20%) with an average silhouette width of 0.04. Descriptions of these clusters can be found in Appendix H. Persona-descriptions were made based on the medoids within the three clusters. The medoid for cluster 1 is participant 306, for cluster 2 participant 292, and for cluster 3 participant 317.

Table 5. Persona-descriptions on the basis of the medoids within the 3 clusters of health- and person-related data, enriched with usage log data

Cluster 1 (n = 15) Senior male	Cluster 2 (n = 5) Middle aged female	Cluster 3 (n = 5) Senior female
Demographic Pete is a 75 years old married male, and has two children. He had vocational education, and is now unemployed, retired.	Demographic Sarah is a 56 years old female, who works full time, part time or voluntarily. Sarah had theoretical education.	Demographic Elizabeth is an 82 years old married female, and has one child. She is unemployed, retired.
Health related Pete was 2 years ago diagnosed with heart failure, and has reduced ejection	Health related Sarah was 1 year ago diagnosed with heart failure, and has reduced ejection	Health related Elizabeth was 2 years ago diagnosed with heart failure, and her left ventricular ejection

fraction and ischemic heart disease. Moreover, he has an estimated Glomerular Filtration Rate of 60. Pete was not hospitalized before the current visit, and has a New York Heart Association classification 2.	fraction. Her the estimated Glomerular Filtration Rate was 88. Sarah has COPD comorbidity, and was not hospitalized before the current visit. Her goal is to maintain a stable weight.	fraction is 43. She has hypertension, and diabetes comorbidity. Moreover, she has an estimated Glomerular Filtration Rate of 47, and has been hospitalized before the current visit.
Person-related Pete did not mention positive ways of coping, and two ways of negative coping. Moreover, he has no smartphone or tablet, but owns a computer. He had a score of 3 on the eHEALs questionnaire, indicating doubts in his skills to use information technology for health, and mentioned that he has no skills in using eHealth technologies.	Person-related Sarah mentioned one way of coping positively, and three ways of coping positively. Moreover, she owns a smartphone, tablet, and a computer. She finds her own skills in using of information technology for health reasonably high (eHEALs mean of 4), and indicated that she has experience with eHealth technologies, but doesn't see an added value.	Person-related Elizabeth has a score 3 on the eHEALs questionnaire, indicating doubts in her skills to use information technology for health.
Logdata iMedisense During the pilot-study, Pete indicated that he had no symptoms in the HF-symptoms-questionnaire. Besides, alarms were mainly generated for heart rate (n = 13), and diastolic blood pressure (n = 10). Few alarms were generated for systolic blood pressure (n = 4), and for weight (n = 1). During the pilot study, Pete shows a usage pattern in which only new measurements are started (n = 77), and sent to the monitoring system (n = 63). He visited his measurement history one time. Besides, he did not use other functionalities within iMedisense. His quality of life after using the monitoring system (EQ5DSL mean of 5) did not change after using the monitoring technology..	Logdata iMedisense Through the HF-symptoms-questionnaire, Sarah indicated a mixed pattern of symptoms. She mentioned that she was restless, forgetful, and had a lacking concentration (n = 4). that she had a reduced effort level (n = 5), a reduced appetite (n = 4), a more than normal increase in fatigue (n = 7), increased shortness of breath (n = 3), and cough or tickling cough (n = 2). Her quality of life increased slightly (EQ5DSL mean of 13) compared to her quality of life before using iMedisense (EQ5DSL mean of 12). During the pilot study, alarms were mainly generated for heartbeat (n = 29). Besides, alarms for diastolic blood pressure were 13 times generated, and the alarm for systolic blood pressure 17 times.	Logdata iMedisense The main symptom that Elizabeth mentioned through the HF-symptoms questionnaire is moisture in legs and abdominal distension (n =37). Besides, she mentioned a reduced effort (n = 3), a more than normal increase in fatigue (n = 4), increased palpitations, and fast paced heartbeat and chest pain (n = 2). During the pilot study, alarms were almost daily generated for systolic blood pressure (n = 58) and for diastolic blood pressure (n = 43). In a much lower amount, alarms were generated for heart rate (n = 5), and for weight (n = 1). Sarah started a new measurement 165 times, sent the symptoms measurement 68 times, and the physical measurement 64 times. Moreover, she opened the

	Sarah started a new measurement 52 times, sent the symptoms measurement 36 times, and the physical measurement 37 times. Besides, she opened her measurement history 54 times, and looked into the day history (n = 2), week history (n = 3), week history (n = 3), and month history (n = 21), blood pressure history (n = 2), heart rate history (n = 4), but not in the year history. She contacted the care provide 4 times, and sent a message 5 times. Lastly, Sarah opened he profile page 37 times, chose a language 2 times, indicated her absence 7 times, and opened the user manual 5 times.	measurement history 87 times, but did not look into the day, week, month, year, weight or blood pressure history. She did look into the heart rate history 2 times. She sent a message through iMedisense 3 times, looked into her profile page 12 times, and choose a language 1 time. Sarah did not open the page for contacting the care provider, to indicate her absence, and she did not open the user manual. Her quality of life increased a little (EQ5DSL mean of 8) compared to her quality of life before using iMedisense (EQ5DSL mean of 7).

Discussion

Conclusions

EHealth personas can be created by integrating data from multiple sources. Our results show that the Persona Approach Twente can be used to cluster data from multiple sources. This way, we explored how we can attain a structured, objective approach for creating eHealth personas, aligned with the iterative approach of eHealth development. Iteratively adding data that is typically collected throughout eHealth development and implementation projects, ensures that an increasingly complete picture of user groups is created. This can be used to tailor eHealth technologies for chronic conditions.

In addition to illustrating this iterative approach to persona-development, we aimed to explore how the approaches as described by Holden [13] and LeRouge [10] can be combined enabling the use of several data collection methods (quantitative and qualitative) for describing user groups. In the creation of clusters, and therewith personas, we found that a richer persona- description can be achieved using a combination of these methods. Yet, the results show that the quality of clusters decreases when qualitative data from the interviews are used in the cluster analysis (as expressed by the lower silhouette width). This however does not mean that the
interview data is invaluable. Rather, it may imply that attention should be paid to what kinds of data are available or should be collected, and how these are collected. Typically, health related data is present for all patients included in a study, whereas the collection of more person-oriented characteristics of our patients or user groups is less standardized and defined. We would argue that information about the ‘person’ should be included, and that information related to LeRouge’s

framework [10] should be questioned in a more structured way.

Besides, we argue that the Persona Approach Twente should be used in co-creation with stakeholders. Since tailoring on the basis of more than on variable is associated with a higher effectiveness of interventions [24], the Persona Approach Twente offers opportunities for increasing the effectiveness of eHealth intervention for chronic diseases. Yet, the increased effectiveness due to this tailoring should outweigh the extra costs involved in tailoring to end users. Moreover, in our illustration of the PAT, we saw that the quality of clusters, and thus personas decreases when adding a larger number of variables. Therefore, we argue that in co- creation with stakeholders, relevant variables should be selected to include for the persona- creation.

Compared to the approach as described by Holden [13], we used a different approach to formulating a persona-description. In Holden's approach, comparative statistical tests between clusters were used to see on which variables these clusters differ [13]. Only the mean variables of these significantly differing variables were then used as a basis for the persona-descriptions. The Persona Approach Twente differs, in that we use the medoids within the clusters, making this approach less labor intensive and less sensitive to extreme values. Moreover, the use of medoids makes it easier to interpret outcomes, since, for example a mean probability value of 0.5 on the variable gender is difficult to interpret, and therefore less useful. Finally, the approach we have described allows for the inclusion of qualitative data in the cluster analysis.

Limitations

Due to the explorative design of this study, the small sample size, of one clinical center and the homogeneous sample accordingly, it remains unclear to what extent results can be generalized across patients with heart failure, and other situations and groups of people. However, the focus of the current study was to further develop the method, so generalization was not a condition for useful results. Nevertheless, the question remains to what extent cluster results can still be used within a development process when collecting a larger amount of data from the group of end users. Moreover, usage log data of iMedisense® could not be used because there was too little variation in that data: adherence was high (almost 100%) and the ways in which users could navigate through the platform were limited. It would be relevant to explore to what extent clustering results are of predictive value for the ways in which users navigate through a system, when indeed adherence and navigation patterns vary. Also, application of remote coaching and education to promote self-management may alter clustering and predictive value of navigation through the system, which warrants further research.

Future Work

In future research we will develop personas including a larger number of participants, allowing to test this combined approach on a larger sample. Moreover, intended use will be coupled with these personas, and usage log data will be used to see whether participants use it as intended. By continuing our research this way, we hope to learn how to attune technological features to our user. We hypothesize that technology personas can inspire developers to put the right persuasive features [25] in the designs, and tailor them accordingly to different users.

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Conflicts of Interest

none declared

Abbreviations

COPD: chronic obstructive pulmonary disease
CRT-D: implantable cardiac resynchronization therapy defibrillator
eGFR: estimated glomerular filtration rate
EPR: electronic patient record
HF: heart failure
HFrEF: reduced ejection fraction
ICD: implantable cardioverter defibrillator
NYHA: New York heart association
PAT: persona approach Twente
UCD: user-centered design

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Appendix A. Syntax Shapiro-Wilk tests

```
DATASET ACTIVATE DataSet1.
EXAMINE VARIABLES=Age Wokeupoften peealotduringthenightandlessduringtheday
Stuffyatnight extrapillows sleepingsonachair Restlessforgetfulandlackingconcentration
Reducedeffortlevel Reducedappetitefullfeeling Morethannormalincreaseinfatigue
Moistureinlegsabdominaldistension Increasedshortnessofbreath
IncreasedpalpitationsfasPATcedheartbeatchesPATin Coughticklingcough LVEF
YearsAgoDiagnosed
EQ5D5L_before PositiveCoping NegativeCoping EHeals_Questionnaire
Alarm_DiastolicBloodPressure
Alarm_Heartbeat Alarm_SystolicBloodPressure Alarm_Weight EQ5D5L_after
StartNewMeasurement
SendSymptomsMeasurement SendPhysicalMeasurement OpenMeasurementHistory
DayHistory WeekHistory
MonthHistory YearHistory BloodpressureHistory HeartrateHistory WeightHistory
ContactCareProvider
OpenProfilePage chooselanguage absence OpenUserManual eGFR
/PLOT BOXPLOT STEMLEAF NPPLOT /COMPARE GROUPS
/STATISTICS DESCRIPTIVES /CINTERVAL 95
/MISSING PAIRWISE /NOTOTAL.
```

Appendix B. Results Shapiro-Wilk tests

	Shapiro-Wilk		
	W	df	p-value
Age	.967	25	.568
Woke up often, pee a lot during the night, and less during the day	.454	25	.000
Stuffy at night, extra pillows, sleepings on a chair	.218	24	.000
Restless, forgetful and lacking concentration	.381	25	.000
Reduced effort level	.649	25	.000
Reduced appetite, full feeling	.433	25	.000
More than normal increase in fatigue	.562	25	.000
Moisture in legs, abdominal distension	.422	25	.000
Increased shortness of breath	.509	25	.000
Increased palpitations, fast-paced heartbeat, chest pain	.567	25	.000
Cough, tickling cough	.676	25	.000
Left ventricular ejection fraction (LVEF) in %	.838	25	.001

Number of years ago diagnosed with HF	.740	24	.000
Quality of life before using iMediSense	.844	24	.002
Number of times the participant mentioned a positive way of coping during the interview	.548	25	.000
Number of times the participant mentioned a negative way of coping during the interview	.754	25	.000
Capacity for engaging in Ehealth	.943	22	.224
Diastolic blood pressure	.868	24	.005
Heartbeat	.808	24	.000
Systolic blood pressure	.855	24	.003
Weight	.297	24	.000
Quality of life after using iMediSense	.857	24	.003
new-measurement	.776	25	.000
confirm butten questionnaire (new-measurement)	.772	25	.000
confirm button send measruements (new measurement)	.776	25	.000
my-history	.284	25	.000
day button (measurements)	.666	25	.000

week button (measurements)	.650	25	.000
month button (measurements)	.661	25	.000
year button (measurements)	.660	25	.000
bloodpressure button (measurements)	.456	25	.000
heartrate (measurements)	.656	25	.000
weight (measurements)	.528	25	.000
contact button (home)	.707	25	.000
my-settings	.709	25	.000
choose language button (settings)	.548	25	.000
absence button (settings)	.458	25	.000
user-manual-button (home)	.577	25	.000
eGFR	.934	25	.110

Appendix C. R code clustering step 1

```
set.seed(1680) # for reproducibility
library(dplyr) # for data cleaning
library(ISLR) # for college dataset
library(cluster) # for gower similarity and pam
library(Rtsne) # for t-SNE plot
library(ggplot2) # for visualization

# Remove participant number before clustering gower_dist <- daisy(Clustering_step1[, -1],
metric = "gower",
type = list(logratio = c(4, 5, 6, 7, 8, 9, 10, 11, 12))

# Check attributes and calculate gower distances summary(gower_dist)
gower_mat <- as.matrix(gower_dist)

# Check observations with minimal and maximal distances Clustering_step1[
which(gower_mat == min(gower_mat[gower_mat != min(gower_mat)]), arr.ind = TRUE)[1, ], ]
Clustering_step1[
which(gower_mat == max(gower_mat[gower_mat != max(gower_mat)]),
arr.ind = TRUE)[1, ], ]

# Calculate silhouette width for many k using PAM sil_width <- c(NA)
for(i in 2:10){
pam_fit <- pam(gower_dist,
diss = TRUE, k = i)
sil_width[i] <- pam_fit$silinfo$avg.width }

# Plot sihouette width (higher is better) using ggplot package sil <- as.data.frame(cbind(1:10,
sil_width))
ggplot(sil, aes(x = V1, y = sil_width)) +
geom_line() +
geom_point() +
labs(y= "Silhouette Width", x = "Number of Clusters") + scale_x_continuous(breaks = c( 1:10 )) +
theme_linedraw()

# Fit PAM for two clusters (lowest silhouette width), and obtain results pam_fit <- pam(gower_dist,
diss = TRUE, k = 2)
pam_fit$silinfo pam_fit$medoids
```

Appendix D. R code clustering step 2

```
set.seed(1680) # for reproducibility
library(dplyr) # for data cleaning
library(ISLR) # for college dataset
library(cluster) # for gower similarity and pam
library(Rtsne) # for t-SNE plot
library(ggplot2) # for visualization

# Remove participant number before clustering
gower_dist <- daisy(Clustering_step2[, -1],
metric = "gower",
type = list(logratio = c(4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 17, 22, 24, 25, 26))

# Check attributes and calculate gower distances
summary(gower_dist)
gower_mat <- as.matrix(gower_dist)

# Check observations with minimal and maximal distances Clustering_step2[
which(gower_mat == min(gower_mat[gower_mat != min(gower_mat)]), arr.ind = TRUE)[1, ], ]
Clustering_step2[
which(gower_mat == max(gower_mat[gower_mat != max(gower_mat)]),
arr.ind = TRUE)[1, ], ]

# Calculate silhouette width for many k using PAM sil_width <- c(NA)
for(i in 2:10){
pam_fit <- pam(gower_dist,
diss = TRUE, k = i)
sil_width[i] <- pam_fit$silinfo$avg.width }

# Plot sihouette width (higher is better) using ggplot package sil <- as.data.frame(cbind(1:10,
sil_width))
ggplot(sil, aes(x = V1, y = sil_width)) +
geom_line() +
geom_point() +
labs(y= "Silhouette Width", x = "Number of Clusters") + scale_x_continuous(breaks = c( 1:10 )) +
theme_linedraw()

# Fit PAM for two clusters (lowest silhouette width), and obtain results pam_fit <- pam(gower_dist,
diss = TRUE, k = 2)
pam_fit$silinfo pam_fit$medoids
```

Appendix E. R code clustering step 3

```
set.seed(1680) # for reproducibility
library(dplyr) # for data cleaning
library(ISLR) # for college dataset
library(cluster) # for gower similarity and pam
library(Rtsne) # for t-SNE plot
library(ggplot2) # for visualization

# Remove participant number before clustering
gower_dist <- daisy(Clustering_step3[, -1],
metric = "gower",
type = list(logratio = c(4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 17, 22, 24, 25, 26, 44, 45, 49, 50, 51, 52, 53, 54,
55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70)))

# Check attributes and calculate gower distances summary(gower_dist)
gower_mat <- as.matrix(gower_dist)

# Check observations with minimal and maximal distances Clustering_step3[
which(gower_mat == min(gower_mat[gower_mat != min(gower_mat)]), arr.ind = TRUE)[1, ], ]
Clustering_step3[
which(gower_mat == max(gower_mat[gower_mat != max(gower_mat)]),
arr.ind = TRUE)[1, ], ]
# Calculate silhouette width for many k using PAM sil_width <- c(NA)
for(i in 2:10){
pam_fit <- pam(gower_dist, diss = TRUE,
k = i)
sil_width[i] <- pam_fit$silinfo$avg.width
}

# Plot sihouette width (higher is better) using ggplot package
sil <- as.data.frame(cbind(1:10, sil_width))
ggplot(sil, aes(x = V1, y = sil_width)) +
geom_line() +
geom_point() +
labs(y= "Silhouette Width", x = "Number of Clusters") + scale_x_continuous(breaks = c( 1:10 )) +
theme_linedraw()
pam_fit$silinfo

# Fit PAM for twhree clusters (lowest silhouette width), and obtain results
pam_fit <- pam(gower_dist, diss = TRUE, k = 3)
pam_fit$clustering pam_fit$medoids
```

Appendix F. Clustering results step 1

In total 25 persons were divided into two clusters. The first cluster has an average silhouette width of 0.12, and consists of 17 persons, which is 68% of the total number of persons. The mean age within this cluster is 69.41 (sd = 7.73). A mixed pattern emerges for the gender of persons within this cluster, with 7 females and 10 males. The mean left ventricular ejection fraction is 35 (sd = 10), and a mean estimated Glomerular Filtration Rate of 64 (sd = 20). A majority of persons have a reduced ejection fraction (n = 15), and ischemic heart disease (n = 12). A small number of persons within this cluster have cerebrovascular comorbidity (CVA or TIA) (n = 5), COPD (n = 4), diabetes (n = 5), hypertension (n = 3), and atrial fibrillation (n = 2). In addition, we see that the majority of persons have a NYHA classification 2 (n = 14), and a small number (n = 3) have a NYHA classification 3. Yet, we do observe that all persons with classification 3 fall within this cluster. This also applies for persons with an Implantable Cardioverter Defibrillator (n = 4). Besides, 3 persons have a Cardiac Resynchronization Therapy Defibrillator. Lastly, the majority of persons within this cluster have not been hospitalized before (n = 13).

The second cluster has an average silhouette width of 0.27, and consists of 8 persons, which is 32% of the total number of persons. The mean age within this cluster is 65 (sd = 11), and a majority are female (n = 7). The mean left ventricular ejection fraction is 46 (sd = 15), and the mean estimated Glomerular Filtration Rate 59 (sd = 19). A clear pattern emerges for the NYHA classification, with all persons having a NYHA classification 2 (n = 8). A majority of persons within this cluster have a reduced ejection fraction (n = 5), hypertension (n = 5), and atrial fibrillation (n = 5). Moreover, the majority of persons within this cluster have been hospitalized for heart failure before (n = 6). Conversely, a minority has diabetes (n = 1), cerebrovascular disease (n = 1), or ischemic heart disease (n = 1) comorbidity. In addition, there are no persons within this cluster having COPD comorbidity, or an Implantable Cardioverter Defibrillator. Only one person within this cluster has a Cardiac Resynchronization Therapy Defibrillator.

Appendix G. Clustering results step 2

The first cluster consists of 10 persons (40%) with an average silhouette width of 0.08. The mean age of persons within this cluster is 63(sd = 10), and all are female (n = 10). Half of the persons are theoretically educated (n = 1) and half had vocational education (n = 1). Moreover, the a large part of persons are married (n = 5), and a small part is not married (n = 2). One person within this cluster is divorced. The mean number of children within this cluster is 1.7 (sd = 0.5), and the mean number of grandchildren 3.5(sd = 2.1). Five persons within this cluster are unemployed, retired or have an early retirement, and three persons a part time employed, full time employed or work voluntarily. The majority of persons within this cluster have a reduced ejection fraction (n = 8), have been hospitalized before (n = 5), and have a NYHA classification 2 (n = 9). A minority of persons in this cluster have a cerebrovascular disease (n = 2), COPD (n = 1), diabetes (n = 3), ischemic heart disease (n = 3), hypertension (n = 3), atrial fibrillation (n = 4). Persons within this cluster do not have a CRT-D to support their heart function, and only one person has an ICD (n = 1). No specific health-related goal becomes apparent for persons within this cluster, with three persons expressing the goal to keep a stable weight, one person to have a healthier lifestyle, one person to maintain control, two persons to limit fluid intake, and one person expressed the goal to stay positive.
Regarding technology use, we see that seven persons in cluster 2 own a smartphone, eight persons own a computer, and six persons own a tablet. All persons are reasonably or very skilled in working with technologies. Also, the majority has reasonable or a lot of experience in working with technology (n = 2), compared to persons who told that they had no or little experience with technology (n = 1). Persons within this cluster use technology for entertainment (n = 3), for social purposes (n = 4), and for gaining information (n = 5). On the other side, a (smaller) number of persons told that they do not use it for entertainment (n = 2), for social purposes (n = 3), or to gain information (n = 2). Moreover, we see that the majority of persons see no or limited added value from eHealth technologies (n = 4), and one person mentioned that he or she sees an added value from these technologies. Besides, two persons mentioned that they miss information about their condition, and one person mentioned that he or she has enough knowledge about the health condition. Lastly, the mean score on the eHEALs questionnaire for this cluster is 3.36 (sd = 0.61).

The second cluster consists of 15 persons (60%) with an average silhouette width of 0.12. The majority of persons within this cluster are male (n = 11), and the mean age is 71 (sd = 6). Four persons within this cluster had vocational education (rest is missing values). The mean number of children is 2.4 (sd = 1.0), and the mean number of grandchildren 4.0 (sd = 2.0). For all persons within this cluster for whom the marital status is known, we see that all are not divorced (n = 7), and all are married (n = 9). The minority is unemployed, retired, or have an early retirement (n = 10), and a small number of persons work full time, part time, or do volunteer work (n = 4). The majority of persons within this cluster have a reduced ejection fraction (n = 12) and ischemic heart disease (n = 10). A minority has cerebrovascular disease (n = 4), COPD (n = 3), and diabetes (n = 3) comorbidity and atrial fibrillation (n = 3). Around one third of the persons within this cluster have hypertension (n = 5), and have been hospitalized before (n = 5). A small number have a CRT-D to support their heart function (n = 4), or an ICD (n = 4). Yet, we do observe that almost all persons with a defibrillator fall within the second cluster. The same applies for the New York Heart Association (NYHA) classification, with two persons having a NYHA 2 classification, and three persons a NYHA 3 classification. Similar to the other cluster, there becomes no clear pattern apparent regarding health-related goals, with 2 persons expressing the goal to keep a stable weight, two persons a healthier lifestyle, one person maintaining control, one person to stay positive, and no persons expressing the goal to limit fluid intake.

For cluster 2, we see a mixed outcome regarding technology owing, with half of the persons owning a smartphone (n = 7), and have of the persons owning a tablet (n = 7). A clear pattern emerges for computer owing, with almost all persons owning a computer (n = 12), compared to persons who do not own a computer (n = 1). All persons who expressed their view on their skills and experience in working with technology, indicated that they have no skills or limited skills (n = 5), and that they have no or little experience with technology (n = 6). Moreover, one person within this cluster expressed that there is missing knowledge about the health condition, and one person mentioned that he or she has enough knowledge about the health condition. Besides, the majority sees added value of eHealth technologies or identifies possibilities of eHealth technologies (n = 4), compared to the persons who do not see an added value (n = 1). Lastly, the mean score on the eHEALs questionnaire is 3.07 (sd = 0.89).

Appendix H. Clustering results step 3

The first cluster consists of 15 persons (60%) with an average silhouette width of 0.09. The majority of persons within this cluster are male (n = 10), and the mean age is 69 (sd = 9). There are no persons within this cluster who indicated that they are divorced, and eight persons mentioned that they are married. The mean number of children for persons within this cluster is 2.1 (sd = 0.7), and the mean number of grandchildren 5.0 (sd = 1.4). Four persons within this cluster indicated that they had vocational education, and for the rest of the persons within this cluster this information is missing. Moreover, the majority (n = 10) indicated that they are unemployed, retired or have an early retirement, and the minority (n = 4) indicated that they are full time or part time employed or do work voluntarily.

Persons within the first cluster are on average diagnosed with heart failure 3.1 years ago (sd = 2.3), have a mean left ventricular ejection fraction of 36 (sd = 10), and the mean estimated Glomerular Filtration Rate is 64 (sd = 19). The majority of persons within this cluster have a reduced ejection fraction (n = 14) and ischemic heart disease (n = 12). Besides, a minority of persons within this cluster have also cerebrovascular disease (n =4), COPD (n = 2), or diabetes comorbidity (n = 4). Moreover, a minority has hypertension (n = 4), atrial fibrillation (n = 2), or a New York Heart Association classification 3 (n = 2). All persons with an ICD fall within this cluster (n = 4), and a large part of persons with a CRT-D fall within this cluster (n = 3). No specific personal goal becomes clear for patients within this cluster, with 2 persons indicating they want to maintain a stable weight, 1 person wants to maintaining a healthy lifestyle, 1 person want to maintain his or her own control, 1 person want to remain positively, and no persons indicated that they want to limit fluid intake. Lastly, we see that ten persons have not been hospitalized before the current visit, and five persons have been hospitalized for heart failure before.

Regarding technology use for persons within this cluster, we see that 12 persons own a computer, and one person doesn’t own a computer. Moreover, seven persons have a tablet, compared to six persons not owning a tablet. Five persons indicated that they have a smartphone and eight persons indicated that they don’t have a smartphone. Three persons indicated that they use technology for entertainment, three persons for social purposes, and three persons for gaining information. Besides, four persons indicated that they are not skills or have very little skills in working with technology, and two persons indicated that they are reasonably or very skilled in working with technology. Similarly, five persons indicated that they have no or little experience with technology. Yet, a majority (n = 4) sees the added value of eHealth technologies, compared to the minority (n = 1) that sees no added value from these technologies. Two persons within this cluster indicated that he or she misses knowledge about the health condition, and one person mentioned that he or she has enough knowledge about the health condition.

Alarms: diastolic blood pressure 15.80 (sd = 12.76), heartrate 11.80 (sd = 14.32), systolic blood pressure 1.53 (sd = 19.25), weight 5.27 (sd = 17.10).

The second cluster consists of 5 persons (20%) with an average silhouette width of 0.12. All persons within this cluster are female (n = 5), and the mean age is 62 (sd = 7). One person within this cluster indicated that he or she had theoretical education, and for the rest of the persons within this cluster, the educational background is missing. Moreover, three persons indicated that they are married, and one person indicated that he or she is not married. Besides, 1 person indicated that he or she is unemployed, retired, or has an early retirement, whereas 2 persons indicated that they work full time, part time, or do volunteer work.

Persons within the second cluster are on average 1.4 (sd = 0.6) years ago diagnosed with heart

failure. Their mean left ventricular ejection fraction is 30 (sd = 8), and the mean estimated Glomerular Filtration Rate 66 (sd = 23). A majority of persons within this cluster have a reduced ejection fraction (n = 4). In contrast, a minority of persons within this cluster have cerebrovascular disease (n = 1), COPD (n = 2), diabetes (n = 1), atrial fibrillation (n = 1), or a New York Heart Association classification 3 (n = 1). There are no persons with hypertension within this cluster, and also there are no persons with a CRT-D or ICD to support their heart function. The majority of persons within this cluster (n = 4) have no prior hospitalization for heart failure. No clear pattern emerges for the goals of persons within this cluster, with three persons indicating their goal is a stable weight, one person maintaining his or her own control, one person to limit fluid intake, on person to maintain positively, and no persons indicating their goal is a healthy lifestyle.
Regarding technology use, we see that all persons indicated that they have a computer, four persons indicated that they have a smartphone, and four persons indicated that they own a tablet. Two persons indicated that they use technology for entertainment purposes, one for social purposes, and two for gaining information. Of all persons having indicated how skilled they are in working with technology, we see that they all (n = 4) indicate that they a reasonably or very skilled. Moreover, the same applies for the experience with technologies, where one person indicated he or she has reasonably or a lot of experience in working with technology. Besides, three persons within this cluster indicated that they see no added value from eHealth technologies, and one person indicated seeing an added value of eHealth technologies. One person mentioned that he or she is missing knowledge about the health condition, whereas one person indicated that he or she has enough knowledge about the health condition.

Alarms: diastolic blood pressure 29.25 (sd = 24.93), heartrate 33.75 (sd = 18.36), systolic blood pressure 26.75 (sd = 23.67), weight 2.50 (sd = 2.38)
The third cluster consists of 5 persons (20%) with an average silhouette width of 0.04. The majority of persons within this cluster are female (n = 4), and the mean age is 70 (sd = 8). One person within this cluster indicated that he or she had vocational education, and for the rest of the persons within this cluster this information is missing. Moreover, 2 persons indicated that they are not divorced, and one person indicated that he or she is divorced. Besides, 3 persons indicated they are married, and one person that he or she is not married. The majority of persons within this cluster are unemployed, retired, or have an early retirement (n = 4).
Persons within the third cluster are on average 1.6 (sd = 0.9) years ago diagnosed with heart failure. Their mean left ventricular ejection fraction mean is 52 (sd = 16), and the mean estimated Glomerular Filtration Rate 53 (sd = 18). The majority of persons within this cluster have hypertension (n = 4), atrial fibrillation (n = 4), and have been hospitalized for heart failure before the current visit (n = 4). Besides, a minority of persons within this cluster have cerebrovascular disease (n = 1), diabetes (n = 1), or ischemic heart disease (n = 1). One person has an CRT-D, and no persons have an ICD. There are no persons with COPD comorbidity, ischemic heart disease, and a New York Heart Association classification 3 (all persons have classification 2). No clear pattern emerges for reduced ejection fraction within this cluster, with 2 persons having a reduced ejection fraction, and three persons not having a reduced ejection fraction. Similarly, no specific goal becomes clear for patients within this cluster, with 2 persons expressing they want to maintain a healthy lifestyle, and 1 person indicating that he or she wants to limit fluid intake, and no persons indicating that the goal is to maintain his or her own control, to remain positive, or to keep a stable weight.
Regarding technology use, two persons indicated they have a smartphone, whereas two persons indicated they don't own a smartphone. Besides, three persons indicated they have a computer, one person doesn't own a computer, three persons own a tablet, whereas one person does not. One person expressed that he or she used technology for entertainment, one person for social purposes, and one person for gaining information. The majority of persons (n = 3) within this cluster are reasonably or very skilled in using technology, compared to persons who a not skilled in using technology (n = 1).

Similarly, the majority has no or little experience with technology (n = 2), compared to persons who have reasonably or a lot experience in using technology (n = 1). Moreover, one person sees no added value from eHealth technology, and one person sees an added value of eHealth technologies. Lastly, one person within this cluster mentioned that he or she misses knowledge about the health condition. Alarms: diastolic blood pressure 15.60 (sd = 16.01), heartrate 18.00 (sd = 19.81), systolic blood pressure 21.80 (sd = 24.32), weight 2.00 (sd = 2.83)