Designing a dashboard for wellbeing data

A recommendation system for individual wellbeing

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Abstract

Due to COVID-19 the overall wellbeing worldwide decreased. Assessing and improving wellbeing became a more important subject. This article describes the design research that uses the My Wellness Check survey created by the Delft University for Technology and aims to create a dashboard for wellbeing. That includes a way of authenticating users to very sensitive data. Also, finding ways how to improve personal wellbeing by using a recommendation system based on different types of filtering and the additional elements that are needed for a recommendation system.

1 Introduction

COVID-19 had and still has a big impact on the world. The overall wellbeing of humans has reduced significantly [1]. Due to this decrease in wellbeing large organizations like the Delft University of Technology created a wellbeing assessment instrument to identify potential harms to wellbeing as well as opportunities to promote it. However, identifying problems with new measurements and surveys is only the first step in increasing the wellbeing of the community. Finding solutions is the difficult part of increasing the wellbeing, furthermore finding solutions for specific human beings will be the most difficult.

The Delft University of Technology created a questionnaire[1] that uses questions to identify the wellbeing of the student or staff [2]. With this questionnaire, the goal was to understand the granularity of wellbeing needs that students and staff have due to COVID-19. But also, the goal was to stimulate bottom-up approaches for dealing with wellbeing challenges. One of the approaches was to promote and design initiatives enabling the student community to take part in the action as well. Via social media all answers to the question "What daily routines are working well for you?" were collected, analyzed and then used in several visuals, see Figure 1. In this paper the goal is to design an automation process of collecting, analyzing and returning possible improvements for wellbeing.

Figure 1: This figure shows a selection of the "It works for me" campaign. In this campaign, the goal was to collect possible solutions for improving wellbeing of students and return these solutions anonymized to their peers [2].

[1] https://tudelft-student.mywellnesscheck.org/

At the end of the questionnaire from the TU Delft, there is a screen that displays a "thank you", information about a student council and links to general information about improving wellbeing and COVID-19, see figure 2. However, there are no concrete proposals made based on the input of the student [3]. Displaying results from the survey is important to make it more meaningful and worthwhile [4]. Also, returning data to the participants is important for the wellbeing because then and only then do participants know what the possible solutions are. So, what would it look like if a user can interact with their survey answers? The main research question for this paper is: **How might we design a dashboard for communicating data to back the community?** The sub-questions are: How do you recommend solutions? How can a student look at their private dashboard when all the data is anonymous? How does one decide what a good solution for wellbeing is? The overall goal for this paper is to take the current end screen in figure 2 and design a dashboard looking like figure 3.

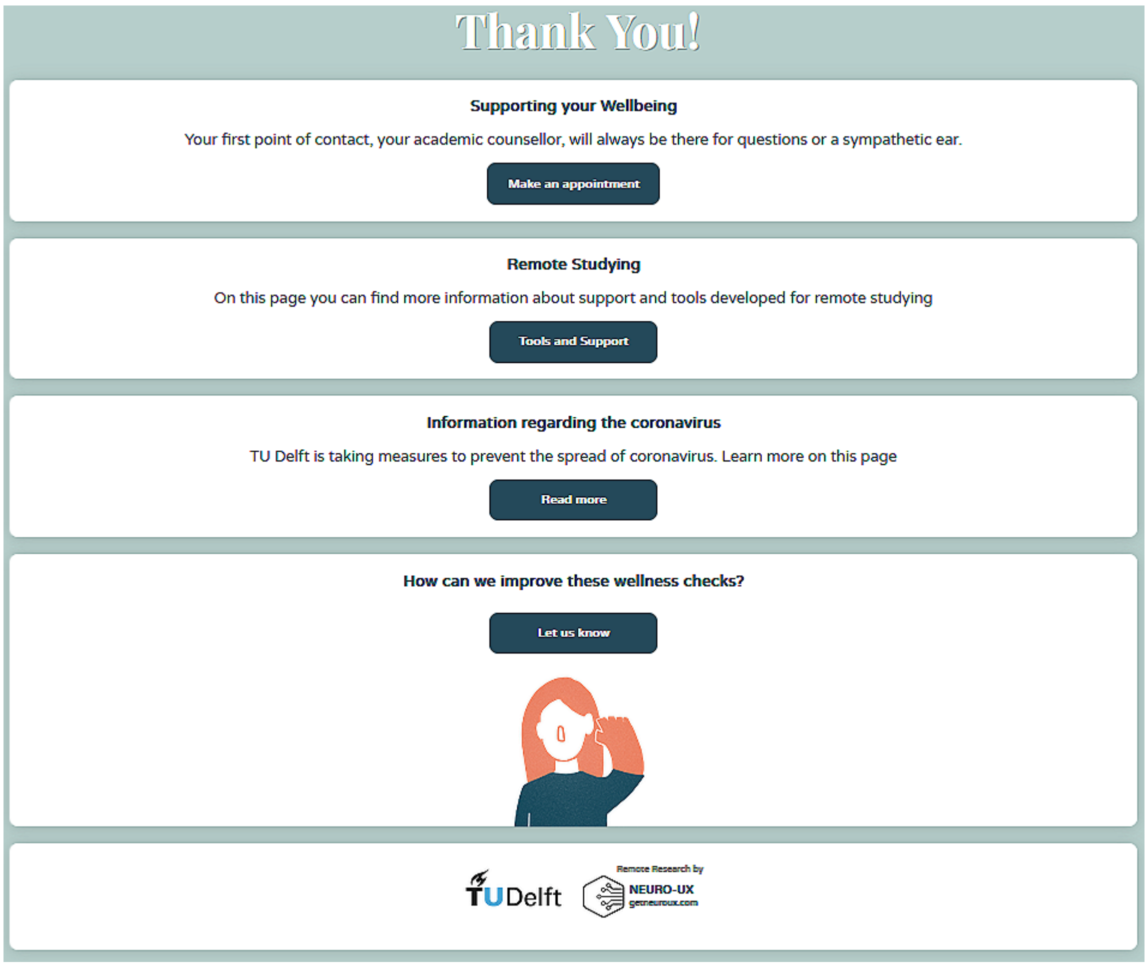

Figure 2: This figure shows the screen that students and staff see after doing the survey from the My Wellness Check [2].

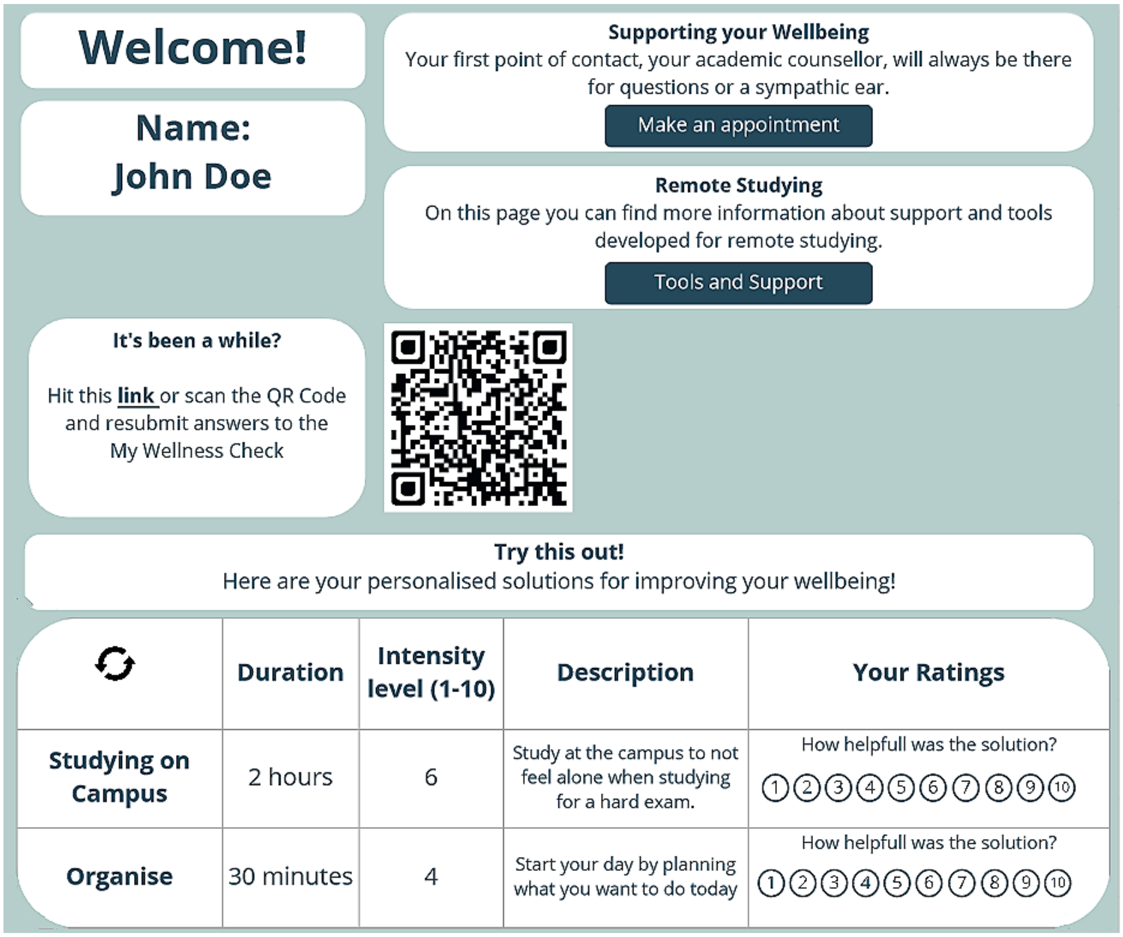

Figure 3: This figure shows an example of what the new dashboard might look like with the newly added elements.

To answer these questions the structure of the paper is as follows. First, in section 2 related work is discussed about wellbeing and returning survey data back to the users with a recommender system. Then in section 3, the new idea for the dashboard is described explaining what elements are needed to improve wellbeing on a personal level. Thirdly, section 4 gives explains the responsible research part of this research project. Section 5, discusses the choices made in this research as well as future work. Finally, section 6 concludes the research.

2 Related work

2.1 Defining wellbeing

The question of how wellbeing should be defined has too many different answers [5]. The first notable was Ed Diener who created a tripartite model of subjective wellbeing which was a hedonic model [6]. This model considers three pillars, satisfaction with life, the absence of negative emotions, and the presence of positive emotions, to determine wellbeing.

Other, eudaimonic, models for wellbeing look beyond the scope of pleasure of a satisfied life. For example, Ryff's six-factor model for wellbeing. As the name states it focuses on six aspects of wellbeing: self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, and personal growth [7, 8]. A third category for wellbeing research focuses on quality of life (QoL) [9]. QoL models propose to take objective as well as subjective indicators, a broad range of life domains, and individual values.

2.2 Recommendation system

The survey from the My Wellness Check has had multiple iterations [2]. The data provided for this research consisted of 1833 participants. This data consisted of actual answers given in the survey. There are objective questions e.g. "At what faculty are you studying" and also subjective question e.g. "Taking all things together, how satisfied or dissatisfied are you with your life as a whole these days?" [2].

To have the students and staff interact with the wellbeing data a new system has to be implemented. To improve the wellbeing of an individual, personalised solutions need to be provided. The recommendation system is not a new concept but it has become more important and more used in the last few years due to applications like Netflix, Amazon Prime, YouTube, etc [10].

Recommendation Systems are software tools that are used to provide suggestions to users according to their requirements [11]. Previous work has separated recommendation techniques into four different categories [12].

- **Collaborative Filtering**
  The Collaborative Filtering approach is to use user ratings of different items and take these ratings to find similar users with similar ratings. Once similar users are found, it will recommend an item that these similar users also rated high. [13].
- **Content-Based Filtering**
  In Content-Based Filtering the recommendations are based on the users previous choices [14]. The items that the user already has chosen before, each one of them has a set of features and based on these features find new items that are similar to the ones that already have been chosen.
- **Demographic Filtering**
  In Demographic Filtering, the recommendations are based on the demographic profile of the user. Features that are used in this type of filtering are nationality, age, gender etc [15]

- **Hybrid Filtering**
  The Hybrid Filtering system is as the name suggests a combination of more than one filtering approach [15]. This approach for filtering has derived from problems such as the cold start [16] and the overspecialization problem.

The data provided is all about the wellbeing of the student or staff. Using a Demographic filtering technique misses the goal as that only looks at facts such as nationality, age and gender.

Collaborative filtering takes user ratings and based on these ratings decide what to recommend. In the scope of wellbeing, if the recommendation system can filter out the good and bad solutions it will increase the chance of providing suitable solutions.
The content-based filtering is used on previous choices made by the participant. Every new user completing the survey has no other input or comparison to other students, meaning the recommender system has too little input to make accurate recommendations. This referred to as the "Cold start" problem. Content-based filtering overcomes this problem by making predictions based on what the new student already likes. So both collaborative filtering and content-based filtering are useful in recommending possible solutions to the user.

To use Content-Based filtering every 'item' must have a set of features [17]. If items can have features that means users are also a set of features. Using the item and user features helps with the cold start problem as mentioned before, as well as with scalability problems that might occur [17]. If a system can distinguish better items and users, a more specific recommendation can be made.

For the wellbeing data provided for this research, user features are created from the input of the survey. The list below depicts the first version of a set of features depicting a user.

- Faculty
- Gender
- Year of Degree program
- Mood
- Life satisfaction
- Physical Health
- Academic experience
- Study environment

To create a list of item features the survey asked the question "What daily routines are working well for you?". This is an open question meaning that the answers that are given were long sentences describing their routines or summation of multiple solutions the participants used/ are using. To overcome this problem the data collected needs to be normalized explicitly. To do this every possible solution needs to be described in a set of features. The list of features given to a possible solution should be short and distinct as a user only intends to look at a small set of features [18]. Using the data that is available the next three features are created:

- Duration
- Intensity
- Description

The first two features are fixed as duration is in minutes and intensity is based on a scale of 1 to 10. Description is a small text describing the activity, e.g. Meditate to clear your mind. Besides these three features every possible solution should also get an item id, user id and user rating as these are needed for the rating system. Every user has a personal id because that is anonymous for another user. The survey consisted of more questions than that there are features listed above, more about this in section 5.

3 New idea

This section describes the new ideas for the dashboard. Figure 3 gives an idea of what it would look like and what to expect from it. First, a solution for logging into a database with anonymous data and privacy issues. Secondly, the issue of incomplete data is addressed and how to solve this. Thirdly, what kind of rating system for the possible solutions is efficient and connects best to the recommendation system.

3.1 Logging in

The My Wellness Checks uses a website that does not require any type of user logging to fill in the survey. In this way, one can not track who submitted which answers. To provide a dashboard of the kind designed in this paper, which is directed at an individual, it is necessary to know who gave what answers. However, it is also important to keep the answers private to the participant as it is about the physical and more important mental health and thus very sensitive to the user.

Single sign-on (SSO) schemes have been widely used by major companies, such as the Delft University of Technology, to manage service authorization and user authentication [19]. The companies can enable third-party applications, My Wellness Check, to obtain user information from a service provider to identify a user. Figure 4 displays a diagram that shows the flow of the SSO.

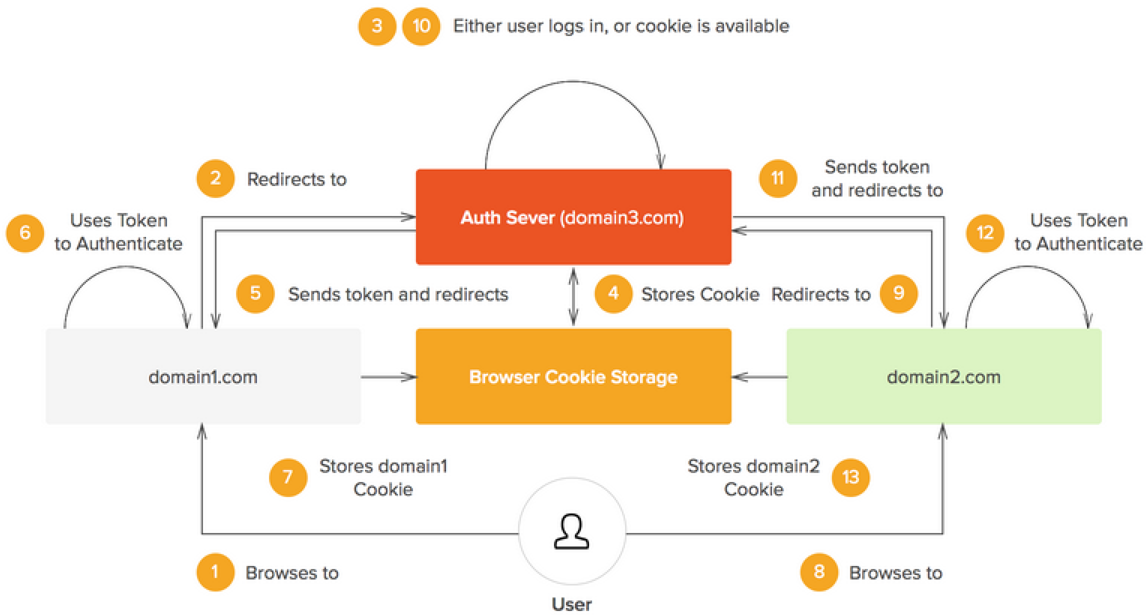

Figure 4: This diagram shows the flow of using a logging system via SSO [20].

The advantages of SSO are:

1. **Time saver.** SSO uses one combination of username and password. Users no longer have to remember or store all the different combinations.

2. **Elevating user experience.** Users no longer have to log in multiple times a day.

3. **Security.** On the user end, if a user only needs one password they are more likely to create a stronger (harder to guess) password. On the service end, SSO reduces the number of login attempts to one a day which means reducing the opportunities for cybercriminals.

3.2 Missing data

The My Wellness Check survey is made in such a way that it is possible to skip over questions. This leads to missing valuable data that corresponds to one or multiple features. There are two approaches to dealing with this such that it will not become a problem. The first possible solution is deleting the set of incomplete rows. This could lead to possibly deleting valuable data [21]. The second approach is imputing the missing data using a k-Nearest Neighbor algorithm. When item x is missing data for a feature the k-Nearest Neighbor searches for the k nearest items with the lowest distance towards x. This distance is measured by using the Euclidean distance, see figure 5, for the features that are available in x.

$$distance = \sqrt{weight * ((x_1 - k_{1.1})^2 + (x_2 - k_{1.2})^2 + .. + (x_n - k_{1.n})^2)}$$

Figure 5: The weight is the total number of features divided by the number of present features. x represents the row with missing data together with a feature selected and k is one of the nearest neighbors [22].

For example, the distance between [3, 5, null] and [2, 4, 8] is $\sqrt{\frac{3}{2} * (3-2)^2 + (5-4)^2} = 3$

Testing the accuracy of different inputs for k is done with the Root Mean Square Error (RMSE). The RMSE is a metric that indicates of how far apart the predicted values are from the observed values. In figure 6, the RMSE is displayed against the number of nearest neighbors. It is shown that k = 12 has the lowest error, increasing k only results in a higher RMSE as k = 50 is equal to a RMSE of 3.09280 and k = 100 to a RMSE of 3.20102. Also, decreasing k leads to a higher error as shown in the figure below.

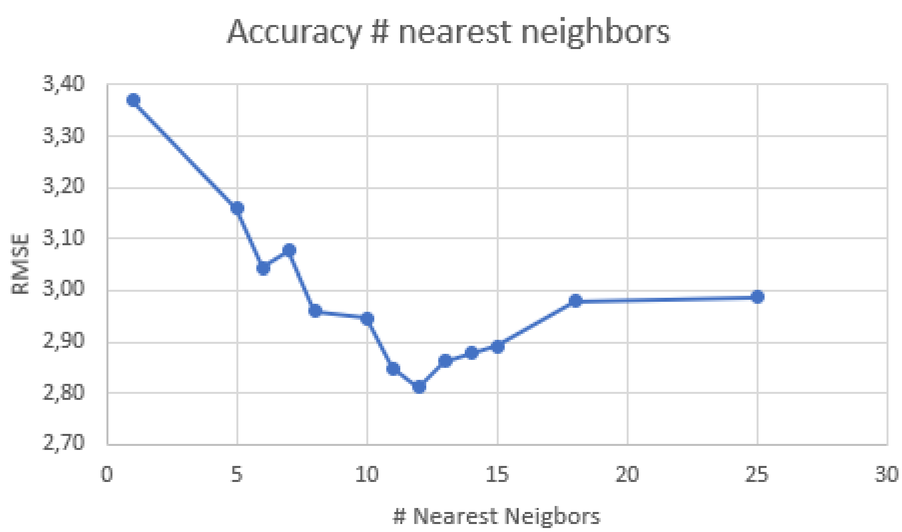

Figure 6: This figure shows the accuracy of multiple different amounts of nearest neighbors using the RMSE.

To test if either deleting data or imputing data is better a bigger experiment should be done. Once a recommendation system is completed both data sets, one with deleted rows and one with imputed data, should be used to predict possible solutions. Test users then experiment with the recommendation system and then judge the predictions made. As predicting a good solution and thus improving wellbeing is the main goal this should then clarify what the better data set is.

3.3 Rating system

The third issue that arises with the recommendation system is the fact that there are no ratings yet for the already available solutions. So, a rating system is needed. As described in section 2.2 the collaborative filtering systems works with user ratings on different items. Collaborative filtering takes the previous ratings of the user who is in need of a new possible solution. Then with the previous ratings, search for users that have similar ratings. Based on these users, predict if the possible solutions that have not been rated by the user in question are good for the wellbeing or not.

An example of collaborative filtering can be seen in figure 7. Here user D needs a new book to read and based on the previous rating of books 2 and 5 user D wants to know if book 3 is suitable. As user D's previous ratings look most similar to that of user B the recommendation would be to dislike book 3 with a thumbs down.

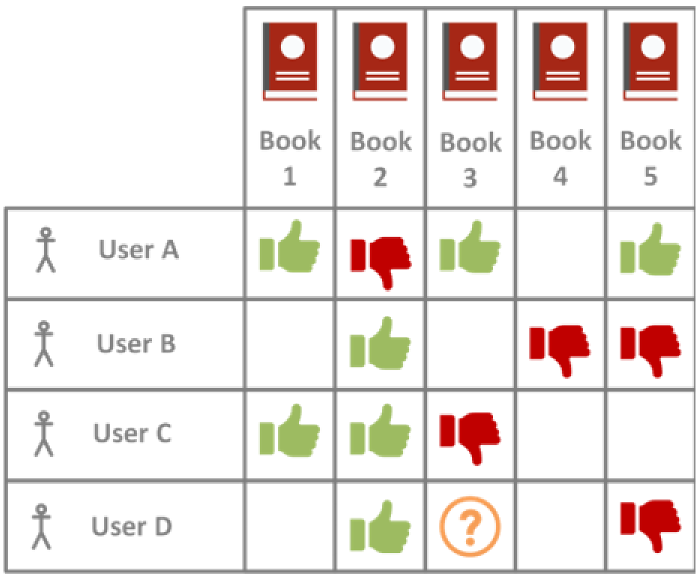

Figure 7: This figure shows an example of items rated per user [23]. It uses thumbs up and down for rating the different books.

There are numerous ways of rating. Some of these are listed below:

1. Linear Numeric scale
2. Likert scale
3. Frequency scale
4. Forced Ranking scale
5. Pick Some (also known as Top Task)
6. Paired Comparison scale
7. Thumbs up/down

If the data is very big a simple thumbs up/down would not be specific enough, even Netflix added a double thumbs up for more specific recommendations [24]. Another example of bad ratings for too large data is the forced ranking scale as it would be too exhaustive to rank everything in a list. For the provided data a linear numeric scale is the most straightforward as it rates each item on a scale of 1 to 10. This could be improved to a scale of 1 to more than 10 if the solutions need to be more specific.

To compare multiple rating systems against each other the user must decide when the predicted possible solution is the best. To test this a large data set of ratings should first be acquired because a small data set of ratings leads to worse predictions as opposed to a large data set. Once this is available users then decide on what system is predicting the better solution.

4 Responsible Research

This research was done with private data provided by the My Wellness Check survey. This data was anonymous and not further distributed, therefore it was ethical to do since it is not harmful to any of the participants. To reproduce the findings based on the wellbeing in this research one must have the data provided from the My Wellness Check survey. Furthermore, the other results are created by doing a literature review from existing research papers and can thus be reproduced accordingly.

5 Discussion and future work

5.1 Limitations

The goal at the start of this research was to design and implement a new dashboard for wellbeing data and implement a recommendation system using the data provided by the My Wellness Check. After investigating the data it was made obvious that implementing a recommendation system was not possible. The first reason is that the data is all anonymous. This meant that you can predict a possible solution but you do not know to who it should go.

The second reason is the lack of data. Students and staff were not obliged to answer every question and thus skipped over questions. This lead to missing valuable data for a recommendation system.

The third and final reason was the lack of a rating system. To predict a possible solution in a recommendation system the users must also rate the possible solutions as this is required for collaborative filtering as described in section 2. Because of these reasons and the scope of the entire research the implementation side of the project was stopped. However, this lead to spending more time researching parts that are required for a recommendation system for the My Wellness Check.

5.2 Future work

As this paper was about researching for design a lot can be done in the future. First, the website that is running the survey should get a SSO login connected to the database of the

TU Delft such that students and staff can log in and visit the dashboard.

Once logged in the main object in the dashboard, the recommendation system, should be visible and ready to be used. To do this every user should correspond to a list of features and feature scores as described in section 2.2. This list of features can also be expanded corresponding to the survey. For the items, the possible solutions, the answers given in the survey should be normalised and given feature scores according to the features provided in section 2.2.

The final issue that should be implemented for the recommendation system to work is the rating system. Collaborative filtering requires user ratings on items to predict a new possible solution for the user.

If all of the above is provided and implemented the dashboard and the survey can then be used to improve wellbeing on a personal level.

6 Conclusions

The research question was: *How might we design a dashboard for communicating data to back the community?*. To answer the main questions smaller sub-questions were formulated.

1. How do you recommend solutions?
2. How can a student look at their private dashboard when all the data is anonymous?
3. How does one decide what a good solution for wellbeing is?

The My Wellness Check survey is assessing the wellbeing of the students and staff of the Delft University of Technology. The questionnaire consists of 19 questions and a "Thank you" screen at the end. The data is then used to improve wellbeing on a general level throughout the campus. The goal was to stimulate bottom-up approaches to dealing with wellbeing. Via social media, the question "What daily routines are working well for you" was asked to fetch new ideas for wellbeing. To automate this process a dashboard where students and staff can log in was required.

The first issue is the fact that all the data is anonymous. To work with a dashboard users need to be able to see what is done with their respective data. To tackle this a login system using SSO should be implemented as this is secure but more important usable by the user but still anonymous to the outside world.

The second issue is about the data. Questions in the questionnaire can be left open by the users leading to missing valuable data at the end. This data can be imputed by using the k-Nearest Neighbor algorithm within the SciKit-learn library inside Python. This algorithm uses the Euclidean distance to find the k nearest neighbors and with these neighbors, the missing data can be imputed. The lowest RMSE was when k equals 12.

The third issue that came up was how do you recommend a possible solution for wellbeing to a user. A recommendation system uses users and items to predict items to the users. Both users and items are made of a set of features that depict the most important aspects.

The recommendation system for this calibre should use both content-based filtering to tackle the cold-start problem and collaborative filtering. As the latter uses user ratings on items the dashboard also requires a rating system. Users need to be able to rate different items within the dashboard such that the predictions made in the future are more precise. The rating can be done by using different techniques such as thumbs up/down or a linear scale rating of 1 to 10.
To conclude, the My Wellness check right now is not fit to create a dashboard to improve personal wellbeing. First, the SSO should be implemented. Secondly, data needs to be complete by either deleting rows or predicting missing values. And lastly, a recommendation system with a rating system should be implemented based on the research of this paper.

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