The Ability of Technical Students to Think Realistically About Machine Learning

Turning sci-fi concepts into realistic applications: What gap do we need to bridge to prevent future engineers from treating Machine Learning like magic?

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Making new and innovative products with machine learning takes a lot of understanding, and it is currently unknown to what extent technical students currently possess this understanding about machine learning. This might impact their ability to be realistic about the capabilities and data requirements of machine learning in relation to the performance of the model. If the people who will be making new and innovative products are not able to stay realistic about the abilities and data requirements of machine learning, this can harm the development of new and innovative applications for machine learning.

As a first step, we designed a smart closet in order to understand what is important when designing for machine learning. We made an interactive UI, and used this as an example in a co-design session with technical students where they were tasked with creating a smart closet themselves. Results from the co-design session are that the participants generally did not have a realistic view about what data would be needed for machine learning to work in a highly social context like a smart closet. Furthermore, machine learning was still often treated as a form of "magic" which is able to do anything, which is far from the truth. Based on our findings, we give recommendations for future research directions.

Keywords and Phrases: Machine learning, Morning routine, Outfit generation, Smart home, Engineers, Data requirements, Technical students

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* Everyone contributed equally to the research, for a detailed overview of the individual contributions, see Appendix A.1.

1 INTRODUCTION

Machine learning (ML) models are becoming increasingly more common and widely used and are already known for some key use cases, including but not limited to spam detection in email, image recognition and motion detection. In some cases, ML is more noticeable for users, like in the form of chatbots or content recommendation in streaming services [7]. In the future, ML is only expected to become more wide spread and used for various purposes. It makes sense to argue that the upcoming generation of engineers and designers, who are currently pursuing technical studies, will be tasked with the creation of various machine learning applications. Some of these applications will be directly utilized by users in the form of products and services. All ML models need specific data in order to make accurate predictions, so it makes sense that if someone wants to make use of a ML feature, they will need to provide it with the necessary data. This means that in order to design applications for machine learning, it is necessary to consider what data would be required from the user, how much data, how it will be collected, and how it will be used. It is essential for this data provision to not become bothersome to the user, since they would be less likely to use it if that is the case [2].

According to existing literature, it is difficult for designers to consider what kind of data would be needed for products using ML [3]. Therefore, our research consists of a study in which technical students, the participants, as a group try to judge the acceptability of data collection for ML from a user's point of view. We researched this topic by making use of a specific potential application for machine learning in the future: A smart closet. This is a highly social and innovative concept which uses ML to generate outfits for the user, taking into account various data sources, some of which need to be consistently provided by the user. We set out to explore how willing users would be to use certain smart closet features by comparing their perceived value to the amount of data needed from the user. Performing this research with technical students allows us to determine the ability of these students to be realistic about machine learning's capabilities and its data requirements. This allows us to answer the following research question:

To what extent are current technical students able to realistically consider the capabilities, data requirements and application of machine learning, when trying to apply this by designing for an innovative and highly social context like a smart closet?

This paper describes a summary of existing literature regarding this topic, our process of conceptualizing a smart closet, the co-design sessions used to gain insights, the analysis of the data collected from these co-design sessions and finally an in-depth discussion about the current state of student's abilities regarding novel machine learning applications.

2 RELATED WORK

2.1 Internet of Things in the Smart Home

Machine Learning, a subfield of Artificial Intelligence (AI), is becoming progressively present in our daily lives and stands to change almost everything, including our homes [1,6]. One development already used by many is the Smart Home Assistant (SHA) which are 'helpers' for the smart home environment. They support users through various skills or actions [8]. The SHA illustrates an integration of technology in our environment that is likely to lead to ambient environments which are personalized, context-aware, able to adapt, and even anticipate the users' needs, behaviours, and wishes [9]. However, all those automated attentiveness comes with a price and by that, we do not only mean the high price tag. In order to anticipate to the users' needs, our homes should learn more about us, thus making it important that we keep this data secure. Connecting our home to the Internet of Things (IoT) makes it a potential target for hackers and raises privacy concerns [1]. While smart home technologies such as SHAs have gathered a lot of interest, limited research has been done on the subject of technology resistance. One study by Raff & Wentzel [8] states it would be worthwhile to further investigate how different design-features affect the perceived level of intrusion meaning the negative feelings such as scary, risky, or invasive which may lead to resistance to the technology.

Accordingly, our study will elaborate on this by letting participants determine features of their choice and think about the data needed to make the features work. As SHAs are already familiar to most people, this study explores the integration of a technology that still seems a more futuristic concept and is highly influenced by social context.

Thereafter they are forced to think about the level of intrusion of the different design-features they came up with. We want to pose the question of to what extent future engineers are aware of the potential harm that this learning and collecting might cause as we found no previous research on this topic.

2.2 Privacy vs. Performance

The performance of ML models mainly depends on the availability of data. Therefore, those systems use existing data but also evolve based on what they learn through their encounters with the world. This raises the open question of what features this may lead to, which highlights the need for reframing the conceptual space of how we design in order to shape the technology towards desirable outcomes. Instead of looking at them as passive tools, we must be aware of what they are capable of [4]. Besides, what should we consider a fair and secure use of data? This is a question that calls for placing the human more firmly at the centre of the design process. Human-centred design requires frameworks for how data has to be selected and what level of autonomy should be programmed into autonomous devices [4].

Through a co-design session, this study puts the potential user at the centre of designing a ML application for the future smart home. Here we observe if our future engineers can ideate features that improve from interaction with the system, but more importantly, whether they know what it takes to achieve the desirable outcomes. What do they think are the limits of data use in relation to the usefulness of a ML application and when becomes automating part of the morning routine disturbing?

Most of the devices used in the world of IoT and applications using ML are not primarily designed with security and/or privacy issues in mind. This results in new security and privacy problems, authentication, access control, confidentiality, data integrity, secrecy, etc. Such considerations should be carefully included in the design process of future IoT devices, systems, and protocols while also creating awareness around privacy and security matters among users [5]. Before such considerations can be made properly it is important that the people involved in the making process know what they're talking about. Thus, our research looks at the understanding of technical students regarding the safe handling of data.

2.3 New Design Challenges

New technology regularly enters the market without paying much attention to design and ML can be seen as a technology that is ready for design innovation [3]. As AI is increasingly considered a design material, it may threaten and even disrupt the everyday job of design [4,10]. Designers should adequately envision and refine new uses for AI that have yet to be imagined [10] but therefore, designers must work to re-understand it [3]. Indeed, a study by Yang et al. [10] found that the focus of current research isn't on AI's capabilities and limitations but on getting designers to understand how AI functions. Dove et al. [3] confirms this by stating that UX articles on the web often expose huge misconceptions about what ML can actually do, and many designers treat it too much like magic. This can be substantiated by a statement made by Martins & Gresse Von Wangenheim [6] in which they say that there is a lack of literature proposing adequate ways to teach ML while there is a common understanding that students must be prepared to thrive in the future with both AI and ML.

One reason making it a challenge to achieve design innovation with ML is that it is very different from human intelligence which makes it a difficult design material to work with. UX-designers and other ML practitioners might struggle with making designs that bridge the ML and human perspectives. Lack of education on how to envision products and services that exploit ML may be a cause that supports the misconceptions. A study by Dove et al. [3] evidenced this by that only three of a total of 51 respondents had taken a class about how to integrate ML into the UX-design of products and services. Moreover, this topic is mostly absent in major UX and interaction design course textbooks. Overall, this shows that (design) students have not been sufficiently prepared.

Assuming that students from a technical university do have the understanding necessary to apply ML in a design and anticipate potential hazards, we invite them to participate in a co-design session in which they reflect on what the smart closet of the future will potentially look like and how it should work in order to avoid affecting our daily lives in a negative manner.

3 DESIGN

The research is about a specific machine learning application, in our case we decided to make it about a futuristic smart closet, which can generate outfits based on rich data. This is an example of a machine learning algorithm being used in daily life and would fit within the morning routine of the user. Additionally, this application could have diverse features and would require a large variety of data in order to perform properly due to its highly social context. This would allow us to both research the intrusiveness of the amount of data gathering and test how well other technical students can brainstorm about features that require machine learning, while being realistic about the data requirements for these features.

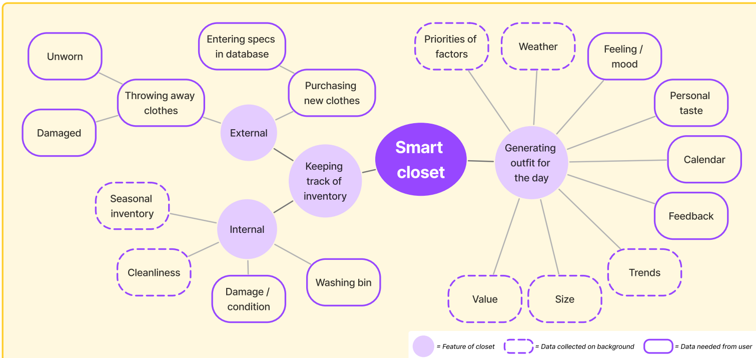

Figure 1: Mind-map with smart closet features and the data needed for these features

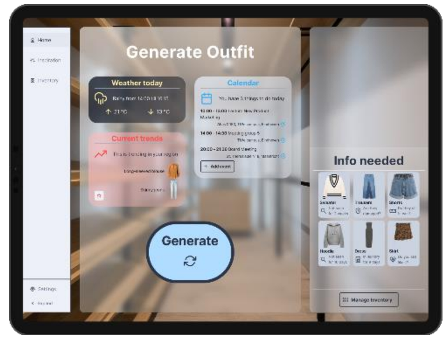

Figure 2: Main page of interactive user interface, to try it out, click here

Our process of designing the smart closet with outfit generation consisted of a brainstorming session, the creation of a user journey flow, and the making of an interactive user interface. While brainstorming, we wrote down ideas about what a smart closet could be able to do on post-its. This included anything from potential features to data used for outfit generation. We then categorized and clustered these post-its into features and data needed for these features, which was then made into a mind-map, which can be seen in Figure 1. Of the needed data, it was also highlighted what should be continuously provided by the user. After determining the features and data, we made a user journey flow to have a more concrete idea where in the UI each feature would be implemented, this can be seen in Appendix A.2.

The interactive user interface, which can be seen in Figure 2, was made using Figma, which allowed us to make interactive buttons and add scrolling behaviour. It is a mid-fidelity prototype in which it is possible to review information, "generate" an outfit and lock or change individual items after an outfit is generated, but the "generated" outfit is always the same. For this research artefact, it was not possible to implement actual machine learning models or data. However, the main goal of this prototype was to present our ideas of what a smart closet could be, not to provide a detailed interactive experience. It is possible to interact with the UI (see **Error! Reference source not found.**). Furthermore, some of the most important screens are shown in Appendix A.3.

The UI prototype has two purposes. Mainly, it serves as an introduction and explanation of our ideas. This can help participants to make their own smart closet features and think of what data would be needed for them. For this reason, we did not make the UI very detailed and intentionally left room for additional features, to prevent participants from merely copying our design. Another purpose of the process of designing a smart closet, is that it gives us a basic understanding of what is needed when trying to implement machine learning in a design and how to think about the data needed for this. This basic understanding can help us analyse the data gathered during our research.

4 STUDY SETUP

As a research method, we performed a co-design session with seven fellow students divided over two sessions. Our aim was to have a diverse set of participants, but in the end most of our participants have a background in Industrial Design. The original goal of this study was to find out what kind of data provision by the user would be perceived as "too much" in the context of a smart closet, with our original research question being: "*How can the experience of the data provision by the user be least intrusive while still providing enough data for a well performing machine learning model in the form of a smart closet?*" We aimed to use this knowledge to find how to balance the general performance of ML with the amount of data provision by the user, because the positive user experience achieved by high performance can be negated by the amount of effort it takes from the user to reach this performance.

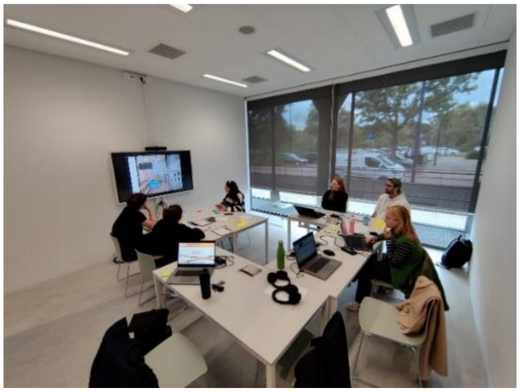

Figure 3: Setup of co-design session

We chose students with a technical background as our participants, because we assumed they would have a good understanding of ML, its abilities, and its data requirements in order to come up with realistic ideas.

The co-design sessions took place in a meeting room on the TU/e campus. Two tables were placed against each other to make a large table around which the participants could sit. The remaining tables were placed at the back of the room and used by the researchers to organize the session and note down observations (see Figure 3). The touchscreen in the room was used to present our UI prototype, post-its were used for brainstorming by the participants and small whiteboards were used to answer questions. Additionally, a smartphone was used to record the audio of the session.

4.1 Session Outline

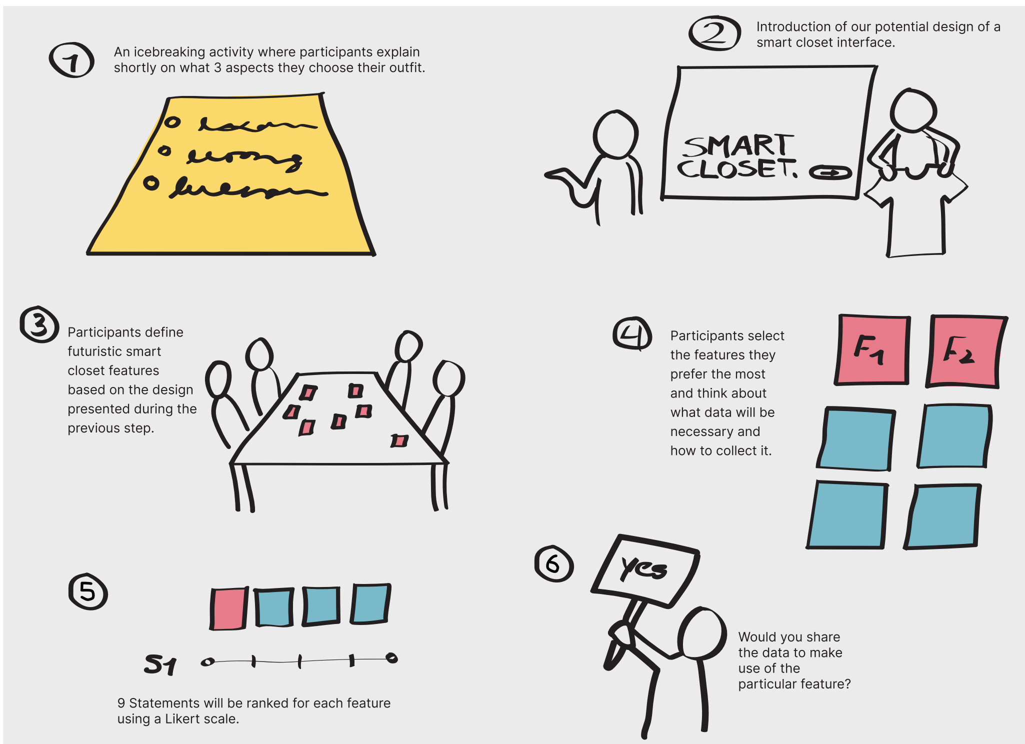

Figure 4: Study setup overview of co-design sessions

A concise overview of the setup of the co-design sessions is provided in Figure 4, with some more details listed in Appendix A.4. The statements used in step 5 can be found in Table 1.

Table 1: Statements asked during co-design sessions and their category

Nr	Category	Statement
1		The data collection method used respects my privacy
2	Intrusiveness	I feel comfortable with the level of intrusion involved in data collection
3		The data collection methods used are non-disruptive to my daily life
4		I believe that the data collected is valuable and serves a meaningful purpose
5	Worthiness	I am willing to provide my data because I see the benefit it brings to me
6		I trust that my data is used responsibly and for purposes that benefit me
7		I am comfortable with the way my data is collected (sensors, apps, manual labour etc.)
8	Acceptability	The transparency of data collection processes is important to me
9		I am willing to provide/share my data when I understand how it will be used and protected

Before the sessions, participants signed a consent form allowing us to collect data during the session, as well as recording the audio (see Appendix A.5). During the sessions, we recorded the audio, wrote down the features created by the participants, their answers to the statements and general observations. The features and answers were directly written down in an Excel spreadsheet prepared before the session, the audio recordings were transcribed and deleted after the sessions.

4.2 Pilot test

Before the main study, a pilot test was conducted in order to test the effectiveness of the study, and some changes were made according to the results of this pilot test. Some of these changes include:

- Because the workshop can take pretty long, we set time limits for each step.
- The statements at the end can be too time consuming, we changed this during the workshops by skipping certain statements and only keeping one per category (see Table 1).
- We decided that we can aid in collecting or thinking of new features to make sure participants don't get stuck with the same features.
- We streamlined the sessions more by breaking it up into clearer steps. Before, we asked for features and datapoints in the same step, now we ask for the features first and data points after.

5 FINDINGS

We divided the findings into 2 parts, the qualitative and quantitative part. In the qualitative part, we extracted the participant's answers directly from the post-its used in the workshop. This is followed by the quantitative part which covers the survey which was conducted later in the workshop determining the participants' views on the intrusiveness, worthiness and acceptability of the predetermined features.

5.1 Qualitative Results

As for the qualitative results, we look at the data from session 1 and 2 separately. In the first session, as seen in Table 2, the participants brainstormed 10 different features with a range from 2 to 9 datapoints required for each feature.

Upon exploring the qualitative data from the first session (see Table 2), it becomes clear that the definition of a "datapoint" is vague and open for interpretation. We can see that the participants label "be in control of the data you share" and "possibility to look at other closets" as datapoints, while these notions better describe a feature which requires data instead of datapoints for a feature. Looking at Table 2, we can see that this misinterpretation is a recurring factor. To further back this finding, in the first session 19 out of the 53 (or 35.8%) labelled datapoints which can be considered features or added functionalities instead of concise datapoints, marked by the asterisk (*) in the figure.

In the second session, as seen in Table 3, the participants brainstormed a multitude of different features and later grouped them together. The features seen in the table resemble a group of the features the participants wanted. The participants came up with 6 different (grouped) features with a range of 2 to 5 datapoints required for each feature.

From this second session we can see that for some of the features, the datapoints which they require are not sufficient enough for the full functionality of the feature. For example, in the feature "Scheduling" the participants picked the datapoints: "Location and destination", "Transport type", and "Local traditions" while they overlooked "Occasion", "Duration", "People involved" and likely more influential factors. Looking at Table 3, we can see that this is a recurring factor, like "Automatic storing mechanism" would need more datapoints besides "Storage space" and "Seasons and weather", like "The different users of the closet", "Placement convenience", "Material properties", and "Likability" to illustrate another example.

We can see that for each feature in the second session, there is a smaller amount of datapoints required compared to features in the first session. This indicates there is a difference between the two groups when it comes to determining the required datapoints. While the datapoints from session 1 contain multiple vague datapoints which can be considered to be separate features, in session 2 we don't see this phenomenon. The datapoints in session 2 seem to be better aligned with the feature it represents, however the amount of datapoints in session 2 remains lacking and would likely need more datapoints to become feasible.

Table 2: Features and their coherent datapoints collected in session 1 (Actually relevant datapoints are in **bold**, if it suggests a feature or functionality it is not in bold)

Feature	"Datapoints" from participants
Link closets with friends to share and check outfits	• Each closet requires its own account • Be in control of which clothes are viewable for each specific friend • Share what you are wearing • Share what clothes are in your closet • Be in control of the data you share • **Style preferences** • Possibility to look at other closets
Laundry	• Configure that the closet notifies you how much clean clothes are left, so you never run out. • **How full your laundry basket is.** • **Link your agenda to find suitable outfits.**
Live clothing information and notifications	• **Location of the clothing pieces** • **The time spent at the current location**
Seasonal directed/dependent inventory	• **When summer/winter clothes should leave the closet** • **Different labels between summer/winter clothes** • Option to select "not in use"
Inventory management	• **Current condition (wear and tear)** • **How often did you wear the clothes recently** • **Seasonal changes** • **Are the clothes still in fashion** • **Track and monitor the sizes** • **Check the location of the items**
Generate an outfit based on 1 pre-selected item	• **The same data that is also used for determining your outfit** • **Style** • **Personal input** • **Closet's inventory** • **Outside temperature**
Shoes and other accessories	• Visually identify the accessories • **Accessories that are worn day in day out** • Baskets with weight sensors to recognize when something is gone from the collection • **Manually input the location of the accessories if tags are not available or possible** • See if a tag can be used or not
Link agenda to find outfit for the day after, but also give recommendations for outfits for on vacation	• **Amount of days away** • Notification if the agenda is not up to date • **Temperature for vacation destination** • **Recognize patterns** • **Agenda linked to dress code for the activity, who, what, where, why** • **Agenda** • **Location for activity**
Weather	• **Inside or outside activity** • **Adjust to the feedback of the user** • **Location of the activity** • Adjust to changing weather conditions, suggest multiple layers • Dress code appropriate to the weather conditions • **Weather app data** • What are others wearing today

	• Advice for different parts of the day • Be able to select who's outfit you want to see
Indication of where clothes are located	• **Start with providing the system with the closet's inventory** • **The exact location where in the closet, clothes are laying** • **Approximation of the clothes' location** • The closet is able to adjust itself, space wise • Advice on where to store clothes in your closet • **Location of clothes**

Table 3: Features and their coherent datapoints collected in session 2

Feature	"Datapoints" from participants
Outfit selection	• Stock data • Trends • Materials & colours • Brand • Preferences and style
Maintenance	• Wear and tear • Stock • Purpose of usability • Material properties
Weather	• Outing location • Method of transportation • Weather and calendar
Scheduling	• Location and destination • Transport type • Local traditions
Automatic storing mechanism	• Storage space • Seasons and weather
Laundry and availability status	• Material properties • Wear status • Cleaning status

5.2 Quantitative Results

As for the quantitative results, we grouped similar features together which resulted in 7 different features, namely: closet management, laundry management, seasonal and trends, outfit creation, event and weather, accessories, and maintenance. A simple overview of how these 7 features came together can be found in Figure 5.

From the conducted statement surveys, as seen in Table 1, we created pie charts which gave us some insight into the intrusiveness, worthiness and acceptability of each feature. Here, it can be noted that out of 237 responses, only 4 (1,7%) of those responses were not in agreement, compared to 59 (24,9%) neutral and 174 (73,4%) agreeing responses. These can be found in Appendix A.6.

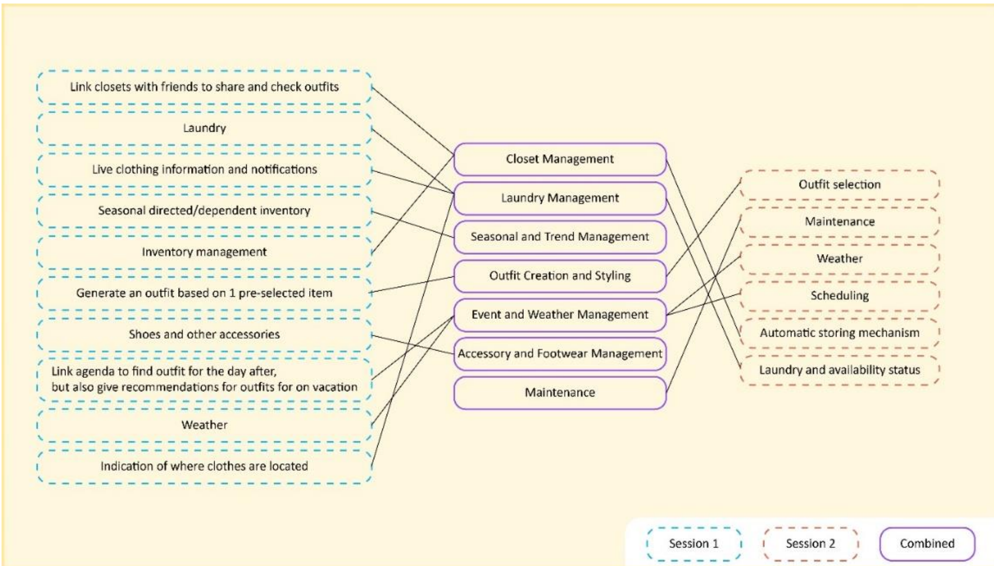

Figure 5: Overview of combined features

6 DISCUSSION

During our co-design session we initially focussed on the question of how machine learning should be used in the future concerning the data provision of the user being perceived as acceptable and worthwhile. During the co-design session and after analysing the data we discovered that the answers given implied a lack of knowledge of ML and therefore a much more interesting question came up. The focal point of this discussion will therefore be: "*To what extent are current technical students able to realistically consider the capabilities, data requirements and application of machine learning, when trying to apply this by designing for an innovative and highly social context like a smart closet?”*

6.1 Everything is Worthy, Acceptable and not Intrusive

The most remarkable finding is that 174 of the 237 responses (73,4%) of our participants agreed to the statements about worthiness, intrusiveness and acceptability of the data points and its features. Since these answers are almost always agreeing, we used qualitative data to further investigate this which will be discussed below. When analysing the transcript, it came to light that the participants developed the closet in a way that their data would always be protected. They also developed it so that they are always in control about sharing their data with whom. This resulted in almost always answering the statements positively (agree of fully agree).

6.1.1Privacy and ML

When looking at the qualitative data it was derived that the participants decided that you can choose yourself what data you want to share, leading to them assuming that their privacy sensitive data would not be shared with anyone unwanted. In this way the participants tended to agree often with the statements concerning the safety of personal data. For example, when the statement was given "*The data collection method used respects my privacy*" for the feature of linking your smart closet to your friend's smart closet. Data points collected, according to these participants, were: personal account (gender, name, body measurements, etc.), looking into the database of friends' closets, what you are wearing and style preferences (Figure X).

From this thought process, it could be derived that they for example didn't consider the company which sells the smart closet, people who develop the ML, doom scenario's (hacking), etc.. "*Well, as we said earlier, you can choose yourself what you want to share. So, it then it becomes your own choice how much privacy you have.*" and "*If I share with my friends I don't mind. If I would link this with the whole world, I think it would be different, but now we have decided that we can choose ourselves with whom we are sharing our data.*" These quotes imply the misconception these technical students have within the usage of data for ML in a highly social context.

The data collected for ML namely cannot be 100% classified for the user only, since their data is needed on a regular basis by the ML algorithm to function (by for example being linked with output factors like socials or stores or input factors like the internet of things). Besides, someone administers the ML algorithm and probably supervises it for further development.

However, they do mind when their (external) data is processed without their knowledge to improve the ML algorithm of the closet: "*it would be a lot of intrusion if it would automatically be read from my apps*". This is remarkable since the participants would like to connect a third-party app to the ML algorithm for an improved UX of the smart closet. Nevertheless, they do mind if this data will be used by a third party in other ways they imagined (even though they gave consent in when connecting the third-party app to the smart closet).

Additionally, participants indicated that they would share personal data with the ML algorithm easily when their data is already on the cloud (with the knowledge that the data of the smart closet is as good protected as the data shared with for example 'Google'): "*And well, you already put personal information on the Cloud, so I think the cloud is not really the problem concerning how safe your data is.*". This perception of the participants could be dangerous since the more places and institutions their personal data is shared with, the higher the chance gets that this data will for example be misused by companies or hacked.

By looking at the qualitative data we see that technical students do want to have grip on their data, also share data if its already on the cloud due to convenience. But they do mind if personal data gets used by external parties on the background without the closet indicating this properly to them.

6.1.2Deriving and Processing Data for ML Features

Additionally, the participants also seemed to have misperception of how this data would be processed. For example, when looking at Table 2, the participants stated that the ML algorithm was able to look into the users' agenda, deriving recommendations for washing based on the activities planned in the agenda. During the session it wasn't discussed how this data would be derived indicating that the participants used a level of magic for the ML. Questions like "how would the ML read out data of the agenda?" and "How does the ML know that 'meeting with Max' should require which outfit?" didn't appear. These are critical questions to let this feature function. It was also remarkable that the technical students didn't question if a feature would be realizable or not, they didn't question the ability of the ML and therefore assumed that the features they came up with were all realizable.

6.2 Needed Data and its Collection

When looking at the post-it's the participants used to define data points needed to perform a feature, it was noticed that misperceptions appeared. The participants didn't seem to be aware what data points are, what data was needed to let a feature function properly and how these data points were collected.

6.2.1Datapoints vs Features

When looking at the findings from session 1 and Table 2 it can be derived that the participants didn't really understand what a data point is. The task here was to write down one data point per blue post-it so that the feature "Linking smart closets with friends to share and check outfits" would be functioning. The technical students thought that a data point needed to let this feature work was "*Being able to indicate if you can look into each other's closets*" or "*Sharing style preference*". These post-its don't refer to a data point like type of shirt, colour, size, state of shirt, etc. but more likely appear to be sub-features. This gave the impression that the participants were not fully aware what data points are and therefore which and how many of them are needed to let the ML of the smart closet make valuable predictions.

6.2.2Data Collection

Because of the lack of ability to derive data points for the features, the participants were also limited in thinking about how this data would be collected (e.g. through GPS, NFC, camera, etc.). Therefore, limitations also occurred when asking the participants about for example the level of intrusiveness or manual labour for each feature. The qualitative data showed that the participants were unaware of the fact that a machine learning algorithm requires a lot of training data to perform optimally. This could be another explanation of the high agreement rate of the qualitative data.

6.2.3Storage of Data

Lastly it seemed that the participants also had a misperception of how storage of data for certain features leading to a possible misperception of the level of privacy of their data. "*R1: should this data be stored in the cloud or do you want it to be in a box in your home for example? P1: I most certainly think that all the personal data I gave my closet shouldn't have to be on the cloud. Only the data the closet needs to function. R1: Yes, and if it for example connects with closets of friends? P1: Yes, then you need the cloud. R1: So, then you need the cloud? P1&3: Yes.*" This conversation implies that the technical students didn't think through while designing the smart closet how their data would be stored compared to certain features and if they find this intrusive in terms of for example privacy. As Hossain et al. [5] implies, most ML applications are not necessarily designed with security and/or privacy issues in mind, which is in line with the finding described in this section.

6.3 Summarized findings

To summarize our findings, we can say that even technical students have many misconceptions when asked to apply ML to, in this case, the design of a smart closet which implies that it is still mostly treated like magic. Our participants show that they want to be in control of the sharing of their data and, thus, their privacy. However, their thought process showed that their requirements and the resulting features did not match the data point they wanted to give up for this purpose. As the study by Raff & Wentzel [8] says "The perceived intrusion describes the degree to which a person perceives that a particular smart technology would lead to continuous observation and uncontrolled and undesired sharing of privacy". Our participants revealed that they would find it intrusive if their data was used without their knowledge, but showed the opposite in their responses to the statements. Besides, they mainly showed a lack of knowledge when it came to thinking about what are the right data points needed for such an algorithm to work properly, how we can collect those data points, how much effort it takes to collect the data, and where the data is stored. This is in line with research from Giaccardi & Redström [4] which states that design methods must be apt to anticipate possible consequences and consider the contextual significance of the data used.

Our findings contribute to the fact that education lags behind in applying ML in a highly social context and thus complements the research of Dove et al. [3]. Furthermore, the fact that the participants mostly agreed to the statements is speculated to be driven by the cause of comfort of ML application in combination with the lack of knowledge, leading to an unrealistic positive view of ML applications [8]. This can be substantiated by the fact that our participants have not made realistic considerations regarding security and/or privacy issues.

6.4 Limitations

For the co-design session, and therefore the research conducted, various limitations were identified. Starting with the knowledge of data needed for certain ML features of the closet. This limitation of the research led to limited exploration of thoughts and opinions of data points and its usage for ML applications.

Furthermore, a limitation of research was that the original research focussed on the question of how ML should be used in the future. It seemed like technical students didn't understand ML that well which is why the research shifted towards how well technical students understand ML. This lead to a misalignments between the codesign session and our new research direction.

Also, only 7 participants participated in the co-design session which is, on a quantitative scale, not optimal and also a limitation of the study. Additionally a thorough understanding of machine learning was not a requirement of recruiting participants. Therefore it should be considered that our findings don't represent all technical students.

Lastly, a mid-fidelity prototype (combined with 'the wizard of oz' technique) was created because of the timeframe of the research. This prototype was could therefore be unclear or incomplete in terms of the presented features.

6.5 Interesting Future Directions

Based on the findings and discussion of our research we are implying some interesting future directions within the field of ML for technical students. Technical students seemed to have a lack of knowledge within the subject of ML even though it has a lot of impact when implementing this more and more into our society. We therefore recommend doing research into how it is possible that technical students have these misconceptions and lack of knowledge about ML. Subsequently if these misconceptions and knowledge gaps would be decreased in the future, we also recommend researching how technical student then would rate the intrusiveness, acceptability and worthiness within ML applications in the future.

7 CONCLUSION

This study addresses the knowledge gap technical students have with regard to designing a futuristic concept that uses an ML algorithm to automate part of the daily routine and operates in a highly social context. Through a co-design session in which we asked technical students to design features for a potential smart closet and, in addition, think about what data is needed to do so, we investigated their attitude towards statements concerning intrusiveness, worthiness, and acceptability. From our findings and previous research on this topic, we see that our future engineers lack realistic knowledge to accomplish such an exercise. Our study contributes to the specific gaps in knowledge that exist among our participants by citing various misconceptions and contradictions. With this, we open the discussion around, for example, improving education on ML and especially the role data plays in it. Further research is desired to discover where these misconceptions and unrealistic views could come from and whether they would judge the statements differently if they had more background knowledge of the capabilities, the ambient behaviour, and the associated dangers of ML. However, it should be noted that our findings are retrieved from a small group of participants who were not asked beforehand about their understanding regarding AI and ML. Thereby, our initial focus of this study was different during the time of data collection making our results rather assumptions. Yet, we found related work that substantiates these findings partially making our research a legitimate start for more research on this topic.

ACKNOWLEDGMENTS

We extend our heartfelt thanks to Lenneke, our project coach, for her guidance and support. Furthermore, we also want to thank the lecturers of this course for the insightful sessions and source of inspiration. We are also grateful to the seven participants from the co-design session for their valuable contributions. Your involvement greatly enriched this research.

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A APPENDICES

A.1 Individual contributions of researchers

Please note that the researchers applied similar amount of effort to the research. Tasks were divided throughout the process in order to work as efficiently as possible. Some parts take more time than others. Also, while every part had someone with the main responsibility over it, everyone regularly checked, gave feedback on and made edits to each other's work.

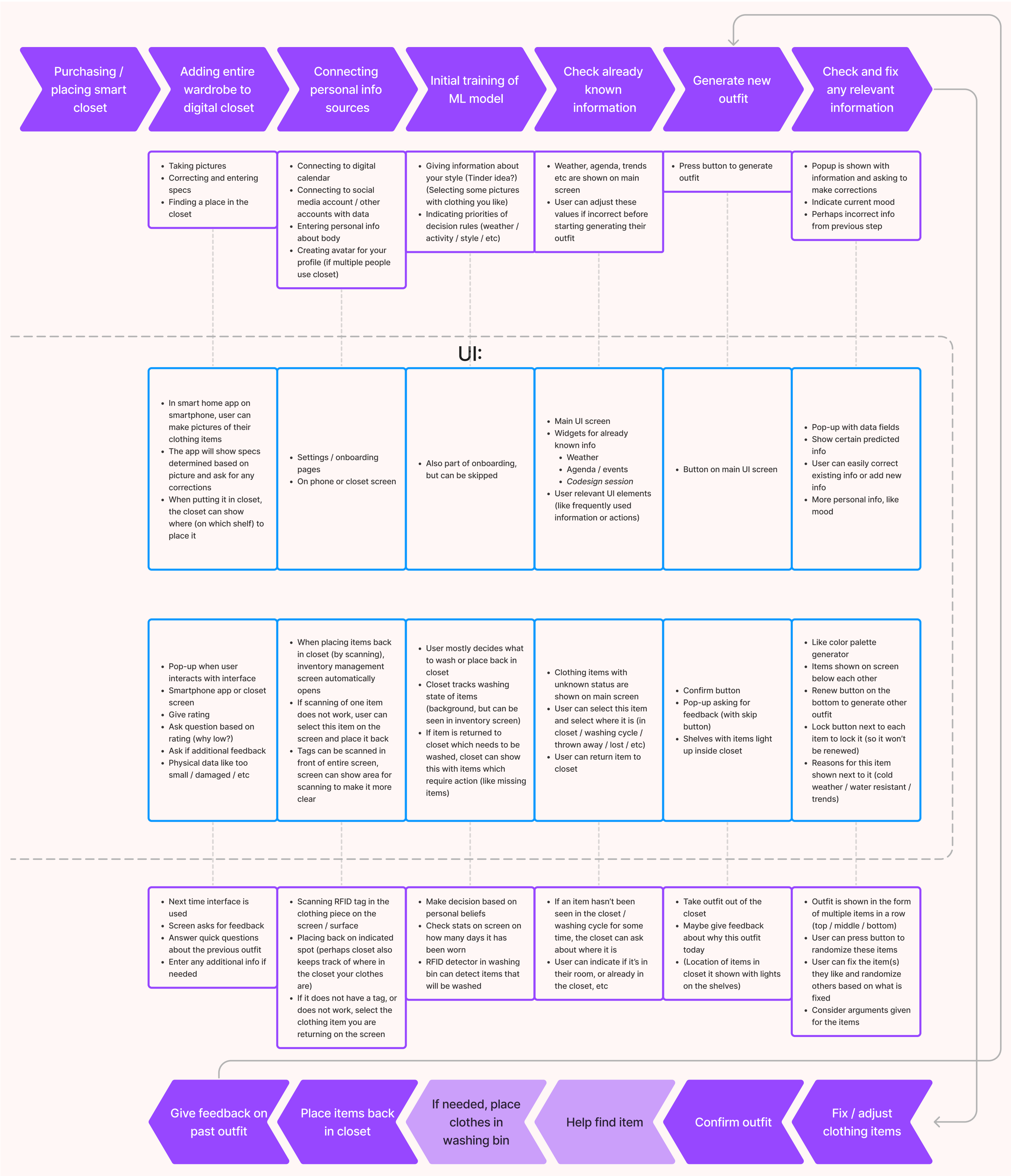
Table 4: Individual contributions of paper

Section of Paper	**Person**
Abstract	Jochem
Introduction	Jochem
Related Work	Blom
Design	Jochem
Study Setup	Jochem
Findings	Boy
Discussion	Alexandra
Conclusion	Blom

Table 5: Individual contributions to the research

Work / tasks	**Person**
Brainstorming and designing smart closet	Everyone
UI Prototype: Main page + Inventory page	Jochem
UI Prototype: Onboarding + Inspiration page	Blom
Making co-design session	Boy + Alexandra
Conducting co-design session	Everyone
Transcribing session 1	Alexandra + Blom
Transcribing session 2	Boy + Jochem
Main analysis of data	Alexandra + Boy

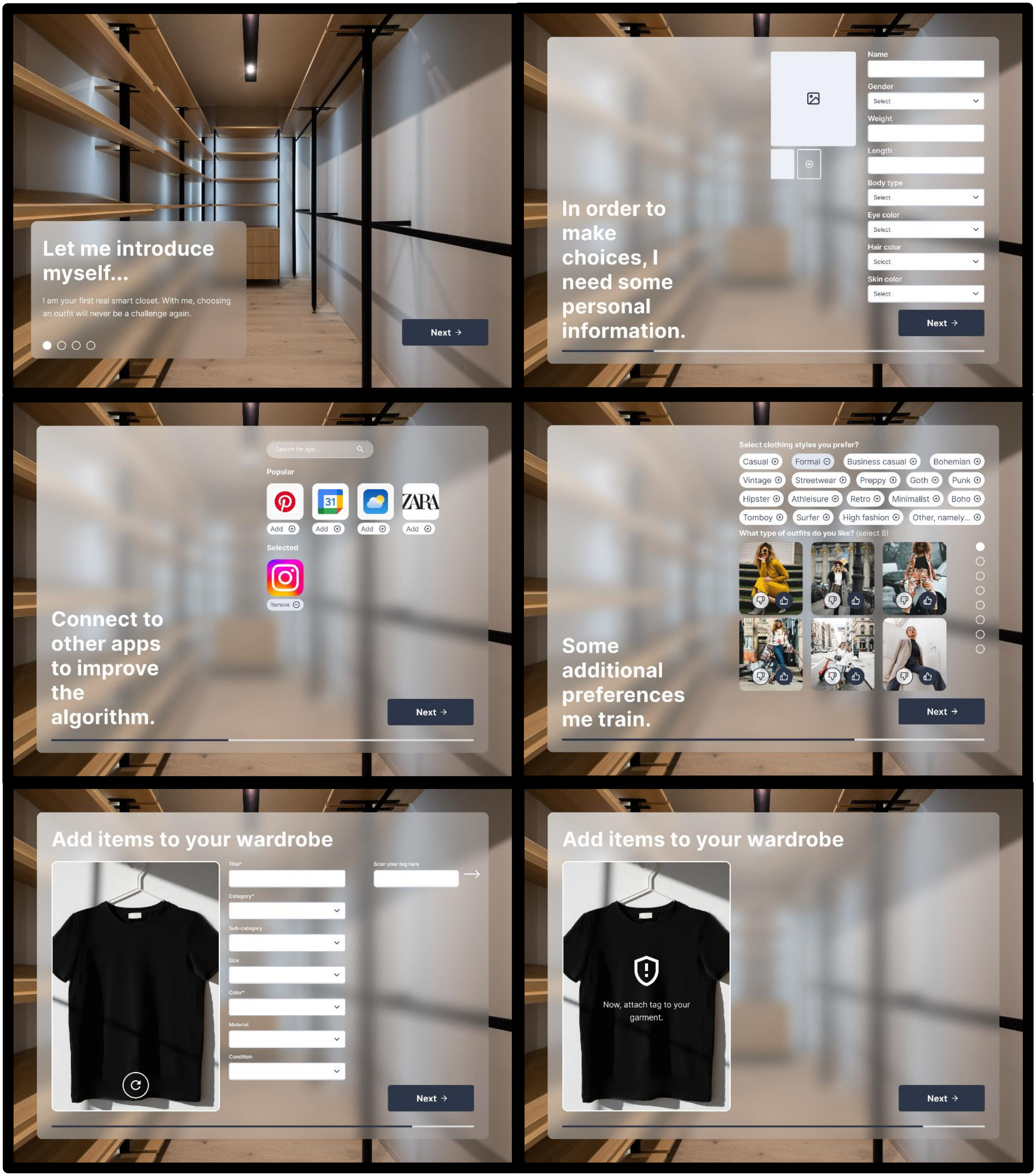
A.2 User journey flow to determine how to structure the UI



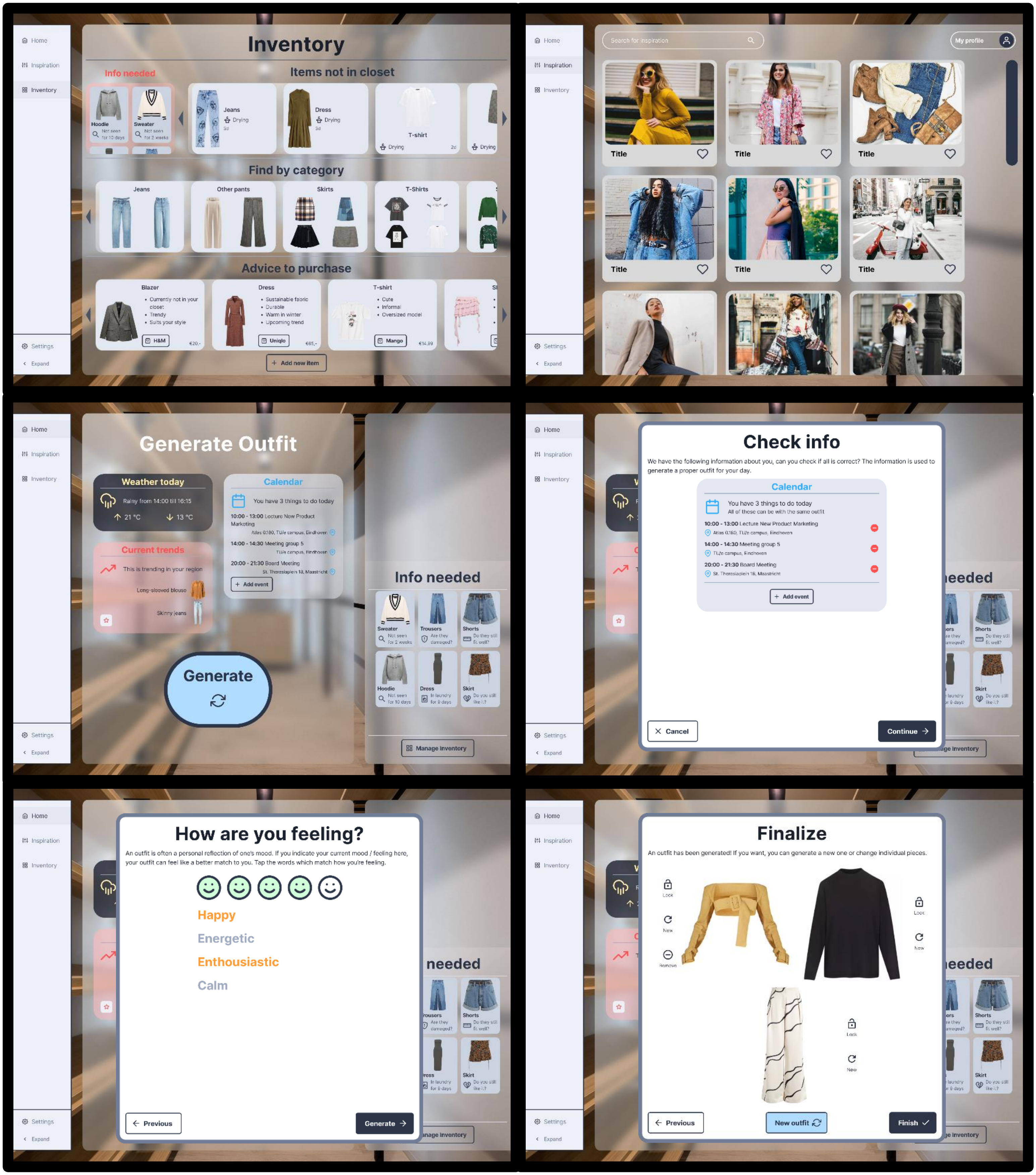
A.3 Some important screens in the UI prototype

You can see and interact with the full prototype by clicking here.

Onboarding phase: This explains the capabilities of the smart closet, but also takes quite a bit of effort to set up and provide it with enough data.



During usage: This clearly shows the value of the smart closet, but at the same time it asks for information and data from the user at multiple places in order to keep functioning properly.



A.4 Detailed co-design session outline

1. All participants write on a post-it how they choose their outfit and what aspects they find important. Afterwards, everyone shares their name and says what they wrote down. – *5 min*
2. We introduce ourselves as the researchers, and present our smart closet UI on the touchscreen. We explain the features and the data needed for those features, and show how the user can provide this data in the UI. – *5 min*
3. After receiving an introduction into the topic of smart closets, we ask the participants write down any feature they would like to have in their own smart closet. For every feature they use one post-it. These can be features we have in our UI, or new features. During this process, we can help them brainstorming by asking questions about what they would find important to have or would want to use. Afterwards, we let the participants select a number of features they think are most important. – *15-20 min*
4. For the features selected, we ask the participants to write down any data necessary for this feature to work. For example, the feature of choosing an outfit based on weather conditions requires data about the weather forecast, how long the outfit will be worn, but also the location of the user. They write down one data point per post-it, we can help brainstorming to keep them thinking about different data needed for this specific feature. – *10-20 min*
5. If the participants are done with the data points, we take all post-its away and leave one feature and their datapoints behind. For this specific feature, and its relevant data points, we present nine statements on the screen for the participants to answer on a Likert scale (1 – 5). They individually write down their answer on a mini whiteboard, and show it to each other and us after. If there are any differences in the answers, we can ask individual participants to explain why they chose this answer. The statements are listed in Table X, during the sessions some statements were left out due to time reasons. Note that all statements are formulated “positively”, which means that if a person agrees, they are generally positive about the feature and its data requirements. – *60-80 min*
6. After having answered the statements for every feature, we ask the participants to raise their hand if they would use a certain feature, and finally if they would want a smart closet in general. – *5 min*

A.5 Consent form used in co-design session

Instructiepagina

Informed consent formulier LR

Dit toestemmingsformulier (incl. privacyverklaring) gebruik je in de volgende situatie:
Je verwerkt in het kader van onderzoek persoonsgegevens met toestemming van de deelnemers als verwerkingsgrondslag. Er is géén sprake van bijzondere of gevoelige (vertrouwelijke) persoonsgegevens (zie FAQ) en een DPIA (zie FAQ) is voor het onderzoek niet noodzakelijk. De beschrijving van het onderzoek is niet heel uitgebreid. Hierdoor kan de privacyverklaring en het toestemmingsformulier worden samengevoegd.

De informatie in de zijbalk is een toelichting bij de betreffende tekst. Deze comments dienen bij afronding uit het daadwerkelijke document te worden verwijderd. De gele blokken geven aan welke informatie in ieder geval aangevuld dient te worden of waar een keuze gemaakt moet worden door de onderzoeker. Gelieve deze informatie in dit formulier in zo eenvoudig mogelijk taalgebruik te delen. Het template moet zo goed mogelijk gevolgd worden en er mogen géén subkopjes verwijderd worden.

Op basis van deze informatie kan een potentiele deelnemer een geïnformeerd en formeel besluit nemen met betrekking tot zowel participatie aan het onderzoek als de verwerking van zijn of haar persoonsgegevens in dat kader.

Integreren in websurvey etc.
Het is mogelijk dit formulier te integreren in een online websurvey. Toestemming kan namelijk ook worden gegeven middels een digitale Ondertekening of het zetten van een vinkje.

Het is mogelijk om onderdelen 1 t/m 6 te vermelden op de hoofdpagina van een website, met daaronder het toestemmingsformulier, en de resterende onderdelen 7 t/m 9 op te nemen in een aparte weblink. Gebruik dan de hiervoor opgestelde tekst zoals opgenomen onderaan onderdeel 6.

Controle
Vul het formulier in door gebruik te maken van track changes en deel deze vervolgens met de data steward van jouw faculteit ter review. Voor aanvullende ondersteuning en maatwerk kan eveneens contact opgenomen worden met de data steward.

Informed consent formulier LR – Versie 1.0 – mei 2022

Informatieblad voor onderzoek "Questioning Machine Learning futures in the field"

1. Inleiding
U bent gevraagd om deel te nemen aan het onderzoek Questioning Machine Learning futures in the field, omdat u onderdeel bent van ons persoonlijke netwerk.

Deelname aan dit onderzoek is vrijwillig: u besluit zelf of u mee wilt doen. Voordat u besluit tot deelname, willen wij u vragen de volgende informatie door te lezen, zodat u weet waar het onderzoek over gaat, wat er van u verwacht wordt en hoe wij omgaan met de verwerking van uw persoonsgegevens. Op basis van die informatie kunt u middels de toestemmingsverklaring aangeven of u toestemt met deelname aan het onderzoek en met de verwerking van uw persoonsgegevens.

U bent natuurlijk altijd vrij om vragen te stellen aan de onderzoeker Alexandra van Dijk via a.n.v.dijk@student.tue.nl, of deze informatie te bespreken met voor u bekenden.

2. Doel van het onderzoek
Dit onderzoek wordt geleid door onder andere Alexandra van Dijk.
Het doel van dit onderzoek is achterhalen wat de ideologie van toekomstige Machine Learning is in het geval van een 'smart closet'.

3. Verwerkingsverantwoordelijke in de zin van de AVG
TU/e is verantwoordelijk voor de verwerking van uw persoonsgegevens in het kader van het onderzoek. De contactgegevens van TU/e zijn:

Technische Universiteit Eindhoven
De Groene Loper 3
5612 AE Eindhoven

4. Wat houdt deelname aan de studie in?
U neemt deel aan een onderzoek waarbij we informatie zullen verzamelen door:
- Wij vragen u 1 keer op locatie te komen zodat wij een workshop kunnen houden waarin wij u interviewen over de behoeftes rondom een 'smart closet'.
- U te interviewen over de acceptabelheid van dataverzameling ter behoeve van machine learning in het geval van een 'smart closet' en uw antwoorden te noteren/op te nemen via een audio-opname. Er zal ook een transcript worden uitgewerkt van het interview.
- Observatie

U ontvangt voor deelname aan dit onderzoek geen vergoeding.

5. Potentiële risico's en ongemakken
Er zijn geen fysieke, juridische of economische risico's verbonden aan uw deelname aan deze studie. U hoeft geen vragen te beantwoorden die u niet wilt beantwoorden. Uw deelname is vrijwillig. Dit betekent dat u uw deelname op elk gewenst moment mag stoppen door dit te melden bij de onderzoeker. U hoeft niet uit te leggen waarom u wilt stoppen met deelname aan het onderzoek.

6. Intrekken toestemming en contactgegevens
Deelname aan dit onderzoek is geheel vrijwillig. U kunt als deelnemer uw medewerking aan het onderzoek te allen tijde stoppen, of weigeren dat uw gegevens voor het onderzoek mogen worden ge bruikt, zonder opgaaf van redenen. Het stopzetten van deelname heeft geen nadelige gevolgen voor u.

Als u tijdens het onderzoek besluit om uw medewerking te staken, zullen de gegevens die u reeds hebt verstrekt tot het moment van intrekking van de toestemming in het onderzoek gebruikt worden.

Informed consent formulier LR – Versie 1.0 – mei 2022

Wilt u stoppen met het onderzoek, of heeft u vragen en/of klachten? Neem dan contact op met de onderzoeker via a.n.v.dijk@student.tue.nl.

Indien u specifieke vragen hebt over de omgang met persoonsgegevens kun u deze richten aan de functionaris gegevensbescherming van TU/e door een mail te sturen naar functionarisgegevensbescherming@tue.nl. U hebt daarnaast het recht om een klacht in te dienen bij de Autoriteit Persoonsgegevens.

Tot slot heeft u het recht een verzoek tot inzage, wijziging, verwijdering of aanpassing van uw gegevens te doen. Dien uw verzoek daartoe in via privacy@tue.nl.

7. Grondslag voor het verwerken van uw persoonsgegevens
De grondslag waarop wij uw gegevens verwerken is toestemming.

8. Welke persoonsgegevens verzamelen en verwerken wij van u?
In verband met het onderzoek verwerken wij de volgende persoonsgegevens:

Categorie	Persoonsgegeven
Functieprofiel	*Studie*
Woning	*Woonsituatie*

9. Vertrouwelijkheid van gegevens
Wij doen er alles aan uw privacy zo goed mogelijk te beschermen. De onderzoeksresultaten die gepubliceerd worden zullen op geen enkele wijze vertrouwelijke informatie of persoonsgegevens van of over u bevatten waardoor iemand u kan herkennen, tenzij u in ons toestemmingsformulier expliciet toestemming heeft gegeven voor het vermelden van uw naam, bijvoorbeeld bij een quote.

De persoonsgegevens die verzameld zijn via audio-opnamen, interviews en andere documenten in het kader van deze studie, worden opgeslagen op opslagfaciliteiten die ondersteund worden door de IT-afdeling van TU/e, opslagfaciliteiten van TU/e met extra beveiligsmaatregelen. Dit betreft OneDrive en dit is beveiligd middels een verificatiecode.

De ruwe en bewerkte onderzoeksgegevens worden bewaard voor een periode van 2 jaar. Uiterlijk na het verstrijken van deze termijn zullen de gegevens worden verwijderd of worden geanonimiseerd zodat ze niet meer te herleiden zijn tot een persoon. De onderzoeksgegevens worden indien nodig (bijvoorbeeld voor een controle op wetenschappelijke integriteit) en alleen in anonieme vorm ter beschikking gesteld aan personen buiten de onderzoeksgroep.

Dit onderzoek is beoordeeld en goedgekeurd op 7-10-2023 door de ethische toetsingscommissie van de Technische Universiteit Eindhoven.

***** Scroll naar beneden voor het toestemmingsformulier *****

Toestemmingsformulier voor deelname volwassene

Door dit toestemmingsformulier te ondertekenen erken ik het volgende:

1. Ik ben voldoende geïnformeerd over het onderzoek door middel van een separaat informatieblad. Ik heb het informatieblad gelezen en heb daarna de mogelijkheid gehad vragen te kunnen stellen. Deze vragen zijn voldoende beantwoord.

2. Ik neem vrijwillig deel aan dit onderzoek. Er is geen expliciete of impliciete dwang voor mij om aan dit onderzoek deel te nemen. Het is mij duidelijk dat ik deelname aan het onderzoek op elk moment, zonder opgaaf van reden, kan beëindigen. Ik hoef een vraag niet te beantwoorden als ik dat niet wil.

Daarnaast geef ik toestemming voor de volgende onderdelen van het onderzoek:

3. Ik geef toestemming om de persoonsgegevens die gedurende het onderzoek bij mij worden verzameld te verwerken zoals is opgenomen in het informatieblad.

   JA ☐ NEE ☐

4. Ik geef toestemming om tijdens het interview opnames (geluid) te maken en mijn antwoorden uit te werken in een transcript.

   JA ☐ NEE ☐

5. Ik geef toestemming om mijn antwoorden te gebruiken voor quotes in de onderzoekspublicaties – zonder dat daarbij mijn naam wordt gepubliceerd.

   JA ☐ NEE ☐

Naam Deelnemer:

Handtekening:

Datum:

Naam Onderzoeker:

Handtekening:

Datum:

Informed consent formulier LR – Versie 1.0 – mei 2022

A.6 Pie charts from answers to statements

Figure 6: Pie chart representing the answers to the intrusion statement: "I feel comfortable with the level of intrusion involved in data collection" and "The data collection method used respects my privacy."

Figure 7: Pie chart representing the answers to the worthiness statements: "I am willing to provide my data because I see the benefit it brings to me" and "I believe that the data collected is valuable and serves a meaningful purpose."

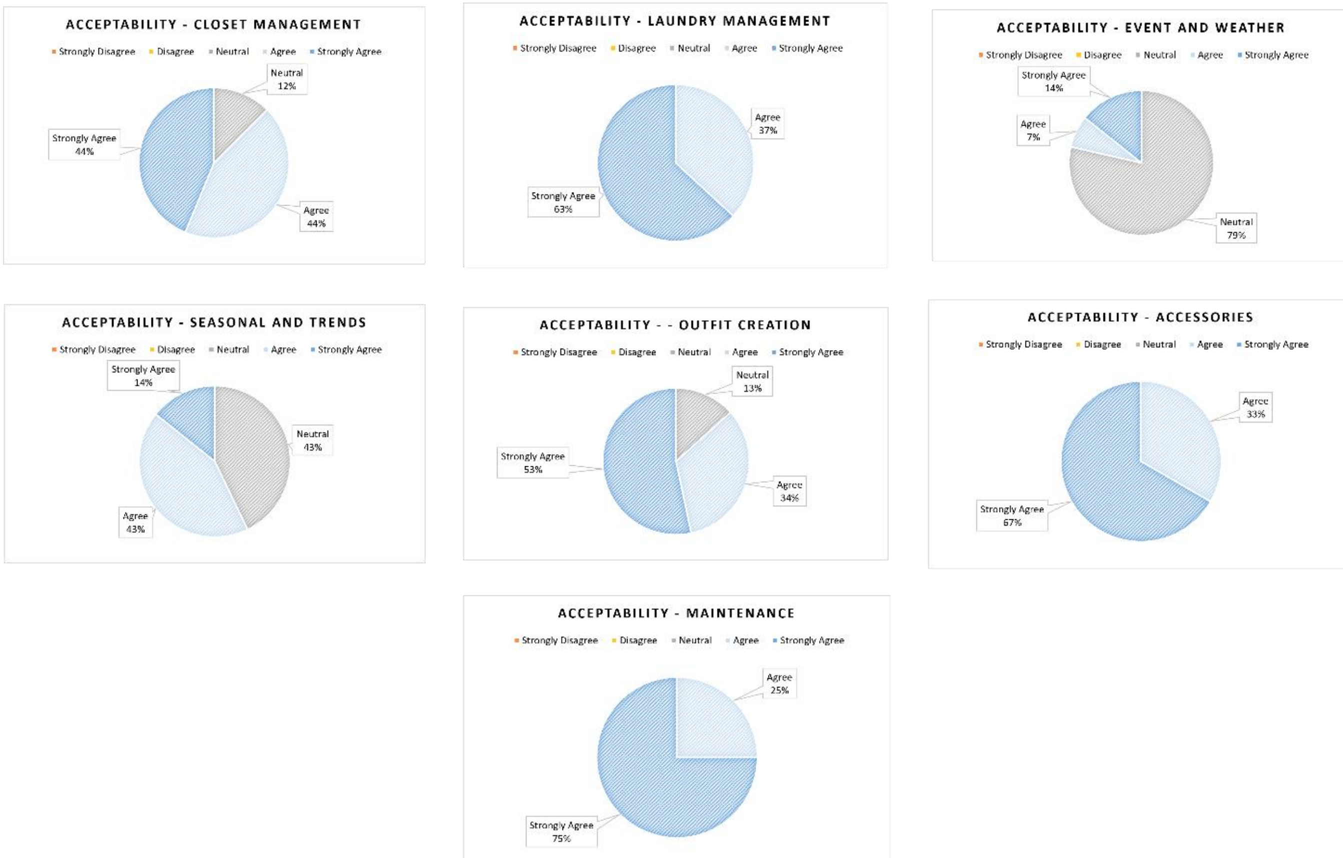


Figure 8: Pie chart representing the answers to the acceptability statement: “I am comfortable with the way my data is collected.