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Facebook data shield: An interactive tangible interface for user data control

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Abstract: Social media platforms like Facebook utilize AI algorithms to personalize content based on user data, raising concerns about data privacy and transparency. We introduce the Facebook Data Shield (FDS), a life-sized interactive installation that empowers users to visualize and control the data shared with the platform. We deployed FDS at a public design event, to explore user data-sharing and control preferences. We conducted an analysis of 81 user interactions, based on data logs and surveys. Our findings reveal a preference for increased data control, particularly concerning online behavior and demographics. We identify five distinct clusters for preferred data-sharing settings, which show limited correlation with demographic information. Finally, we discuss the potential for predicting preferred data-sharing settings through machine learning based on our data, and implications for social media platform design. This study contributes to the ongoing discourse on data governance and user autonomy in an era of AI-driven content curation.

Keywords: user study, data sharing, social media, tangible interaction

1. Introduction

Social media platforms try to keep their users engaged by offering personalized content. For example, the posts and the order in which they are shown on platforms such as Facebook are determined by an AI algorithm and optimized to keep a user's attention (Meta, 2021). To learn what is interesting to each individual user, Facebook collects a multitude of data. Such data range from those "voluntarily" offered when signing up to the likes users give to Facebook posts, to even their behavior on other websites (Joler et al., 2016c).

For Facebook, the goal is not only to provide users with the most engaging experience, but also to use the collected data to generate revenue by serving targeted ads using Online Behavioral Advertising (OBA) (Fiesler & Hallinan, 2018; Habib et al., 2022). However, for users, it is hard or even impossible to get a full understanding of what data is being collected and how it is used (Habib et al., 2020, 2022; Hsu et al., 2020; Joler et al., 2016b, 2016c).

While not all data is known, when users are confronted with a known selection of the data being collected, most feel uncomfortable, although some also acknowledge the purpose and usefulness of using that data for targeted advertising (Calbalhin, 2018; Habib et al., 2022; Pew Research Center, 2019; Ur et al., 2012). In addition to privacy concerns on an individual level, data collection also poses risks for society at large as profiling users can lead to discrimination, create filter bubbles, and contribute to spreading fake news (K. Ali & Zain-ul-abdin, 2021; M. Ali et al., 2019; Flaxman et al., 2016; Rocha et al., 2021).

In this study, we employ the Facebook Data Shield (FDS), a life-sized interactive installation that applies a critical design approach to provide users with awareness and control over their data (Sinsel et al., 2023). Our aim is to investigate users' data sharing and control preferences. To explore these preferences, we introduced the FDS at a public design event and gathered survey and log data from 81 visitors who engaged with the installation.

Our results validate the findings of a prior exploratory study indicating that users are mainly concerned about sharing behavioral and demographic data (Sinsel et al., 2023). Moreover, users prefer increased data control and detailed information about what data is being collected. Furthermore, we identified five distinct clusters in data-sharing preferences and assessed the feasibility of using demographic information to predict these preferences through machine learning. Finally, we discuss and reflect on the implications of our findings for social media platform design.

2. Background and related work

2.1 Data for personalized ads

Facebook, and with it many other social media platforms, leverages data to generate revenue while offering their services for free to users (Habib et al., 2022). This data is for example used for *online behavioral advertising (OBA)* where user data is used to create specific profiles to personalize the ads shown in users' feeds (Boerman et al., 2017; Ur et al., 2012).

The data that Facebook collects for this purpose is not only diverse but also opaque. Joler et al. (2016a, 2016b, 2016c) attempted to identify the data that is being collected, the storage, algorithm processes and how this is used for targeting. They could not uncover all of this as Facebook is not transparent but using for instance patents, they could showcase the broad range of data being collected.
In addition, the control Facebook offers users is limited. For example, Facebook currently allows users to change how their feed is generated, by selecting one of three settings: most relevant posts first; only posts from favorites; new posts first. However, this setting is hidden and needs to be activated each time the application is opened. Moreover, users could hide or report certain posts in their newsfeed and control some ad settings. Even though a few controls are offered, these are often hidden inside menus and users feel like Facebook makes it intentionally hard to find these settings (Habib et al., 2022).

2.2 Data awareness and control

Not all users are aware that they can control certain privacy settings and even fewer will have read the Terms of Service in which it is detailed for which purposes Facebook uses data. Calbalhin (2018) found that users' awareness of Facebook's privacy settings, meaning that they have read the ToS, has decreased over time, possibly due to the increasing complexity of Facebook's ToS. Paradoxically, the number of users who control their privacy settings has increased, with a majority of the users controlling some settings (Calbalhin, 2018). Controlling settings does not require users to read the ToS, explaining why these two trends can co-exist.

2.3 Different perspectives on data collection

Users' awareness and their willingness to share data differs among Facebook users. While many were uncomfortable seeing all the data Facebook collected about them, some users appreciated receiving targeted ads and were therefore willing to share their data (Habib et al., 2022; Pew Research Center, 2019; Ur et al., 2012). Habib et al. (2022) identified four types of Facebook users: The "privacy concerned" users are highly concerned about privacy and actively utilize controls to prevent tracking and reduce personalization. "Advertising curators" have low privacy concerns, occasionally find ads helpful, and use controls for better personalization. "Advertising irritated" users are annoyed by ads, have low privacy concerns, and use controls to minimize ad frequency and repetition. Finally, "advertising disengaged" users are indifferent to ads, have moderate privacy concerns, show minimal control engagement, and vary in objectives.

2.4 Transparency in recommender systems

Several studies investigated how transparency in recommender systems can be increased (Afridi, 2019; Gedikli et al., 2014; Luria, 2023; Sonboli et al., 2021). Gedikli et al. (2014) evaluated ten different types of explanations and highlighted that some explanations can increase transparency. A study conducted by Luria (2023) highlighted that users are most interested in seeing what personal data is used, what inferences are made from this and if they have any control. Moreover, for transparency reports texts should be straightforward, specific and demonstratable. However, these studies did not identify which topics users are willing to share on Facebook nor did they explore how to make this information tangible.

2.5 Tangibility and privacy

To make data controls easier to understand and use, previous studies have investigated how data privacy settings can be made tangible. Most of these works have focused on privacy in IoT devices (Ahmad et al., 2020; Delgado Rodriguez et al., 2022; Mehta, 2019; Muhander et al., 2022). For example, PrivacyCube gives users insight into the type of data being collected by active IoT resources, where it is stored, for what purpose, and who has access to the data (Muhander et al., 2022). The Facebook Data Shield (FDS) (Sinsel et al., 2023) differs from these examples in that it focuses on social media and leverages a critical design approach, rather than being user-centered and directly applicable to the Facebook interface.

3. Design of the Facebook Data Shield

The Facebook Data Shield is a life-sized interactive installation that empowers users to visualize and control the data shared with the platform (Figure 1). Various data points collected by Facebook (e.g. user’s likes, comments, or age) are represented by tangible buttons that can be activated/deactivated by pressing them. Active buttons indicate users’ willingness to share that data type with the platform to personalize content, and vice versa. The FDS is composed of (i) the *core,* an inner circle with five general data categories collected by Facebook, (ii) the *detailed layer,* a flipping disk around the core containing 26 data variables, each connected to one of the data categories in the core, and (iii) the *outer rim,* a lighted circle which gives feedback about the personalization level by changing the speed and intensity of the lights (the higher the speed/intensity, the more data is being shared).

Table 1 summarizes all the data categories and variables included. In the initial configuration, the detailed layer is hidden. Users can decide to interact with the installation by controlling the core, or by revealing the detailed layer and controlling all data variables individually.

A preliminary version of the FDS was employed by Sinsel et al. (2023) in a small-scale user study with 10 participants. In this work, we created an updated version of the FDS which is able to record interactions automatically and send them via Wi-Fi to a database (Figure 2). Moreover, the FDS functionalities were extended to include responsive lights and visitor detection using a plate with a pressure sensor (Figure 3). Finally, a 'See More' button was added to the back of the detailed layer. When pressed, this button activates a motor that flips the detailed layer to reveal all the data variables (Figure 2).

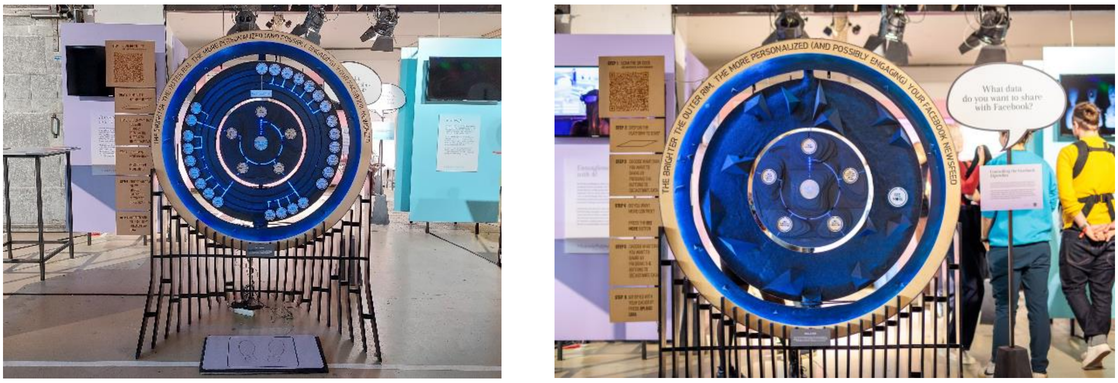

Figure 1 The FDS with the detailed layer visible on the left and with the detailed layer hidden on the right (©Image by Twycer).

Table 1 All data categories and variables included in the Facebook Data Shield

Data categories in core	**Data variables in detailed layer**
Your interactions with your social network	Your interactions with Facebook groups Your interactions with Facebook events Your interactions with Facebook pages Friends' interactions with Facebook pages Friends' interactions with you Your interactions with friends
Your behavior	Contents you shared Your likes Your comments Contents you created How long you interacted with a content Your behavior on the web Your behavior on Facebook-owned plat-forms
Your technological setup-up	Type of device Internet quality
Your demographic information	Your demographic information Your resi-dential location Your native language Your education status Your career information Your relationship status Your gender Your age
Post-related information	Public engagement Moment of publication Subject of post Type of post

Figure 2 The Facebook Data Shield in action with on the left the detailed layer rotating around the core (©Image by Twycer) and on the right a visitor standing on the pressure sensor while interacting with the FDS.

4. Method

During a public design event, the FDS was deployed to explore users' preferences in terms of data sharing and control. We aimed to investigate what data people are willing to share with Facebook, what level of granularity on data control they desire and whether it is possible to identify patterns in people's data setting preferences.

To this end, we collected demographic data through a survey and recorded the interaction logs with the FDS.

4.1 Procedure

As described above, visitors at the design event were invited to participate in the research by the researcher and/or by scanning a QR code that was placed next to the FDS. The QR code opened a webpage on which participants could give consent and complete the survey. In the survey, participants could give consent to participate in the research, answer basic demographic questions as well as whether they used Facebook, how often and for what purposes.

Once finished, the final page of the survey showed two buttons that needed to be pressed simultaneously in the core. Participants were invited to step onto the platform with the pressure sensor and the researcher would press the given two buttons until the light in the core would turn green. This button combination was used to connect the log data from the interaction with the data from the survey.

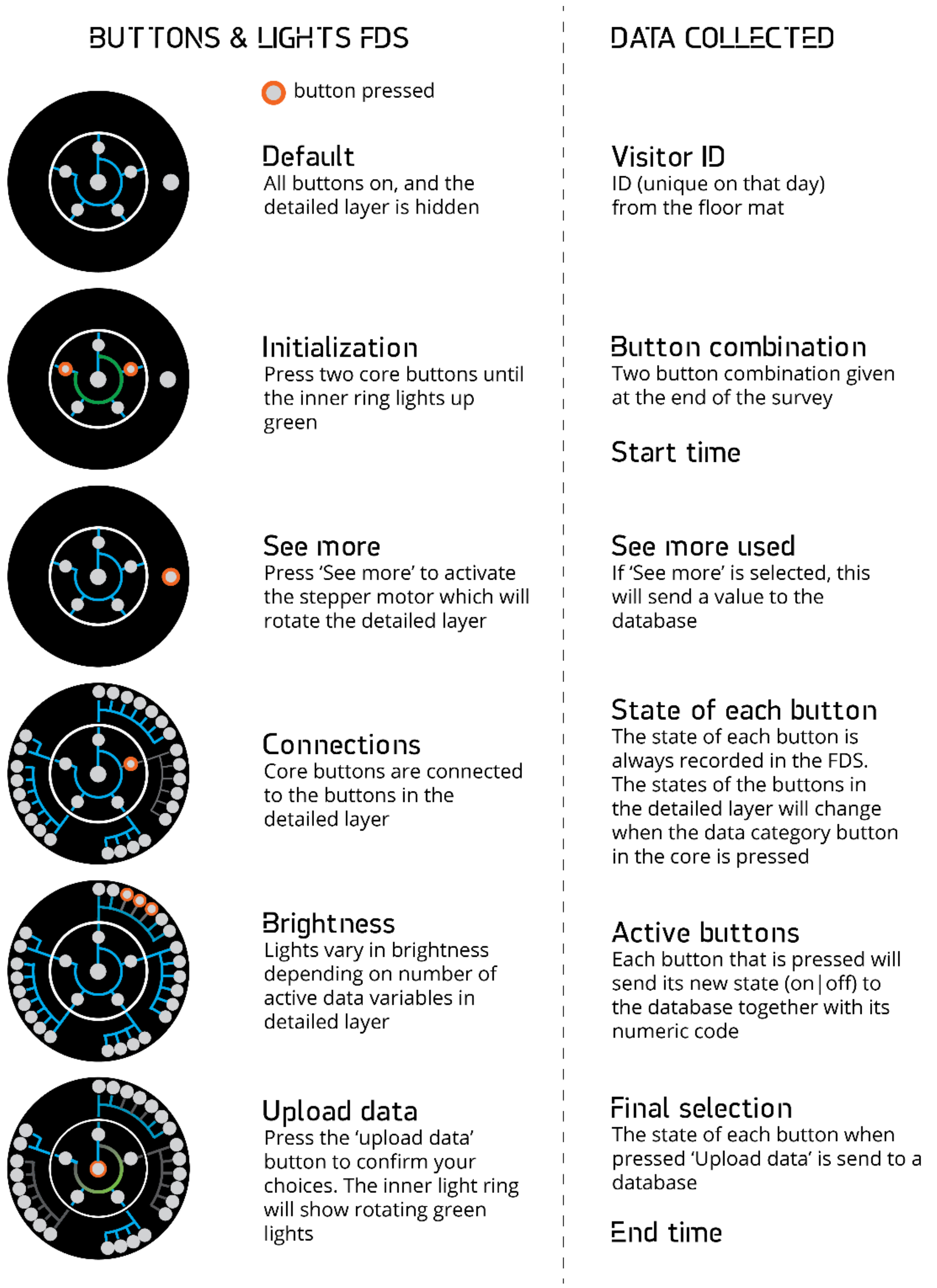

Figure 3 Overview of the different states and interaction possibilities with the FDS and the type of data that is collected when that action is performed.

Next, participants received an explanation about how the FDS functioned. Firstly, it was explained that they should (de)activate the data categories and variables that they did (not) want to share with the Facebook algorithm. Secondly, the function of the outer rim was explained, i.e., that the light would become less bright and move slower when more data was deactivated as the algorithm could no longer personalize their newsfeed. Finally, it was explained that the *detailed layer* was hidden but they could press the 'See more' button if they wished to see it.

Once participants were finished, the researcher checked if they were satisfied with their choices or wanted to change them or see more details in case the *detailed layer* was still hidden. If they were indeed satisfied, they would press *"Upload Data"* to confirm their choices. After pressing this button or after having left the pressure sensor, the FDS would reset itself and flip the *detailed layer* to hide it again. A short visual overview of the main interactions can be found in Figure 4.

These instructions were also displayed beside the FDS in case no researcher was present.

Participants gave their explicit consent for the collection of survey data and a small note was placed at the FDS that anonymous data would be collected from all visitors who interacted with it. The study protocol complied with the University Ethical Review Board procedures and all data were managed in accordance with GDPR regulations.

4.2 Data cleaning

Only data points from participants who completed the survey and pressed the upload button were selected for analysis. In addition, since the quality of data uploaded by participants who were not assisted by a researcher was inconsistent, only data from visitors who interacted with the FDS in the presence of one of the researchers were used. This reduced the number of valid data points from 708 to 81. A visual overview of the data cleaning steps can be seen in Figure 5.

In addition to this valid dataset, one extra dataset was created containing all the "upload" data from when one of the researchers was present, regardless of whether it matched with a survey entry.

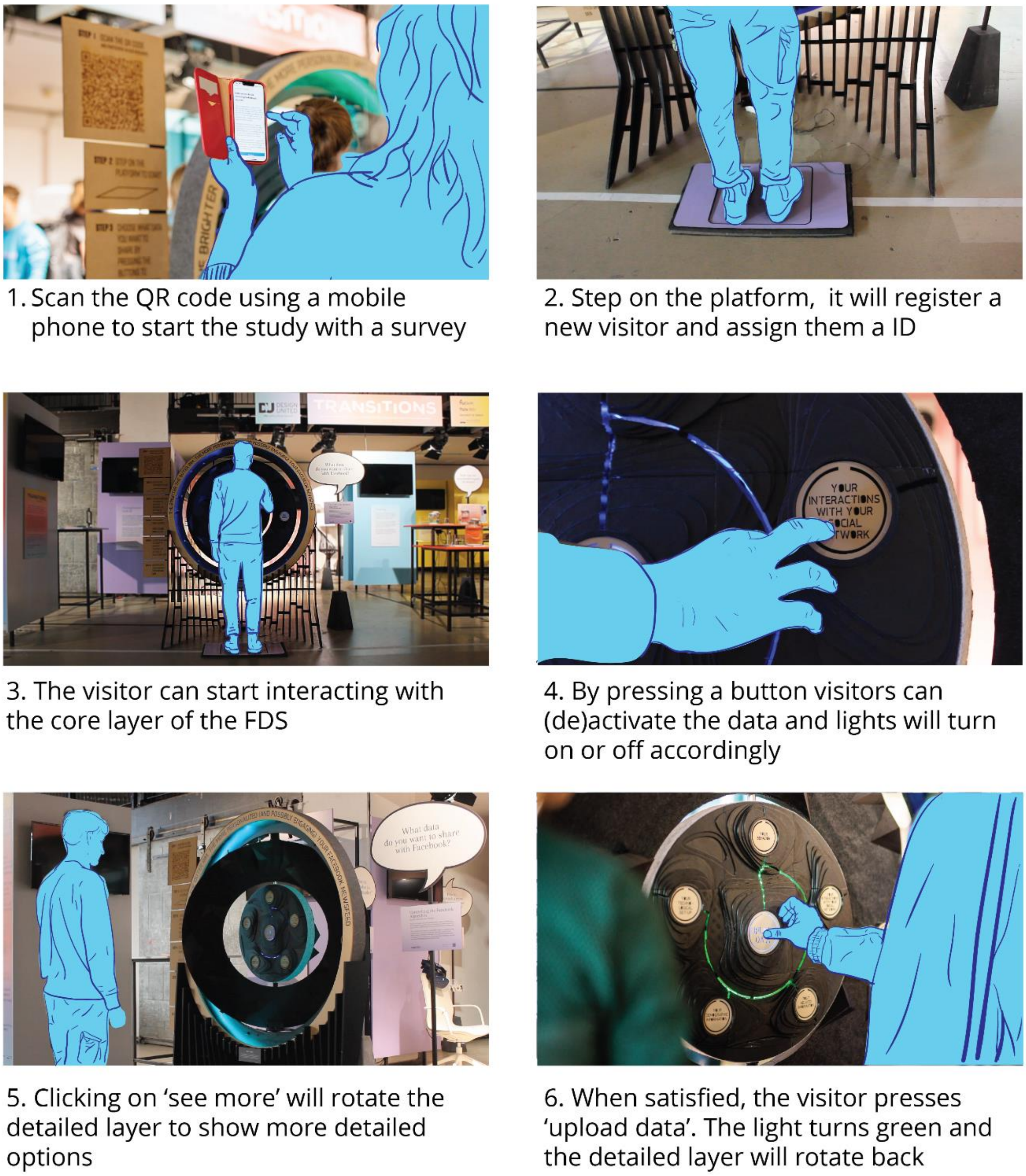

Figure 4 The interaction sequence with the Facebook Data Shield (first and sixth image © by Twycer)

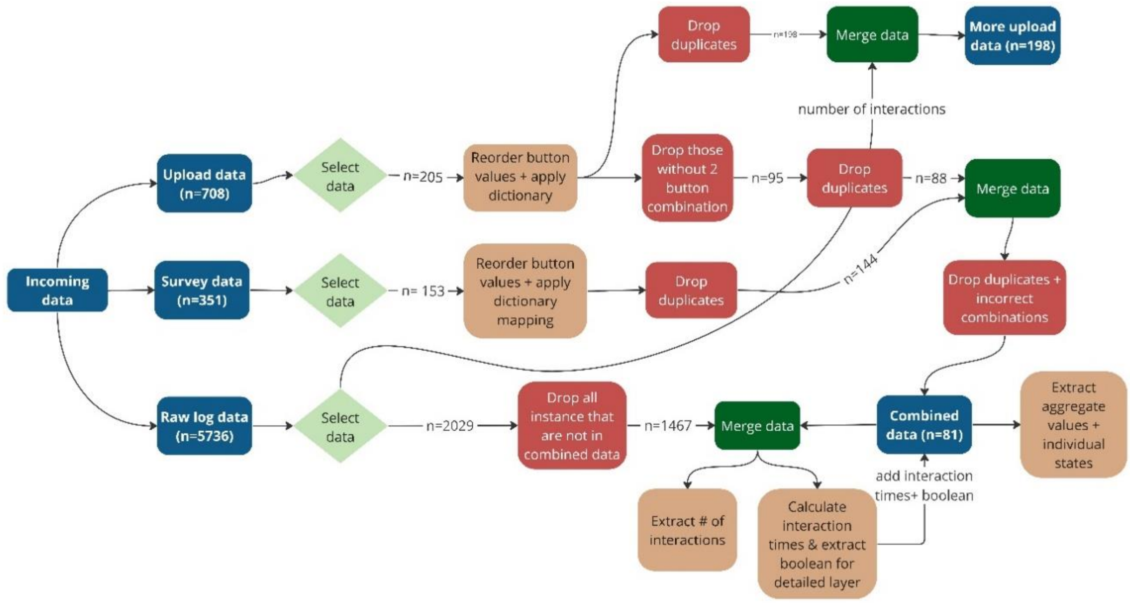

Figure 5 Visualization of the data cleaning process for the three types of data: upload data, survey data, and raw data

4.3 Data analysis

Clustering

To identify patterns in the log data, we used clustering algorithms (k-means, BIRCH and affinity propagation algorithms). The number of clusters was determined experimentally by evaluating the created clusters visually in heatmaps. These heatmaps showed if variables were active or not and a good cluster should show a coherent pattern.

The clustering was repeated on three different data sets extracted from the valid research data, plus the extra dataset including all “upload” data. The first, the *'data-sharing dataset'*, contains the states of each button (0= deactivated, 1 = active) when a user pressed *'Upload data'*.

The second dataset has the number of interactions with each button by each participant, this will be referred to as the '*interaction dataset'*.

The third data set contained all the survey data, ‘*the survey dataset*’, in which the age and frequency of Facebook use were re-coded as numeric variables in order to keep their relationship in subsequent clustering. To cluster the third dataset, a different approach was needed, since normal clustering algorithms use a distant metric that requires numerical data. Instead, the distance was calculated using Gower distance, a metric suitable for numerical and categorical data (Lasaosa, 2021). A matrix with Gower distance was passed directly into a DBSCAN clustering algorithm.

A fourth dataset was created with the data when a user pressed '*Upload data'* from all the visitors who interacted with the FDS when one of the researchers was present, e.g. similar to the '*data-sharing dataset'* but for more users. This was done to see if the patterns found in the '*data-sharing dataset'* corresponded with this larger data set. The same clustering algorithms were used.

Comparing Groups
To determine if there was a difference in the number of active variables between users with and without a Facebook account, we employed a Welch two-sample t-test. To compare the number of active variables based on age, gender, frequency of Facebook use and purpose of using Facebook, one-way ANOVA's were used.

ML Algorithms
To determine if the demographic data collected via the survey could be used to predict the settings of the five general data categories, different ML algorithms were trained on each of the five data categories. For each category, we trained the following models: ZeroR, OneR, J48, and Logistic regression which resulted in a total of 20 models.

5. Results

5.1 Identifying data sharing and control patterns

The clustered data were visualized in heatmaps (Figures 6). The heatmaps show whether a variable was active (colored rectangle) or not (black rectangle) when the user pressed 'Upload data' (Figure 6), or the number of interactions with each button (Figure 7). Each user is represented in a column and each row represents a data button. Therefore by looking horizontally, you can see the general setting for different data buttons and by looking vertically the pattern for a specific user. If a clear pattern was visible in which data buttons were active, this would be considered a successful clustering.

While the results of each clustering algorithm differ, recurring patterns could be identified.

Clustering the data-sharing dataset

Different numbers of clusters were tried as well as different clustering algorithms on the upload data. The k-means clustering algorithm with k=5 showed the best results in the heatmap (Figure 6). In this heatmap, the first cluster contains participants who mainly kept 'Post related information' and 'Your technological setup' active; a second cluster who deactivated almost all data; a third cluster with participants who had 'Your demographic information' active, 'Your social interactions' deactivated and the others half-active; a fourth cluster with participants who had most data active; and a fifth cluster with participants who deactivated the data categories 'Your behavior' and 'Your demographic information'

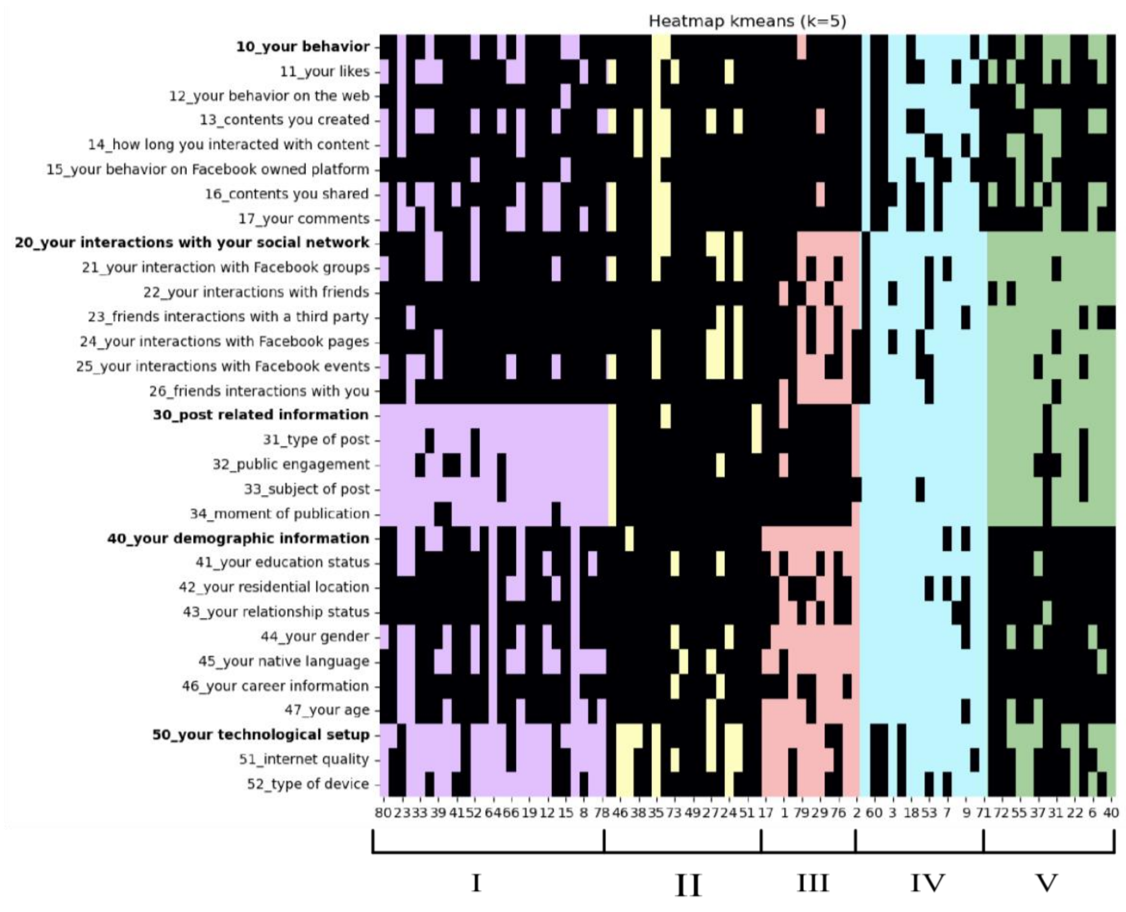

Figure 6 A heatmap of the results of K-means clustering (k=5) which shows five patterns in the data-sharing dataset

Clustering on Facebook purpose

In the preliminary study on the FDS, data suggested a correlation between the active variables and the purpose for which users used Facebook (Sinsel et al., 2023). To validate this finding, participants were clustered based on the main purpose for which they used Facebook. A heatmap of this data was generated with an overlay of the Facebook purpose (Figure 7). No clear pattern could be identified, indicating that there is no or little correlation between the purpose for which people use Facebook and which variables they leave active.

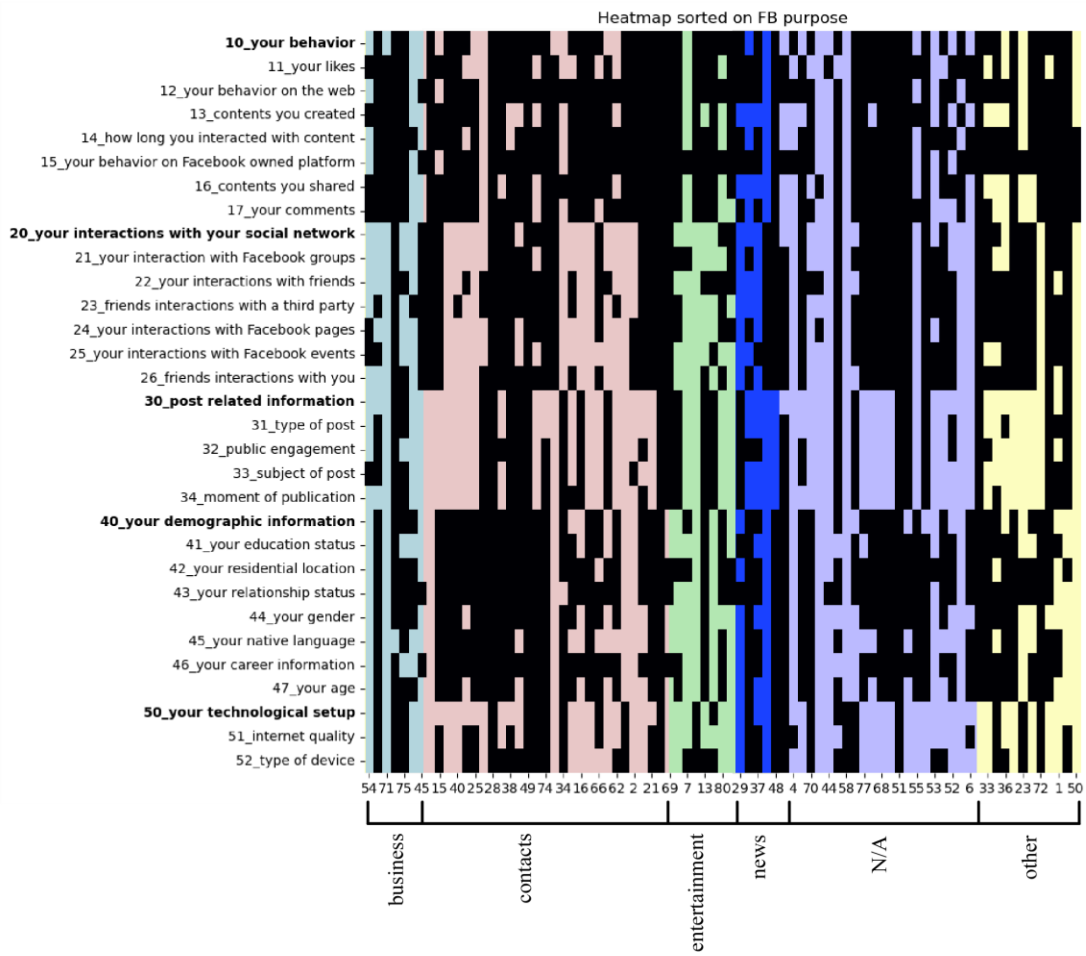

Figure 7 The upload data clustered based on the main purpose of using Facebook (N/A in case the participant had no FB account). No pattern can be found in this heatmap.

Clustering interaction data

The clustering heatmap of interaction data identifies that the majority of interactions took place in the core and not in the detailed layer (see the bands with lighter colors in Figure 8). There is no noticeable difference in the number of interactions in the detailed layer for each group of data variables. Only 7 participants (8.64%) did not press the 'See more' button.

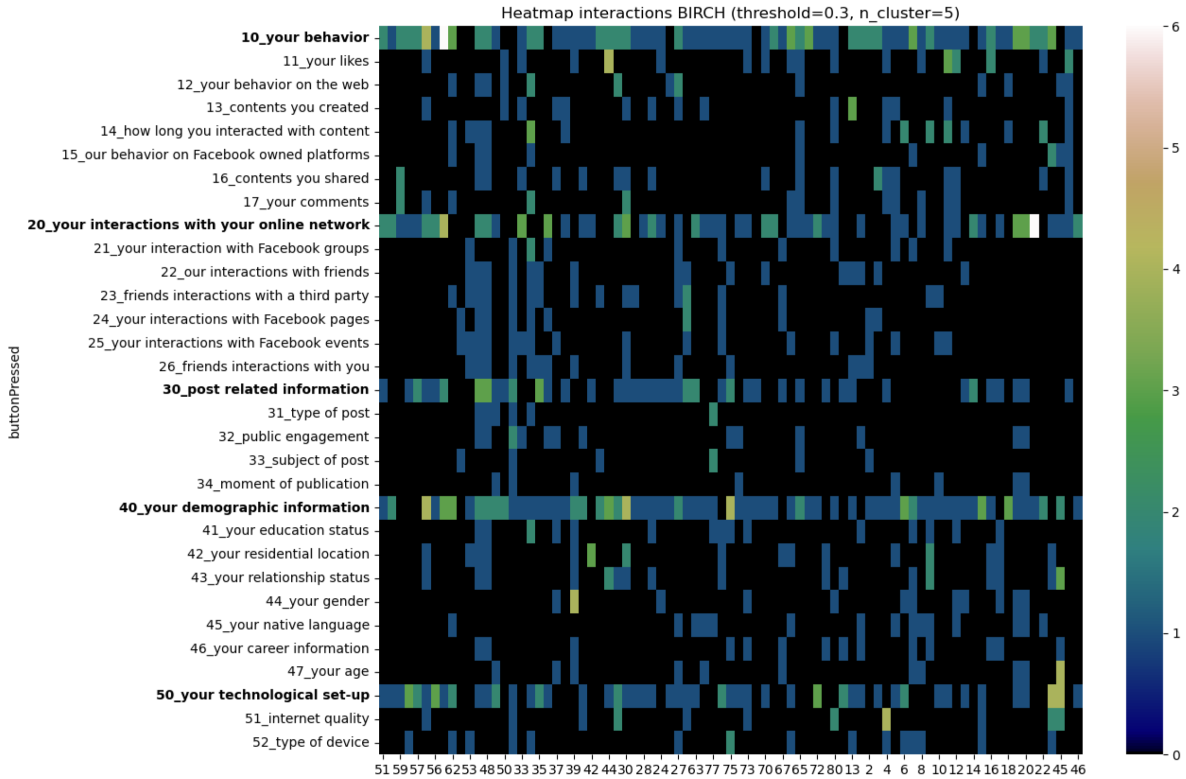

Figure 8 The results of clustering on the interaction data (number of interactions) using the BIRCH algorithm (threshold 0.3, 5 clusters). It shows that most interactions took place in the core.

Survey data

The best result for clustering the survey data was found with four clusters and one extra cluster with noise. The first cluster contained participants who had a Facebook account but no other similarities, the second cluster contained all participants who did not have a Facebook account, the third and fourth clusters were smaller and contained instances that were similar. Cluster 3 only contained females in the age range 18-24 with Facebook and who used it monthly for contacts. The fourth cluster contained males mostly in the age range 18-24 who used Facebook weekly for contacts, and the majority used it also for entertainment.

The data-sharing dataset was also sorted based on these participant clusters and visualized in a heatmap (Figure 9) but no pattern can be seen in what these clusters (de)activated.

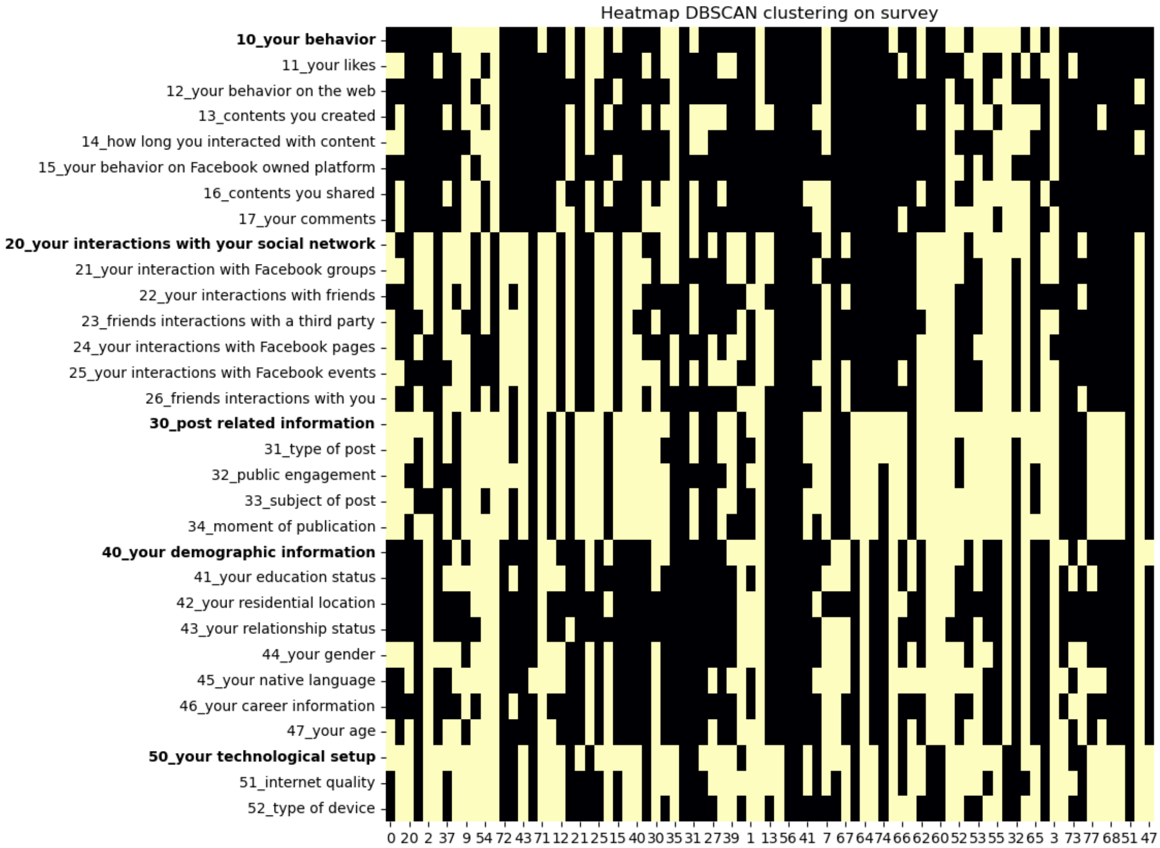

Figure 9 The heatmap of data-sharing dataset after clustering the survey data. No clear clusters can be identified

Extended data-sharing dataset

To compare the data-sharing dataset between those who completed the survey and interacted with the FDS to all visitors who interacted with the FDS when a researcher was present, the same clustered heatmaps were generated (Figure 10). The identified clusters are): (i) almost all active, (ii) 'Post related information and 'Your technological setup' only active,

(iii) ’Your behavior’ only deactivated, (iv) ’Your demographic information’ active, 'Your social interactions’ deactivated and the others half-active, and (v) almost all deactivated.

Four of these clusters were similar to the before-identified clusters (Figure 6). The cluster with only ‘Your behavior’ active is different from the earlier identified clusters. In the previous clustering, this cluster contained participants who deactivated the data categories ’Your behavior’ and ’Your demographic information’.

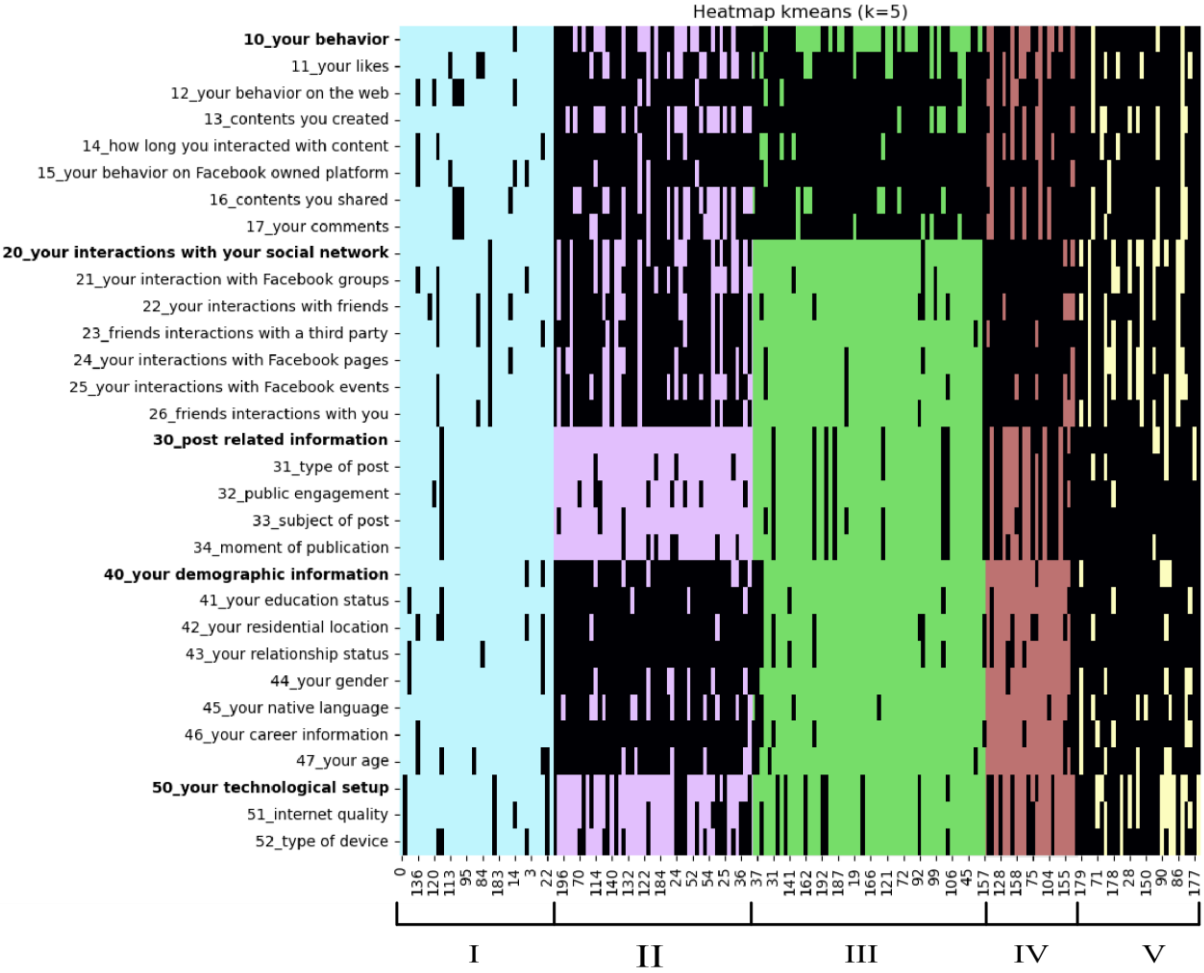

Figure 10 The heatmap of the upload data from all visitors who interacted with the FDS when a researcher was present. Similar patterns can be observed as in Figure 6.

5.2 No significant influence of demographic data

Based on the data and the Welch two sample t-test, no significant difference was found in the number of total active data buttons (both data categories and variables) between participants who had a Facebook account and those without (p=0.49). There were also no significant differences in the number of active data buttons for the other independent variables in the survey (age, gender, frequency of Facebook use, purpose of using Facebook) (see Table 2).

Table 2 Results of the one-way ANOVA's for the independent variables with more than two options

	df (between groups, within groups)	**F-value**	**p-value**
Age	(5, 69)	0.44	0.82
Gender	(2, 78)	2.56	0.08
Frequency of Facebook use	(5, 75)	1.98	0.09
Purpose of using Facebook	(5, 75)	0.85	0.52

5.3 Predicting data-sharing settings

Because clustering algorithms did not highlight correspondences between data-sharing settings and survey data (Figure 9), we set out to determine if preference settings could be predicted from demographic and usage information through other ML algorithms. The results for predicting the final setting for each of the five data categories based on the survey data can be seen in **Error! Reference source not found.**. The accuracy scores vary between 46.9%, meaning that a random guess would be a better predictor, to 75.3%. No specific algorithm consistently performed best. Nevertheless, logistic regression seemed less suited for the task, as the accuracy scores were in general low. Different attributes were used for OneR, of which only Facebook use, i.e., the frequency of use, gives a good result. The others only slightly outperform random predictions.

5.4 Frequently deactivated data

The data-sharing dataset (see Table 4) and the heatmaps (see Figure 6) show that the most frequently deactivated data category is 'Your behavior', followed closely by 'Your demographic information'. Participants also interacted most, e.g. activating and/or deactivating it, with the button 'Your behavior'. 'Your technological setup' and 'Post-related information' were the least deactivated, only in 29.6% of the cases, and had also fewer interactions.

Table 3 The accuracy scores for the four types of algorithms for each of the five data categories. For OneR, the attribute used is given within brackets. The percentages in bold indicate the highest accuracy score.

Algorithm	**Your behavior**	**Your interactions with your social network**	**Post related information**	**Your demographic information**	**Your technological setup**
ZeroR	**67.9%**	51.9%	70.4%	60.5%	**70.4%**
OneR	58.0% (Facebook purpose)	46.9% (gender)	**75.3%** (Facebook frequency)	55.6% (age)	64.2% (age)
J48	**67.9%**	**64.2%**	70.4%	60.5%	59.3%
Logistic regression	51.9%	60.5%	60.5%	55.6%	**70.4%**

6. Discussion

This study sets out to determine what data people wish to share with Facebook, what level of granularity on data control they desire and whether patterns emerge in people's data setting preferences.

Some data categories turned out to be more sensitive than others, as shown by participants being less willing to share behavior and demographic data, while being less concerned about data on their technological infrastructure, as well as their posts contents, social engagement, and metadata.

Table 4 An overview of how many participants had each data category activated or deactivated when pressing 'Upload data' and how many interactions with each button happened in total

Data categories	**Activated**	**Deactivated**	**Number of interactions**
Your behavior	26	55	256
Your interactions with your social network	42	39	159
Post-related information	57	24	112
Your demographic information	32	49	178
Your technological set-up	57	24	149

6.1 Pre-selecting privacy settings with manual controls

Our results show that some correlations can be found between demographic data and preferred data-sharing settings through ML algorithms. This finding suggests that the use of ML could be explored within the actual Facebook interface to automate pre-selections for privacy settings based on individuals' demographic and usage information. However, because the accuracy of these ML models ranges between 64.2% and 75.3%, resulting in incorrect privacy selections in around 30% of the cases, manual control should still be offered.

Pre-selections could also be based on the general results, rather than individual preferences. As in the prior study, participants deactivated 'Your behavior' and 'Your demographic information' most often, suggesting that these categories might be deactivated for all users (Sinsel et al., 2023).

6.2 High-level control with detailed information

The second research question focused on the level of granularity participants preferred to have over their control. During the interaction, participants could choose to press the *'See more'* button which would make the detailed layer visible. Out of 81 participants, only 7 did not look at the detailed layer. However, when looking at the heatmaps of the number of interactions, it is clearly visible that the majority of interactions happened with the data categories in the core. This suggests that participants prefer to receive information on a more detailed level, but control data on a higher level for example by (de)activating all settings related to demographic information at once. Similar findings emerged from a recent study on transparency in recommendation systems (Luria & Michal, 2022). Scholars found that participants mainly want information about the data that is collected and how it is shared with third parties, what data is collected from other sources, and how users can make changes to the algorithm.

6.3 Types of Facebook users and identified clusters

The five identified clusters in the data-sharing dataset match to a certain extent with the type of Facebook users identified by Habib et al. (2022).

The *privacy concerned* are related to the cluster which deactivated all data and/or those that deactivated ’Your behavior’, ’Your demographic information’ and ’Your interactions with your social network’, as the goal of this type of user is to prevent being tracked. The *advertising curators* can be connected to the cluster that had almost all data categories and variables active, given the fact they have low privacy concerns and prefer better personalization. For the *advertising irritated* and *advertising disengaged* it is harder to pinpoint them to one specific cluster since the motivations of the participants are not known.

Habib et al. also describe the level of engagement with their privacy settings for each type of Facebook user (Habib et al., 2022). However, when looking at the interactions with the FDS (see Figure 7b), these groups cannot be identified as the majority of the people had medium to high engagement. This could be due to the fact that the threshold for interacting with the FDS is much lower than finding the privacy control settings on Facebook, as well as the fact that people were curious to experience the installation during their visit and hence were more willing to explore it.

Our clusters therefore confirm previous findings and provide additional information on specific data-sharing preferences for each type of Facebook user.

6.4 Increasing data awareness at public events

Presenting the FDS at a public design event also showed that this could be a possible approach for increasing awareness among visitors about what data is collected by online platforms. Having a life-sized interactive installation raised the interest of many visitors and invited them to interact with it. Although visitors' reactions ranged from surprise and shock about the amount of data shared to confirmation and acceptance all visitors were triggered to reflect on their data sharing practices. This also resulted in discussions among visitors who visited together and had different opinions.

6.5 Reflections and recommendations

By deploying the FDS at a public design event we were able to raise awareness among visitors but also gain insights in certain data sharing preferences. While these findings are not always surprising, previous literature identified similar user types and preferences for control (Habib et al., 2022; Luria, 2023), we offered a new physical approach that can offer new types of interactions and perspectives. Based on the findings and the experience we would like to raise a few questions for future work to consider and design recommendations.

Our data showed that based on some initial data it would be possible to pre-select certain privacy settings, which raises a situation where data is needed to determine which data is needed. How does the user experience this, would they be more willing to offer this data and what would be the motivation? How can designers adapt their designs in a data-centered society to give users more control and increase the transparency of data usage?

Due to the lack of qualitative results, we are not able to answer these questions fully but we offer certain suggestions. Firstly, when designing an artefact with the main aim of raising awareness, we believe the visibility and surprise factors are important elements to consider as they first invite the user and next trigger reflection. In contrast, when designing user control, it is important to be transparent and complete while also not overloading users with options. A layered menu where users can choose which elements they want to control in more detail could be one solution.

7. Limitations

A limitation of this study is the lack of qualitative data that could explain the quantitative data. For instance, audio/video recording of the interactions with the FDS could have provided relevant insights, since participants tended to explain their choices. The results should therefore be seen as first insights and not a full understanding of the user experience and reasoning. Moreover, the current sample is limited in size and diversity and conducting the study with multiple audiences could result in more insights.

In terms of interaction, participants missed an end marker. The experience ended if they pressed "*Upload data*" or stepped off the floor mat, which participants found unrewarding. For future research, we suggest including a small takeaway for participants. For the FDS, this could have been a receipt with their choices or a card with instructions on how to change privacy settings on Facebook.

Finally, the FDS did not prove to be sufficiently self-explanatory, and visitors often did not read the textual instructions. As a result, participants interacted in different manners and showcased unwanted behaviors, e.g., forcing the detailed layer to rotate manually. Taking this into account, the decision was made to only include data from when a researcher had been present to guide the interaction, which resulted in a decrease in sample size. Clearer visuals could have helped, as well as pre-recorded auditory instructions.

8. Conclusion

In this study, we deployed the Facebook Data Shield (FDS) to explore preferences for data sharing and control among users (Sinsel et al., 2023). During a public design event, we collected data from 81 visitors and used them to identify five clusters in data-sharing preferences. These clusters differ in which type(s) of data they are willing to share. Moreover, our findings show that participants are mainly aversive towards sharing behavior and demographic data. No significant findings were found between the demographic data and the number of active variables. We also trained ML models to predict the preferred data-sharing settings. The models achieved accuracy scores between 64.2% and 75.3%. Preselecting privacy settings based on these models would still result in invalid settings for a third to a quarter of the users but might be an improvement to the current situation when users are also offered manual control.

A limitation of this study is the absence of qualitative data to explain the quantitative findings. It is therefore not possible to further expand on or validate the motivators identified in an earlier study. The insights from this research can be used to better understand how people could control data sharing with Facebook, as well as provide an exemplar of how privacy settings in social media can be made tangible and how this can be used in design research.

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