MASTER

Social media in event recommender systems

Verzuu, J.S.A.

Award date:
2021

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Joris Verzuu
0920851

Supervisors:
dr.ir. M.C. Willemsen
Msc Y. Liang
prof.dr. C.C.P. Snijders
dr. U. Matzat

Eindhoven University of Technology

Department of Industrial Engineering and Innovation Sciences

March 2020

Abstract

Event recommender systems bring specific problems to the table that most other forms of recommender systems do not have to deal with. The main issue for event recommender systems has to do with the time-specific nature of events, which results in a permanent cold-start problem. This is a problem which occurs when new items are added to a recommender system of which no user-item interaction data has been collected yet. This makes it hard for most popular recommendation algorithms to accurately recommend this item. Because events take place in the future, they are always 'new items' in an event recommender system. The same problem occurs when new users are added into a recommender system, the system has no data on the user's preferences yet. This makes it hard for recommender systems to accurately recommend items to this user.

To solve the item-side cold-start problem, research and development has looked into content-based event recommender systems where recommendations are done based on the content of the events instead of user-item interactions. To solve the user-side cold-start problem, social media profiles of the user are used for quick preference elicitation.

The current study developed a content-based event recommender system. In one variation of the event recommender system, preference elicitation was done explicitly, where participants indicated which topics they liked. In the other variation of the event recommender system, the same explicit preference elicitation method was enhanced with implicit data from users' social media profiles. Again the participant indicated which topics they liked, but 5 topics were pre-selected by the recommender system based on the participant's interests extracted from the content of their Twitter profile.

The results showed that people were much less likely to use the event recommender system when they were asked to share their public social media information. Furthermore, event recommender systems which use implicit preference data from users' social media profiles do not lead to a better user experience than event recommender systems which use an exclusively explicit preference elicitation. This led to the conclusion that people would rather not share their social media information with event recommender systems.

The current study was done in cooperation with the Den Bosch Data Week (DBDW). For the DBDW, it was investigated whether there was a demand for an event recommender system for the DBDW and how it should be implemented.

The current study's suggestion for the DBDW would be to create a mobile app containing the DBDW event program, with as an added functionality a simple content-based event recommender system.

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1. Introduction

The city of Den Bosch, The Netherlands, has been profiling itself as a leading city in terms of data science. It has a fast growing ICT sector, the Jheronimus Academy of Data Science (JADS), and many companies involved in data science (Den Bosch toonaangevende datastad, n.d.). One of the ways in which the city has been promoting itself is through the Den Bosch Data Week (DBDW). This is an annual, week-long event where people can visit a wide variety of exhibitions, lectures, interviews, and other talks on the topic of data science throughout the city of Den Bosch. In 2020, the third edition of the DBDW took place. As this event is visited by many, and is dedicated to showcasing the many ways in which data can be used. Together with the DBDW organization of the Den Bosch municipality, the current study took this opportunity to study the user experience of event recommender systems and the visitors' interest in one.

Different from recommender systems in other domain, the events in event recommender systems are time-specific and one-and-only items (Cornelis, Lu, Guo, & Zhang, 2007). This makes using collaborative filtering techniques difficult, as they require user-item interactions for recommendations (Ricci, Rokach, & Shapir, 2011). These interactions are not available in an event recommender system as events take place in the future, thus no interactions between the users and the events have occurred yet. To overcome the issues that come with recommending events, Horowitz, Contreras, & Salamó (2018) used a content-based algorithm for their event recommender system, where the interests of the users were extracted from their LinkedIn profile and were matched with the contents of the events in order to give recommendations.

However, currently it is not clear in what way using social media profiles for preference elicitation in event recommender systems affects the user experience of such event recommender systems. Using social media for this purpose may have both positive and negative consequences for the user experience. It decreases the effort people have to put into the system which may lead to a better user experience. On the other hand, it also brings along privacy issues. These issues may lead to more privacy concerns among the users of the event recommender system which may in turn lead to a worse user experience.

To investigate in what way using social media for preference elicitation influences the user experience, and whether or not their positive effects on the user experience outweigh the negative effects on the user experience, the current study developed an event recommender system based on the ideas of by Horowitz et al. (2018). The current study was carried out with a between-subjects design where the preference elicitation method of the event recommender system between two conditions was manipulated. In one condition the preference elicitation method was exclusively explicit, whereas in the other condition the same preference elicitation method was used, but was enhanced with implicit data extracted from the user's Twitter profile. The user experience of the developed event recommender system was studied using the idea of the user-centric evaluation framework from Knijnenburg, Willemsen, Gantner, Soncu, & Newell (2012) as guidance. Participants of the current study were asked to use the developed event recommender systems, and answer questions on their attitude towards the system, and experience with the system.

1.1. Event recommender systems

The goal of recommender systems is to help users with their decision making when they are confronted with many items which may cause information and/or choice overload. Recommender systems evaluate the preferences of a user, and based on these preferences the system recommends items which it thinks the user would like most. Recommender systems have been researched extensively since the 1990's (Hill, Stead, Rosenstein, & Furnas, 1995; Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994; Shardanand & Maes, 1995). They are widely used, and many variations have been developed, such as movie recommenders (Netflix), music recommenders (Spotify), and systems recommending items in web shops.

More recently, event recommender systems have been researched and developed. What sets event recommender systems apart from other types of recommender systems, is that events are so-called one-and-only items. As opposed to repeat-appeared items, which can be consumed multiple times (e.g., movies, songs, items in a web shop, etc.), one-and-only items are unique and time-specific (e.g., events) (Cornelis, Lu, Guo, & Zhang, 2007).

For repeat-appeared items, collaborative filtering is one of the most popular recommender system algorithms. Collaborative filtering is a recommendation method which relies on user-item interactions such as item ratings. There are mainly two different approaches to collaborative filtering; the neighbourhood approach, and latent factor models (Ricci et al., 2011). Neighbourhood approaches calculate the similarity between either users (user-user collaborative filtering) or items (item-item collaborative filtering), based on the ratings users have given to already consumed items. Item-item collaborative filtering generates recommendations based on similar items the user has rated highly before, and user-user collaborative filtering generates recommendations based on items that the user has not consumed yet, but which other people similar to the user rated highly. Latent factor models transform both items and users to a latent factor space. Based on user-item interactions the user's affinity towards latent factors becomes evident, and items with similar affinity to these latent factors are recommended.

Unfortunately, using collaborative filtering for one-and-only items is very difficult, as one-and-only items are not rated by users due to their time-specific nature. Events will take place in the future, which means they have not been rated by users yet. The lack of ratings for items in a recommender system is referred to as the cold-start problem (Ricci et al., 2011). In recommender systems with repeat-appeared items, the cold-start problem occurs when a new item or new user is introduced into the system. In case of the item-based cold-start problem, the new item has not received any ratings yet, which makes it hard for the system to correctly recommend this item or make recommendations based on this item. As time goes by, this new item receives more ratings and the system starts to recommend this item more accurately. Event recommender systems have a permanent item-based cold-start problem as events in the system will be new, unrated items at all times (Horowitz et al., 2018). To overcome this permanent cold-start problem, different recommendation methods aside from collaborative filtering need to be explored in order to be able to give accurate recommendations.

One of such methods is content-based recommendation. Content-based algorithms are another popular method used in recommender systems, and are often combined with collaborative filtering algorithms to partly overcome the cold-start problem. Instead of looking at item ratings, content-based recommender systems look at specific features of the items. Users are recommended items that have similar features to items that the user has liked in the past (Ricci et al., 2011). In the case of event recommender systems, content-based algorithms can partly make up for the lack of effectiveness of collaborative filtering algorithms, by matching the interests of users with the topics of the events (Cornelis, Guo, Lu, & Zhang, 2005). Cornelis et al. (2005) developed a method for event recommenders that used a hybrid between a content-based algorithm and a collaborative filtering algorithm within a fuzzy relational framework. This fuzzy relational approach recommends future events based on similar events from the past that the user liked.

Another event recommendation approach taken by Guo & Lu (2007) was a combination of item-item collaborative filtering and computing a semantic similarity/relatedness between events. Even if there were no ratings available for specific events, the system could still rely on the semantic similarity to give recommendations to users. To calculate semantic similarity and semantic relatedness there are many different methods. The basic principle behind semantic relatedness is to quantify the relationship between two words or concepts based on the similarity of their meaning (Feng, Bagheri, Ensan, & Jovanovic, 2017).

1.2. Preference elicitation methods; explicit, implicit, and hybrid

Aside from collaborative filtering techniques not working well for event recommender systems due to the inherent cold-start problems associated with events, there is also a cold-start problem for new users of a recommender system. As long as the preferences of the user stay unknown, it is impossible to give personalized recommendations to the user. One way to get information about the user's preferences is to ask about his/her preferences explicitly, which is also referred to as explicit preference elicitation.

Another way to get the user's preferences is through implicit elicitation. This is done through for example the observation of user's purchasing history, browsing behaviour, and also in some experimental cases through mouse tracking, or even eye tracking (Ricci et al., 2011; Chen, & Wang, 2016; Schneider, Weinmann, vom Brocke, & Schneider, 2017).

Horowitz, Contreras, & Salamó (2018) took a different approach to implicit preference elicitation. For their 'EventAware' recommender system, they used natural language processing tools on users' social media profiles to extract the interests of the users and build user profiles. This approach is similar to the semantic relatedness approach taken by Guo & Lu (2007), but instead of computing the semantic relatedness between events, the semantic relatedness between the preferences of the user and the event are computed. This way of computing the semantic relatedness between the user preferences and events also resolved the user-side cold start problem, as long as the user had a social media profile with enough personal information to build an initial user profile from.

1.3. Privacy issues in recommender systems

With people being more reliant on technology and online services, data security has become an important issue. Even more so since data breach scandals such as the Cambridge Analytica scandal in 2018 came to light. Cambridge Analytica bought Facebook data about tens of millions of American citizens without their consent, and used this data for their own purposes. Partly because of these data breach scandals, people have been becoming increasingly aware of how companies take more data from people than they need, and share or sell this data more than they should, often without permission (Lapowsky, 2019).

People's privacy concerns are affected by perceived risk associated with disclosing personal information (e.g. risk of opportunistic behaviour, or data leaks), and the control they have over what information gets released online (Xu, Michael, & Chen, 2013). Due to lack of transparency, often it is not exactly known what companies, apps, and websites will do with people's personal data, which increases the privacy concerns people may have. This makes people sceptical when they are asked to share their data. Although this scepticism is justified, this is a hindrance for companies and apps, such as event recommender systems which need personal data in order to give accurate recommendations.

There is an inherent trade-off between the accuracy of a recommender system and the user's information privacy; the more data available to the recommender system, the better the system is able to predict what the user might be interested in. Some examples of personal data that is being collected by recommender systems are: user preferences (derived from explicit and implicit elicitation), purchase or consumption history, and user's demographic information (Jeckman et al., 2018). For the collection of user preferences, the EventAware app by Horowitz et al. (2018) extracted personal data from social media profiles of the users. Even though the EventAware app was reviewed positively by its users, currently there is no literature on how using social media for preference elicitation in event recommender systems exactly affects the user experience. Using social media profiles for preference elicitation does bring along privacy issues, but it is also a useful and accurate way to quickly gather a user's interests, which may lead to a more fluent, personalized, and thus better experience with the event recommender system.

Privacy protection techniques can help relieve some of these privacy concerns. For example, educating people about online privacy issues to raise peoples' awareness towards privacy consequences might lead to people being more careful with their personal information online (Tsai, Egelman, Cranor, & Acquisti, 2011). However, Tufekci (2018) showed that although privacy-aware people were more reluctant to join social networks, once they did, they still disclosed a lot of personal information. In case of the EventAware app by Horowitz et al. (2018), the users were asked access to their social media profile only once. There was no further option to share more, or less information than the app initially required from the user. This would mean that based on the findings of Tufekci (2018), privacy-aware people would be less willing to use the EventAware app, as the only option was to either use the EventAware app and give access to your social media profile, or to decline and not be able to use the app. However, the effect of people's privacy-awareness on the amount of personal information that they shared is further discredited by a study by Barth, de Jong, Junger, Hartel, & Roppelt (2019), who found that regardless of people's privacy awareness, their self-reported privacy concerns were in contradiction with their online data sharing behaviour. Based on the findings of Barth et at. (2019), deciding whether to use or not to use an app such as the EventAware app by Horowitz et al. (2018) is not solely dependent on one's privacy concerns regarding giving access to one's social media profile. Barth et al. (2019) found that the functionality, design, ratings, and reviews of an app outweighed the privacy concerns one may have when considering downloading and using an app.

Although the users are responsible for their own personal data in many ways, it is also the legal and ethical responsibility of the recommender system to handle the personal data of users with care. When handling personal data, it should be avoided that users' data is being used beyond its intended scope; the data should not be used for purposes other than was intended, the data should not be shared with other people than was intended, and the data should not be stored for longer than was intended (Jeckman et al., 2013). Because users don't know what happens behind the scenes once they have given a system their data, it is important that they can trust the recommender system, expecting it to handle their personal data with care.

In conclusion, using social media for preference elicitation in event recommender systems may increase privacy concerns users have, and some potential users might even refrain from using the event recommender system. However there are also potential benefits to using social media for preference elicitation. As recommender systems get access to more data, the accuracy of the recommendations increases as well. Using personal data also enables the possibility for a more fluent, and personalized experience which may further improve the user experience of the system. The difficulty lies in finding the right balance between the amount of personal data the user needs to give access to, and the perceived value of the benefits the user gets in return.

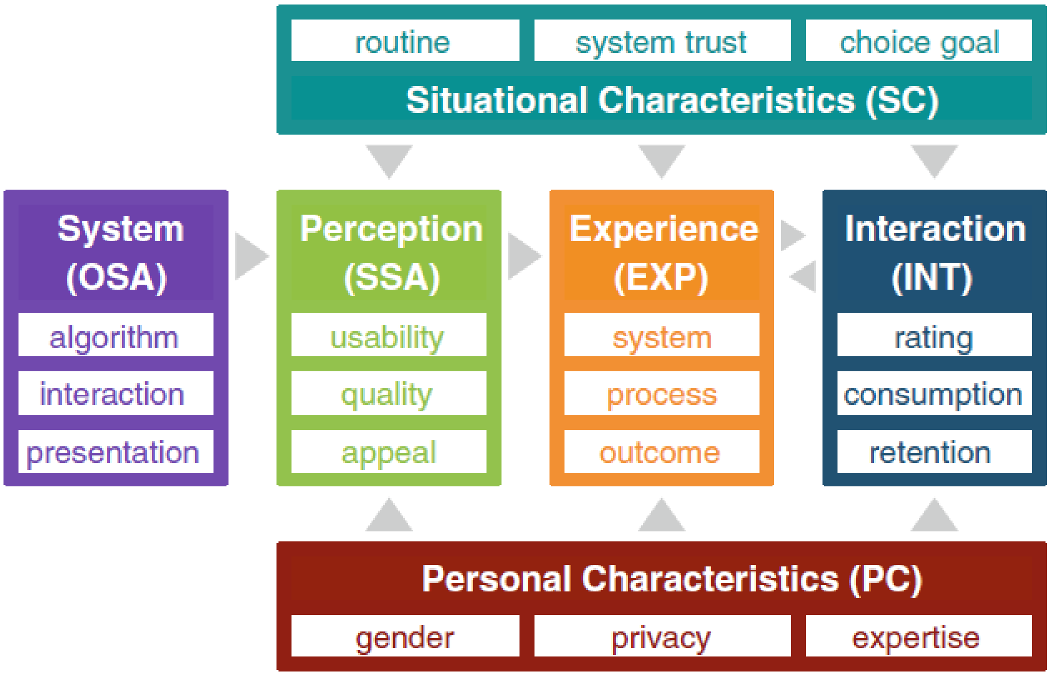
1.4. User experience in event recommender systems

In the field of recommender systems, research started out by focusing on developing and improving algorithms to increase the accuracy of recommender systems. Only later, research started focusing more on the user experience side of things. This is also the case for the events domain; algorithms have thus far been the main focus of research. However the effectiveness of a recommender system is dependent on more than just the quality of the algorithm. Other factors determining the effectiveness of a recommender system include the amount of trust users feel like they can place in the system, the transparency of the underlying algorithm of the recommender system, the novelty of the items the recommender system recommends, and the amount of control the user has over what the recommendation system recommends (Swearingen & Sinha, 2001).

To investigate people’s attitudes towards an event recommender system using social media for preference elicitation, and the human-recommender system interactions (such as the privacy concern), the current study conducted a user experiment. In order to analyse this, the user-centric evaluation framework developed by Knijnenburg, Willemsen, Gantner, Soncu, & Newell (2012), was used (Figure 1). The user-centric evaluation framework is a framework developed for evaluating the user-experience of recommender systems, the framework consists of 6 interrelated concepts. The variables measured in the current study were al fit into the framework.

Figure 1

User-Centric Evaluation Framework



Note. Reprinted from *Recommender systems handbook* (2nd ed., p.312), by Ricci, Rokach, & Shapira, 2011, Springer, Boston, MA.

1.5. Research questions and hypotheses

Following the previous work by Horowitz et al. (2018), in the current study, social media was also used for preference elicitation. Whereas Horowitz et al. (2018) were focussed purely on the development and accuracy of their event recommender system, the current study wanted to take a closer look at the user experience when using social media for preference elicitation in an event recommender system. The social media profile of a user is filled with personal information, and can be used in a lot of ways to extract the interests of this user. Using social media profiles might thus be a convenient way to build an initial user profile for an event recommender system, as this circumvents the user side cold-start problem. This in turn might result in a better user experience as users will not have to go through the effort of explicitly indicating their preference. Also the quality of recommendations might improve, as the recommender system gets more data to work with. On the other hand, using privacy sensitive data from social media profiles might also negatively affect the user experience of event recommender systems through an increase in privacy concerns of the user. The privacy concerns of users are affected by the control they have over what is shared. As soon as users need to give an event recommender system access to their social media profiles, they partly lose control over what information is shared with the system.

Are people willing to share their social media profiles with event recommender systems, or do they mistrust the system and are they afraid that their personal information might be disclosed without their consent?

The following research question was formulated:

RQ1: How does the use of social media for preference elicitation influence the user experience of an event recommender system?

As mentioned earlier, the use of social media profiles for preference elicitation in an event recommender system does have some issues, most notably the privacy concerns of the user. This led to the following hypotheses:

H1: Preference elicitation through social media leads to a higher level of privacy concerns as opposed to explicit preference elicitation

H2: A higher level of privacy concerns decreases user experience

On the flipside, social media profiles of the users can be used for implicit preference elicitation. This means that the user needs to put less effort into the system to get recommendations.
This led to the final hypotheses:

H3: Preference elicitation through social media leads to less effort to use the event recommender system as opposed to explicit preference elicitation

H4: Lower effort to use the recommender system leads to an increased user experience

With these 4 hypotheses the current study aimed to find out whether using social media for preference elicitation is worth the trade-off between privacy concerns and user experience.

Finally, as the current study was done with the DBDW and its organization in mind, the goal of the current study was also to lay the foundations for developing an event recommender system that could be used for DBDW events in the future. The event recommender system would recommend visitors exhibitions, interviews, lectures, etc. present at the event that they might like to attend to.
To research this, the second research question was formulated:

RQ2: What is the added value of a recommender system for events such as DBDW and how should it be implemented?

2. Method

2.1. Design

The current study was a cross-sectional study, with a between-subjects design with two conditions. To study the research questions and test the hypotheses a content-based event recommender system was developed which was called the 'DBDW online recommendation app', the technicalities of the app are further described in section 2.3.1. The independent variable that was manipulated between the two conditions was the use of social media for preference elicitation in the DBDW online recommendation app. Aside from the recommendation functionality of the DBDW online recommendation app, the app also featured a survey to measure the dependent variables which are described later.

2.1.1. Selected social media platform

When selecting a social media platform for preference elicitation in the DBDW online recommendation app, Facebook was the main consideration, as it was the world's largest social media platform in 2020. Unfortunately due to the COVID-19 outbreak, the Facebook personnel in charge of validating individual Facebook developers were not doing any new validations. This meant that the Facebook API could not be used for the current study and alternative options were explored. Ultimately it was decided to use Twitter instead, which has been used successfully for constructing user profiles for recommender systems in earlier research (Abel, Gao, Houben, & Tao, 2011; Lu, Lam, & Zhang, 2012).

Although the number of Twitter users is lower than the number of Facebook users, there are also some benefits to using Twitter over Facebook. Tweets are often public data, meaning that it is easier to get access to them, and may lead to less privacy concerns for the participants. There is also lot of data in tweets which can be extracted using natural language processing tools.

There are however some issues with using Twitter for implicit preference elicitation too. First off, it needs to be assumed that topics people are Tweeting about in some way reflect their interests. Then for natural language processing tools to extract topics from texts is also no simple feat, these issues are further discussed in section 2.3.1.1.

2.1.2. Experimental conditions

Two versions of the DBDW online recommendation app were built to serve as the two experimental conditions. It was reasoned that by making a purely implicit preference elicitation condition and a purely explicit preference elicitation condition, the two conditions would differ too much from each other. As the current study is mainly interested in the effects of using social media for implicit preference elicitation, the actions performed by the participants should be as similar as possible.

It was thus decided to use an explicit preference elicitation method in both conditions. In one condition the explicit data was enhanced with implicit preference data extracted from users' social media profiles, which the current paper will henceforth refer to as the 'social media condition'. In the other condition no enhancement with implicit data from users' social media profiles was used. This condition will be referred to as the 'explicit condition'.

As classified by the user-centric evaluation framework for researching recommender systems, the two preference elicitation methods were the objective system aspects (OSA) of the DBDW online recommendation app.

2.1.3. Participant condition assignment

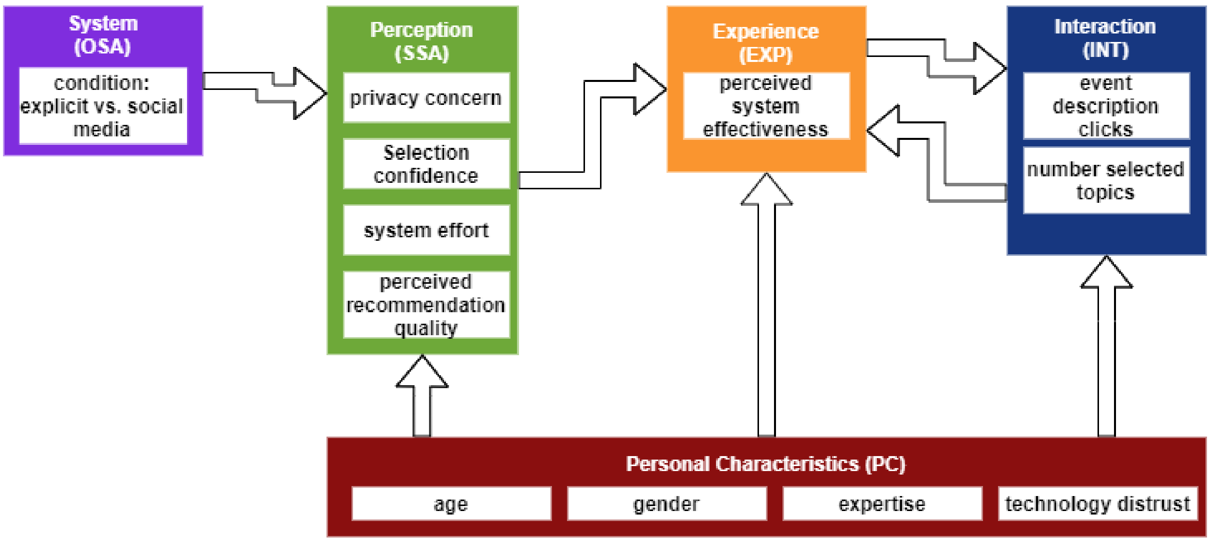
In order to keep the participant sample in both conditions as similar as possible, ideally only people active on Twitter would be suitable for taking part in the study, thus preventing comparison between active Twitter users and non-active Twitter users. The participants active on Twitter would then be randomly assigned to either condition. However, it was assumed that by only allowing active Twitter users to participate, this would limit the number of potential participants too much. Instead of selecting participants based on their Twitter activity, an adjustable 70/30 ratio was used where 70% of the active Twitter users were selected for the social media condition and 30% were selected for the explicit condition. Participants without a Twitter account were also approached, and were placed in the explicit condition automatically. This meant that the study was not completely randomized, but it offered a trade-off between getting sufficient participants in the social media condition and still being able to compare the 30% of those active on Twitter in the explicit condition to the participants not active on Twitter in the explicit condition. It was important to be able to compare these two groups, to see if they were similar or not.

2.1.4. Dependent variables

As mentioned earlier, the current study used the User-Centric Evaluation Framework developed by Knijnenburg et al. (2012). In Figure 2 the framework was adapted to correctly depict the aspects of the current study, including all variables of interest.

Figure 2

User-Centric Evaluation Framework of the DBDW online recommendation app



The measured dependent variables were age, gender, knowledge about data science (expertise), general trust in technology (technology distrust). These variables were classified by the user-centric evaluation framework as the personal characteristics (PC). PC's are factors that might influence the perception, experience, or the interaction with the event recommender system, but cannot be influenced by the recommender system.

System specific privacy concerns (privacy concern), effort to use the recommendation app (system effort), confidence in that the right topics were selected (selection confidence), and perceived recommendation quality were also measured dependent variables. With the technology distrust and system specific privacy concerns variables, the current study measured to what extend participants were concerned that the DBDW online recommendation app would disclose privacy sensitive information. With the system effort and selection confidence variables the current study measured how much effort the participants felt they had to put into the DBDW online recommendation app. And with the recommendation quality variable, the current study measured the perceived recommendation quality of the DBDW online recommendation system. These variables were classified by the user-centric evaluation framework as the subjective system aspects (SSA). SSA’s are the mediating variables between the OSA’s and the user-experience (EXP), and describe the way the user perceives the OSA’s.

Finally, perceived system effectiveness was also a measured dependent variable, which was used as an indicator for the overall user experience of the DBDW online recommendation system. Perceived system effectiveness was classified by the user-centric evaluation system as an experience variable (EXP). EXP variables indicate the user’s attitudes towards the recommender system.

Additionally, several observable variables based on the participants’ interaction with the DBDW online recommendation app were measured. The details of these system-interaction variables will be explained later in section 2.4. The system-interaction variables were included in the user-centric framework as interactions (INT). INT are the user’s observable behaviours during their usage of the recommender system.

For research question 2 specifically, a couple more dependent variables of exploratory nature were measured. These variables measured the user demand for a recommendation tool for the DBDW, what the participants liked and disliked about the DBDW online recommendation app, and in what way a potential recommender system should be implemented.

2.2. Participants

The current study tried to use a convenience sample by sharing the study amongst people interested in the Den Bosch Data Week prior to the event, and contacting people who went to the DBDW after the event had ended. However too few responses were received through these means. To recruit more participants, the JSF participant database from the TU/e was used. Through the JSF participant database, data from around 30 participants was acquired. Because this was not nearly enough to be able to draw significant conclusions from the results, the Prolific participant database was used next. Until this point only 2 participants had indicated to be active on Twitter. In order to make sure participants would be selected for the social media condition, only participants active on Twitter from the Prolific participant database were allowed to participate. Participants acquired through the JSF participant database were either of Dutch nationality, or were living in the Netherlands at the time of their participation. The participants from the Prolific participant database were international participants.

Of the 235 participants who partook in the current study, 144 completed the experiment, of which 8 were recruited through the initial convenience sample, 32 through the JSF participant database, and 104 through the Prolific participant database.

Of these 144 participants, 3 were excluded from the data analysis because of their inconsistent answers and very fast response times of ±3 minutes and 30 seconds (*M* = 7.63 minutes, *SD* = 6.01 minutes). This indicated that they did not complete the study seriously. 4 other participants were excluded from the data analysis because careful inspection of the data indicated that they were outliers.

Of the remaining 137 participants, the age ranged between 18 and 54 years (*M* = 24, *SD* = 6.97). Of the participants, 65 were male, 71 female, and 1 other. 41 of the participants took part in the social media condition, and 96 took part in the explicit condition.

2.3. Materials

2.3.1. DBDW online recommendation app

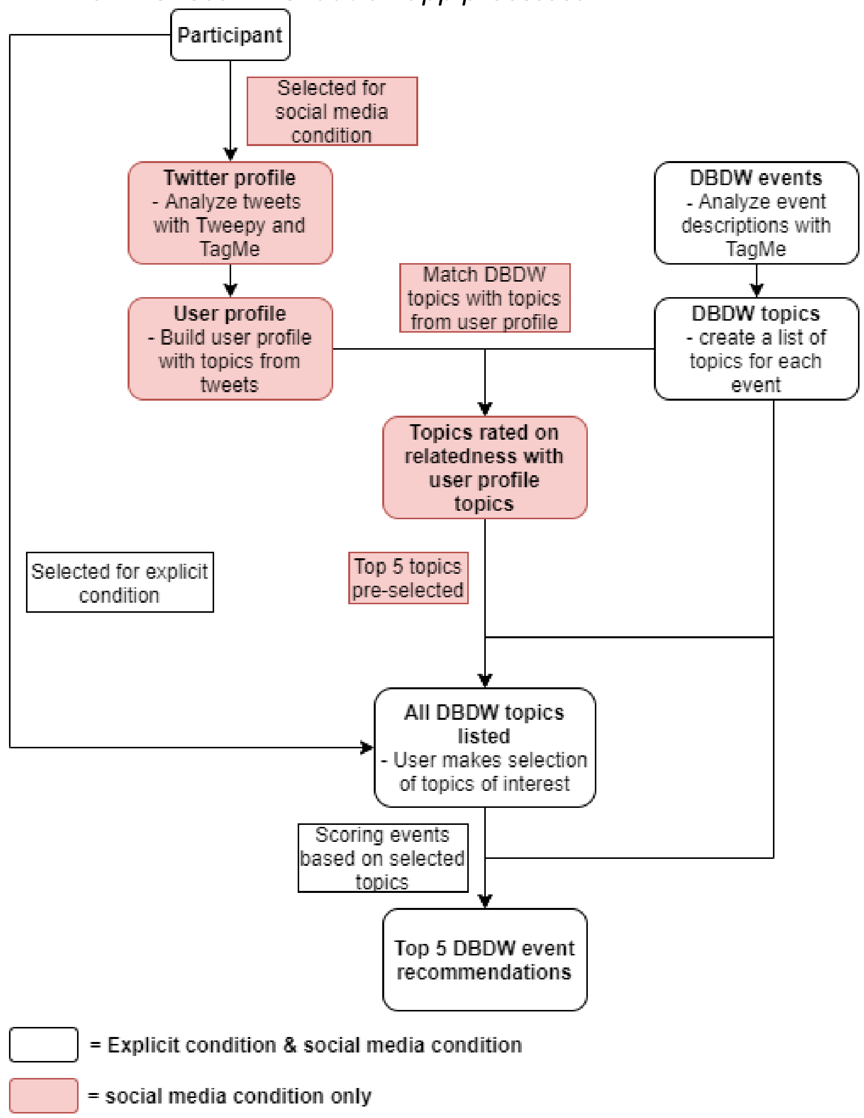
The DBDW online recommendation app was a content-based event recommender system recommending events of the DBDW based on the topics of interest of the user.

The DBDW recommendation app used the Tweepy library (Roesslein, 2020), which is a python library for accessing the Twitter API. The DBDW recommendation app also used the TagMe API (Ferragina, & Scaiella, 2010). TagMe is a natural language processing tool specifically for short texts such as for example tweets. It finds meaningful concepts (annotations) in these texts and links these to corresponding Wikipedia pages with its annotation tool. With its relatedness tool it can calculate a relatedness score between two annotations based on the overlap in in-linking pages between the corresponding Wikipedia pages. Earlier work showed that using a combination of tools such as TagMe works very effectively for extracting concepts to be used by recommender systems (Musto, Semeraro, Lops, & de Gemmis, 2014). However, for simplicity sake, the current study decided to stick with using the TagMe tool only, as optimizing the accuracy of the recommender system was not the focus of the current study.

Figure 3 shows an overview of the processes of the recommendation system of the DBDW online recommendation app. These processes are discussed in detail in the following sections. The programming code of the recommender system can be seen in Appendix A, the interface of the DBDW recommendation app can be seen in Appendix B.

Figure 3

DBDW online recommendation app processes



2.3.1.1. Constructing the DBDW topic list

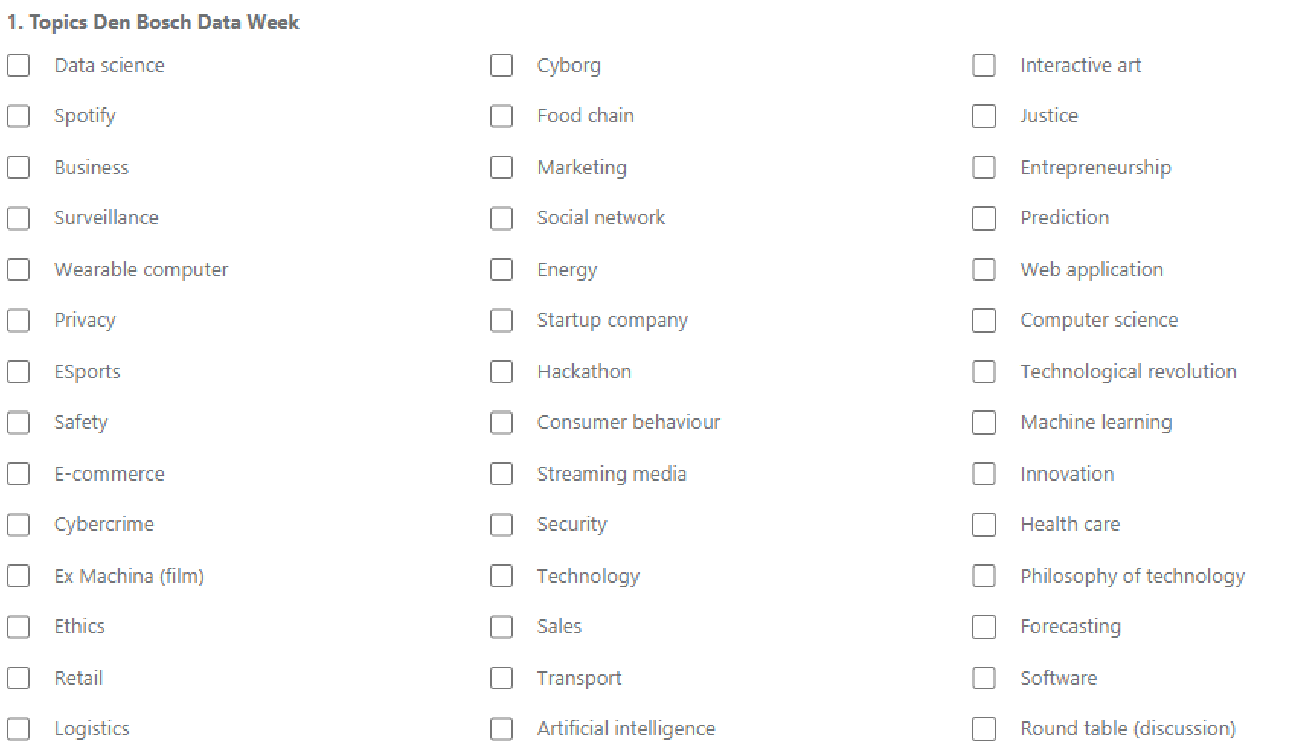
Most of the DBDW events had descriptions associated with them. The DBDW online recommendation app analysed these event descriptions with the TagMe annotation tool, and extracted topics from these descriptions. However, the TagMe annotation tool does make mistakes in selecting topics and linking them to Wikipedia pages.

A major issue that natural language processing tools struggle with is the ambiguity; words and sentences can have multiple alternative interpretations which are dependent on the context. It is very difficult for AI to choose the correct interpretation (Jusoh, 2018). Due to this ambiguity issue, the TagMe annotations sometimes did not make sense in the context of the topic descriptions. Another issue with the annotations that TagMe made, was that some annotations were irrelevant to the topic of the event. TagMe calculates the probability that an annotation is of significant importance to the text it analyses, only annotations above a certain probability threshold are selected as significant annotations (Ferragina & Scaiella, 2010). This threshold is set by the user. It was noticed that when a higher threshold was selected (threshold of 0.3), some important annotations were left out, which is likely due to the ambiguity issue. Additionally, when using a higher threshold, some event descriptions were left without any annotations at all. However, when the threshold was lowered (threshold of 0.2), more unimportant annotations were made. It was decided to use the lower threshold of 0.2 to make sure no important annotations were missing, and manually select the important annotations from the complete list of annotations made by TagMe. Annotations that were deemed 'unimportant' were mainly annotations that did not make sense in the context of the event descriptions, or annotations that did not contribute to describing the content of the events.

In the end this resulted in a list of 42 annotations, which contained the names of the Wikipedia pages that the TagMe tool linked the event description texts to. The names of these Wikipedia pages were used as the DBDW topics describing the DBDW events in the DBDW online recommendation app (Figure 4).

Figure 4

List of DBDW topics of the DBDW online recommendation app



1. Topics Den Bosch Data Week

Data science	Cyborg	Interactive art
Spotify	Food chain	Justice
Business	Marketing	Entrepreneurship
Surveillance	Social network	Prediction
Wearable computer	Energy	Web application
Privacy	Startup company	Computer science
ESports	Hackathon	Technological revolution
Safety	Consumer behaviour	Machine learning
E-commerce	Streaming media	Innovation
Cybercrime	Security	Health care
Ex Machina (film)	Technology	Philosophy of technology
Ethics	Sales	Forecasting
Retail	Transport	Software
Logistics	Artificial intelligence	Round table (discussion)

2.3.1.2. Explicit preference elicitation

For the explicit preference elicitation all 42 DBDW topics were listed, and the user was asked to select the topics they found interesting. At least 5 topics had to be selected to make sure that enough DBDW events could be recommended. The order of DBDW topics was randomized, in order to prevent any bias that might occur due to selecting topics based on their position in the list.

2.3.1.3. Implicit preference elicitation (social media condition only)

The Tweepy library was used for accessing public tweets of users of the DBDW online recommendation app in the social media condition. For this functionality, the Twitter screen name of the user was required. With the TagMe annotation tool, the user's tweets were analysed and topics from these tweets were extracted. The tweet's topics were then matched with the topics from the DBDW events, and the relatedness scores between these two topics was calculated with the TagMe relatedness tool. The DBDW topics were sorted from most relevant to the user to least relevant to the user, based on the relatedness score.

The sorted list of DBDW topics was then used to enhance the explicit preference elicitation method by reorganizing the order in which topics were displayed (DBDW topics with the highest relatedness scores first, topics with the lowest relatedness scores last). Also the five topics that had the highest relatedness scores were pre-selected, these pre-selected topics could be unselected.

2.3.1.4. DBDW event recommendations

To calculate the recommendation score of a DBDW event, it was checked how often the topics selected by the user occurred in the DBDW event description relative to the total number of topics present in the DBDW event description. The event recommendation score would be high if the topics selected by the user had many occurrences in the event description relative to the total number of topics in the event description, and vice versa. In the end, the top 5 DBDW events with the highest scores were recommended to the user.

As a side note, this approach for giving recommendations is similar to a term frequency approach where the importance of a word in a text is based on its frequency in the text divided by the number of texts from the data set.

2.3.2. Survey questions

Intertwined in the recommender system were some survey questions. Four demographics questions asking the participant for their age and gender, what social media platforms they use regularly, and how much they know about data science. Six short questionnaires: one questionnaire on general trust in technology, one on system specific privacy concern, one on effort to use the system, one on selection confidence, one on perceived system effectiveness, and one on perceived recommendation quality. All of these questionnaires had only three questions. This was done in order to keep the experiment as short as possible. With the exception of the selection confidence questionnaire which designed by the current study, the other questionnaires were derived from questionnaires used by Knijnenburg et al. (2012). From these questionnaires, generally the three items with the highest factor loadings were picked. When selecting the questions, it was also attempted to get a good mix of positively phrased questions and negatively phrased questions, and avoiding questions that were too similar.

Finally six exploratory questions were added to the survey.

See Appendix C for a list with all the survey questions.

2.4. Procedure

After the DBDW online recommendation app was put online, the link to this app was spread through JADS. Visitors of DBDW who indicated that they wanted to be contacted for evaluation were sent an email with the link to the app after the DBDW event had ended. Also the JSF participant database from the TU/e and the Prolific participant database were used for participant recruitment. After reading and agreeing to the online informed consent, participants were asked to fill in some demographics questions. Participants were then split into the two conditions, the social media condition, and the explicit condition. Participants who indicated that they were active Twitter users were split into the social media condition

and the explicit preference elicitation condition on a 70/30 ratio respectively. Participants who indicated that they were not active on Twitter were all selected for the explicit preference elicitation condition.
In the social media condition, the participants were asked to give their Twitter screen name. On the next page, the top five most relevant topics based on the topics extracted from the participants twitter were pre-selected, with all topics ordered from most relevant to least relevant. In the explicit condition, no topics were preselected and the DBDW topic order was randomized (Figure 4). The participants were asked to select at least 5 topics. The number of topics selected were stored in the database as a measure of interaction (INT) of the participant with the DBDW online recommendation app.
After the topic selection, the participants were asked questions on the technology distrust, privacy concern, system effort, and selection confidence variables. After filling out these questions, the participants were given the five recommended events from the DBDW that best matched their interests based on their selection of DBDW topics. The events were displayed as large buttons with the event title written on the button. When the button was pressed, the event title folded out downwards, displaying the description of the event as well as the date and time of when the event took place. The DBDW recommendation app stored which buttons were clicked and how often they were clicked for each participant to measure participants' interaction (INT) with the DBDW online recommendation app. On the same page the participant was asked some final questions measuring the perceived recommendation quality, and perceived system effectiveness variables. Also the exploratory questions for research question two were asked. After answering these final questions, participants were redirected to a final webpage thanking them for their participation.

2.6. Statistical analysis

First an exploratory factor analysis and multiple confirmatory factor analyses were performed to check whether the questions asked in the survey measured the intended variables.
Next, *t*-tests and structural equation modelling (SEM) were used to test the hypotheses and answer the research question. *T*-tests were used to determine whether there were differences of privacy concerns (H1) and differences of system effort (H3) between the explicit condition and the social media conditions. SEM was used to analyse the relationships between the measured latent variables (system specific privacy, system effort, selection confidence, system effectiveness, recommendation quality, and technology distrust) and the observed variables (explicit vs social media condition, system-interaction variables, age, gender, and expertise) of the current study, all in one model to answer H2 and H4.
For the statistical analysis the Stata statistical software, and R statistical software were used. For the exploratory factor analysis Stata was used. For the confirmatory factor analysis, both Stata and R were used. And for SEM, R was used.

3. Results

3.1. Participant condition assignment

79 out of the 137 participants indicated that they were active on Twitter, of which 38 were selected for the explicit condition. The 58 participants who did not indicate that they were active on Twitter were automatically selected for the explicit condition. *T*-tests on all the measured latent variables were performed to examine whether there was a significant difference between the participants active on twitter who were selected for the explicit condition and the participants not active on twitter in the explicit condition. The *t*-tests showed no significant differences of any of the variables between these two groups (Table 1). This meant that there was no concern for a selection bias, and the data could be analysed normally.

Table 1

t-test results of the differences between active Twitter users and non-active Twitter users in the explicit condition

Variable	***t***(95)	***p*** (two-tailed)	**mean non-active Twitter users**	**mean active Twitter users**
privacy concern	0.72	0.47	-0.11	-0.25
system effort	0.46	0.65	-0.02	-0.11
selection confidence	-0.45	0.65	-0.01	0.09
technology distrust	-0.77	0.44	-0.06	0.10
recommendation quality	0.13	0.9	0.09	0.07
system effectiveness	0.16	0.88	0.11	0.08

Even though a 30/70 ratio was used to divide participants active on Twitter in the explicit and social media condition respectively, in reality the ratio was almost 50/50. 38 participants active on Twitter were in the explicit condition, and 41 participants active on Twitter were in the social media condition. This was because there was a substantial number of participants in the social media condition who quit the experiment. As shown by a Fisher's exact test, there were relatively more participants who quit the experiment in the social media condition than in the explicit condition (p=0.003). In the social media condition 27.6% (16/58) of the participants quit the experiment, whereas in the explicit condition 8.9% (10/112) of the participants quit the experiment. Most of the participants who quit in the social media condition did so when they were confronted with the question to insert their Twitter account name (87.5%). For this reason the current study ended with an uneven division of participants among both conditions, with 96 participants in the explicit condition and 41 participants in the social media condition.

3.2. Factor analysis

An exploratory factor analysis suggested that there were 5 latent variables among the asked questions in the current study, instead of the 6 latent variables that the current study hoped to measure (Figure 5). However, as further explained below, it was decided to create the intended six latent variables after all.

Figure 5

Exploratory factor analysis on the survey questions

variabe	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
privacy concern 1		0.8645				0.2196
privacy concern 2		0.8964				0.1958
privacy concern 3		-0.8608				0.252
selection confidence 1					-0.5802	0.516
selection confidence 2					0.6757	0.5278
selection confidence 3					0.6925	0.5285
system effort 1			0.5772			0.6102
system effort 2			-0.5489			0.5395
system effort 3			-0.4635			0.6106
technology distrust 1				0.7463		0.445
technology distrust 2				0.7375		0.3503
technology distrust 3				0.7816		0.3691
recommendation quality 1	0.8455					0.2293
recommendation quality 2	0.8609					0.2667
recommendation quality 3	0.7819					0.3103
system effectiveness 1	0.595		0.4623			0.2994
system effectiveness 2	-0.4308		-0.5995			0.3404
system effectiveness 3			0.6649			0.4679

Note. Blanks represent absolute loadings below 0.3.

The exploratory factor analysis showed that the questions on system effectiveness were loading on the same factor as the questions on recommendation quality, and were also loading on the same factor as the questions on system effort. In both cases the factor loadings of system effectiveness were relatively low. When looking at the questions of system effectiveness and of system effort, there seemed to be no common ground between their content. Also a confirmatory factor analysis showed that system effort had a low convergent validity (Table 2), meaning that system effort was not accurately measuring the actual effort people had to put into the recommender system. For these two reasons it was decided not to combine the system effectiveness and system effort questions into a single variable.

When looking at the questions of system effectiveness and of recommendation quality, the square root of the average R^2 of both recommendation quality and system effectiveness (Table 2), was higher than the correlation between the two variables (r = 0.87). This correlation can be seen in the structural equation model discussed in section 3.4. (Figure 7). This meant that the questions for recommendation quality are somehow better at predicting the latent variable of system effectiveness and vice versa, suggesting a bad discriminant validity between the two variables. Still, the recommendation quality questions and the system effectiveness questions seemed too distinct to be combined into a single variable. It was reasoned that one possibility as to why the exploratory factor analysis suggested the system effectiveness questions and the recommendation quality questions to be combined into a single factor, was that there was not much more to the event recommender system used in the current study than the recommendations themselves. The DBDW online recommendation app was a simplistic event recommender system, and there was not much interaction with the system. So aside from the recommender system giving recommendations, there was little to like or dislike about the system. Upon further investigation of the relationships between the variables, it was found that privacy concerns did not affect recommendation quality, while privacy concerns did affect system effectiveness. This was in line with the expectations of the current study. Recommendation quality should not be affected by privacy concerns, as the perceived quality of recommendations should be a subjective measure separate from the privacy concerns users have. System effectiveness however, measures the overall experience with the event recommender system, which should be influenced by the privacy concerns users have. The effect of privacy concerns on system effectiveness, and lack thereof on recommendation quality was the deciding factor not to merge the recommendation quality and system effectiveness variables.

To check the convergent validity of the measured variables, the Cronbach's alpha and the average R^2 of the items in the confirmatory factor analysis were inspected (Table 2). The higher the Cronbach's alpha, and the average R^2 values, the more precise a variable is measured by its questions. As a rule of thumb, the Cronbach's alpha should be 0.6 or higher, and the average R^2 should be over 0.5.

Table 2

Chronbach's alpha and average R^2 for each latent variable

Variable	Chronbach's Alpha	Average R^2
privacy concern	0.85	0.74
selection confidence	0.44	0.37
system effort	0.46	0.33
technology distrust	0.63	0.49
recommendation quality	0.81	0.63
system effectiveness	0.71	0.59

The confirmatory factor analyses showed a good convergent validity for privacy concern, and recommendation quality ($\alpha > 0.8$, $R^2 > 0.6$). System effectiveness, with a Cronbach's alpha of 0.71 and a R^2 of 0.59, also showed a decent convergent validity. The problem with system effectiveness was that the third question ('I can find better events using the DBDW recommendation app'), had a relatively low factor loading, suggesting that this question was not measuring system effectiveness as well as the other two questions were. However because only 3 questions were asked per variable, removing one was not possible as at least 3 items per factor are required to perform a meaningful confirmatory factor analysis (MacCallum, Widaman, Zhang, & Hong, 1999).
The convergent validity of technology distrust is not as good as was hoped, with an average

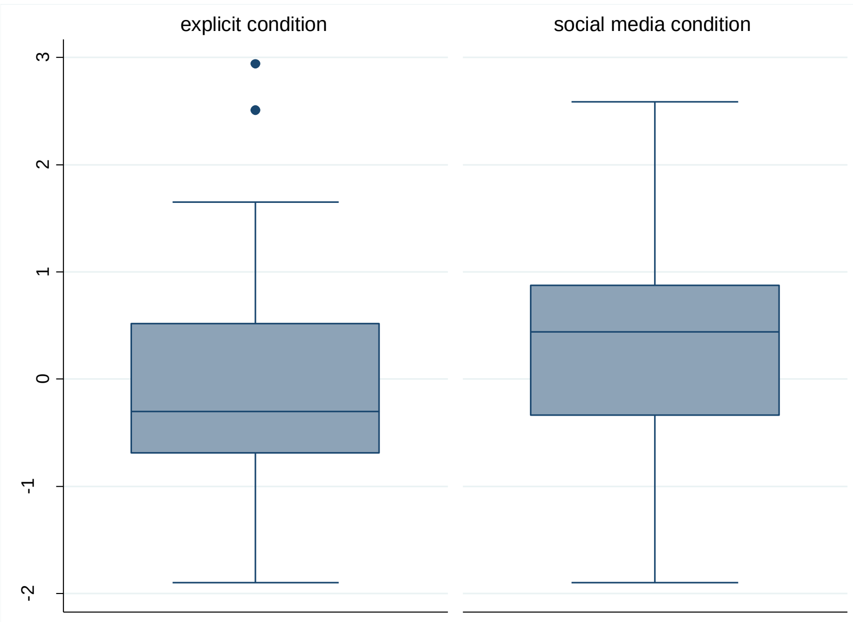
R^2 of 0.49 and a Cronbach's alpha of 0.63, the values are both very close to the recommended thresholds of 0.5 and 0.6 respectively. Nonetheless it was decided to keep using technology distrust for further analyzation, but the effects on the variable and the effects of the variable should be interpreted carefully.
Finally, the convergent validities of selection confidence and system effort were not up to par. With the Cronbach's alphas and R^2 far below the recommended thresholds, it was decided not to use these variables for further analyses with the structural equation modelling.

3.3. Social media condition vs explicit condition

For the first hypothesis: 'Preference elicitation through social media leads to a higher level of privacy concerns as opposed to explicit preference elicitation', the results of an one-tailed unpaired *t*-test showed that the level of privacy concern in the social media condition was significantly higher than the level of privacy concern in the explicit condition thus supporting H1, $t(136) = -2.93$, $p = .002$, $d = -.54$ (Figure 6).

Figure 6

Level of privacy concern for each of the preference elicitation conditions



Unfortunately due to the low convergent validity of system effort, the current study was unable to provide the results needed to answer hypothesis 3: 'Preference elicitation through social media leads to less effort to use the event recommender system as opposed to explicit preference elicitation'. Even so a one-tailed unpaired *t*-test was performed. The results showed that there was no significant difference between the means of system effort between the social media condition and the explicit condition, $t(136) = -.04$, $p = .52$, $d = -. 01$ (Table 3). Also exploratory analyses were performed to see whether there were significant differences of the other measured variables between the explicit and social media conditions. Aside from privacy concern, no other variables showed a significant difference between the explicit and the social media condition (table 3).

Table 3

t-test results on differences between the social media condition and explicit condition for the latent variables

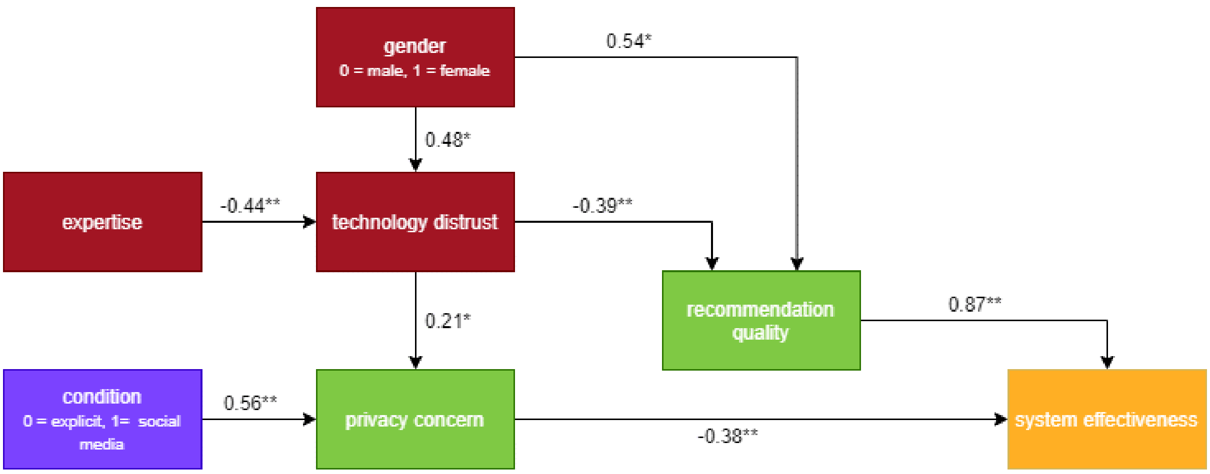
Variable	***t*(136)**	***p***	***d***	***mean* explicit condition**	***SD* explicit condition**	***mean* social media condition**	***SD* social media condition**
privacy concern	-2.93	0.002 (one-tailed)	-0.54	-0.16	0.99	0.35	0.94
system effort	-0.04	0.52 (one-tailed)	-0.01	-0.06	0.9	-0.05	1.08
selection confidence	0.41	0.68 (two-tailed)	0.08	0.03	0.99	-0.05	1.06
technology distrust	0.62	0.54 (two-tailed)	0.11	0.01	0.1	-0.01	0.86
recommendation quality	0.32	0.75 (two-tailed)	0.06	0.08	0.92	0.03	0.8
system effectiveness	0.19	0.85 (two-tailed)	0.04	0.01	0.87	0.07	0.93

3.4. SEM

System effort was not included in the structural equation model due to its low convergent validity. Also when added to the model, system effort showed relationships to other variables which were unexpected, and could not be explained. This further indicated that the questions for system effort were indeed not measuring the intended latent variable. For this reason the current study was unable to answer hypothesis 3: ‘Preference elicitation through social media leads to less effort to use the event recommender system as opposed to explicit preference elicitation’, and hypothesis 4: ‘Lower effort to use the recommender system leads to an increased user experience’, with the help of the structural equation model.

Figure 7

Structural equation model



Note. Significance levels: $**p < 0.01$, $*p < 0.05$. Numbers on the arrows represent the regression β-weights indicating the strength of the relationship between the variables. Variables are standardized to have a SD of 1.

SEM was used to investigate the relationships between the variables of the current study. With the help of the resulting structural equation model (Figure 7) hypothesis 1: 'Preference elicitation through social media leads to a higher level of privacy concerns as opposed to explicit preference elicitation', and hypothesis 2: 'A higher level of privacy concerns decreases user experience', could be investigated. In the current study, the variable system effectiveness was used as an indicator for the overall user experience of the DBDW online recommendation app.

The structural equation model showed that condition (0 = explicit condition , 1 = social media condition), had a positive effect on privacy concern. This meant that participants in the social media condition had a significantly higher level of privacy concern than participants in the explicit condition, thus again supporting H1. In turn, privacy concern had a significant negative effect on system effectiveness, supporting H2.

Aside from the variables; condition, privacy concern, and system effectiveness, also expertise, gender, technology distrust, and recommendation quality were found to have significant effects on other variables in the model. Technology distrust is negatively affected by expertise, while being positively affected by gender. Meaning that people who were more knowledgeable on the topic of data science were less distrusting towards technology, and that females were more distrusting toward technology than males.
In turn, technology distrust negatively affected recommendation quality, and positively affected privacy concern. The more distrusting someone was of technology, the lower they perceived the quality of the recommendations given to them by the event recommender system, and the more concerned they were about their privacy.
Gender also had a direct effect on recommendation quality, females perceived the quality of the recommendations higher than males. However, it should be noted that when analysing the total effect of gender (direct + indirect through technology distrust) on recommendation quality it was found that the indirect effect of gender (p=0.09) and the total effect (p=0.11) of gender were insignificant (Figure 8).

Figure 8

R output of direct and indirect effects of gender on recommendation quality

Effect	**Estimate**	***SE***	***p***
indirect effect of gender	-0.188	0.111	0.092
direct effect of gender	0.536	0.224	0.017
total effect of gender	0.348	0.215	0.106

Finally recommendation quality positively affected system effectiveness. The higher the perceived recommendation quality, the higher the perceived effectiveness of the event recommender system. Although hypotheses 1 and 2 were supported, condition did not significantly affect system effectiveness or recommendation quality. This meant that the effect size of the indirect effects of expertise, technology distrust, and gender on system effectiveness through recommendation quality added up enough to counteract the negative effect of privacy concern.

3.5. User-system interaction variables

The participant's interaction with the event recommender system was tracked where possible. The topics that were selected were stored, and the clicks on the event descriptions of the recommendations were stored. For each of the two observations, many of the participants did not engage in any interaction. 41% (56/137) of the participants only selected 5 topics, which was the minimum number of topics required, and 52% did not click on an event description more than once. So instead of creating continuous variables for the user-system interaction, binary variables were created (0 = no/little interaction, 1 = interaction). For the number of topics selected, the threshold was 5 selected topics, for the number of event descriptions clicked, the threshold was 1 click.

It was analysed whether the binary variable of the number of topics someone selected (topic interaction) or the binary variable of the number of times someone clicked the event descriptions (description interaction) influenced the user experience (system effectiveness) and recommendation quality, or vice versa.

When added to the structural equation model, the multiple regression results of the topic interaction variable (β=-0.16, p=0.58), and the description interaction variable (β=-0.40 p=0.17) did not predict system effectiveness significantly. Recommendation quality was not significantly predicted by topic interaction (β=0.35, p=0.13), and also not description interaction (β=-0.10 p=0.68). Neither were the topic interaction and description interaction variables being predicted by recommendation quality and system effectiveness. Topic interaction (β=0.04, p=0.83) and description interaction (β=0.01, p=0.60) were not significantly predicted by recommendation quality. And topic interaction (β=0.11, p=0.44) and description interaction (β=-0.13, p=0.36) were not significantly predicted by system effectiveness.

3.6. Demand for an DBDW event recommender system

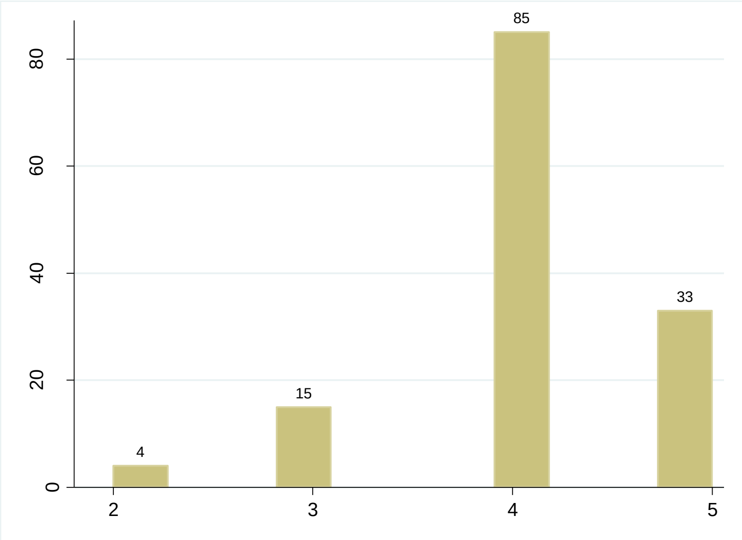
It should be taken into consideration that the current study was not able to gather participants who actually visited the DBDW. Moreover, most participants were unlikely to know about the DBDW at all. It's a relatively new event in The Netherlands, and most participants (100/137) were internationals gathered through prolific. The exploratory questions in the survey about the demand for an event recommender system for the DBDW (henceforth referred to as DBDW questions), were specifically formulated for visitors of the DBDW. These questions were analysed nonetheless, but it should be kept in mind when interpreting the results that the participant sample was not representative of the DBDW visitors.

Because the participants had not visited the DBDW and the DBDW questions were being used for exploratory purposes, the analyzation of the DBDW questions were not tested statistically. Instead the results of the DBDW questions were inspected manually.

DBDW question 1 asked the participants to indicate whether or not they agreed with the statement: 'I feel like the DBDW online recommendation app is a useful addition to the DBDW event.' Results showed that 86% (118/137) agreed or agreed strongly with this statement (Figure 9).

Figure 9

Answers to DBDW question 1: ‘I feel like the DBDW recommendation app is a useful addition to the DBDW event.’

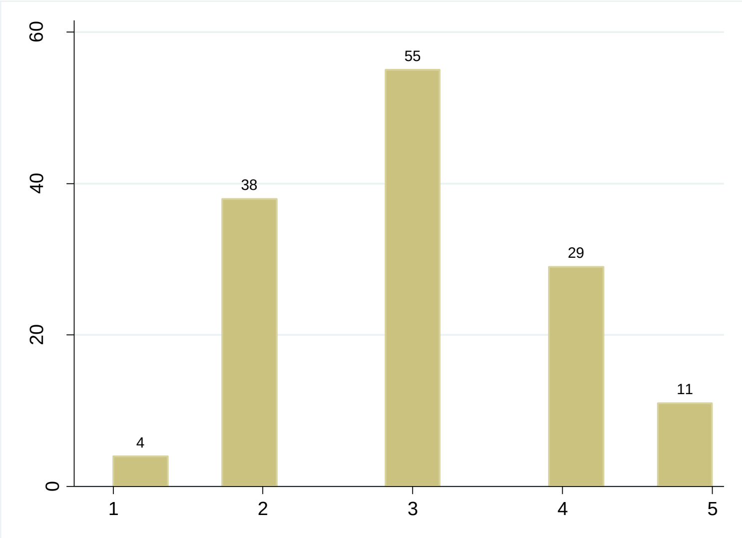


Note. 1 = strongly disagree, 5 = strongly agree.

DBDW question 2 asked the participants to indicate whether or not they agreed with the statement: ‘I would rather decide myself which event to go to than using a recommendation app.’ The results of DBDW question 2 were normally distributed (Figure 10). 40% (55/137) of the participants indicated that they had no preference for either using a recommendation app or deciding themselves which event to go to. 31% (42/137) of the participants disagreed with the statement, indicating that they would rather use a recommendation app. And 29% (40/137) of the participants agreed with the statement, indicating that they would rather decide themselves which event to go to.

Figure 10

Answers to DBDW question 2: 'I would rather decide myself which event to go to than using a recommendation app.'

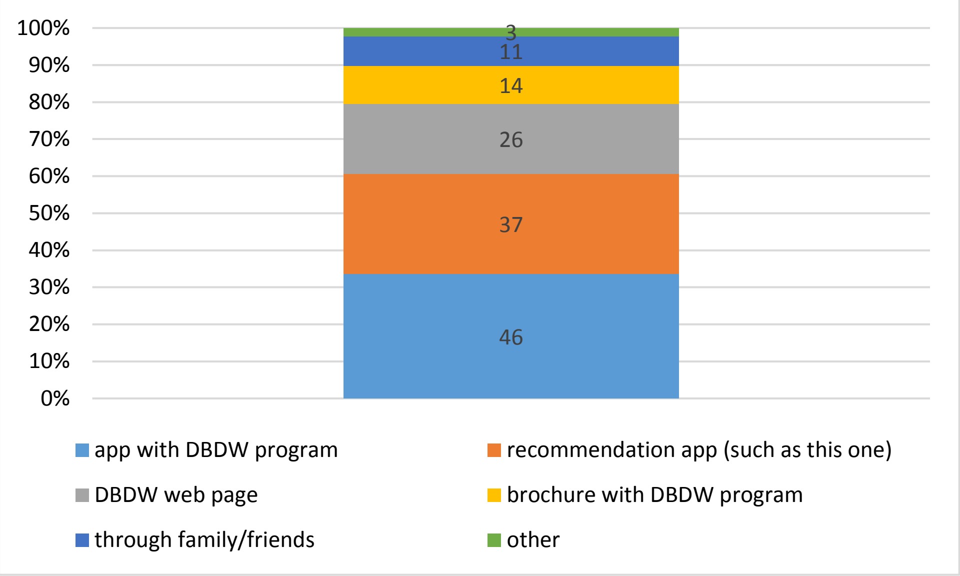


Note. 1 = strongly disagree, 5 = strongly agree.

DBDW question 3 asked the participants in what way they would prefer to decide to which event to go to. The options were: brochure with the DBDW program, app with the DBDW program, DBDW web page, recommendation app (such as this one), through friends/family, other. The results showed that participants had a clear preference for deciding which even to go to with the help of online platforms, with a DBDW app with the program being the most popular option (34%, 46/137), followed by an event recommender system (27%, 37/137), and the DBDW website (19%, 26/137) (Figure 11). The other options combined (brochure with DBDW program, through family/friends, and other), amounted for 20% (28/137) of the given answers.

Figure 11

Answers to DBDW question 3: 'How would you prefer to decide to which event to go to? Choose one.'

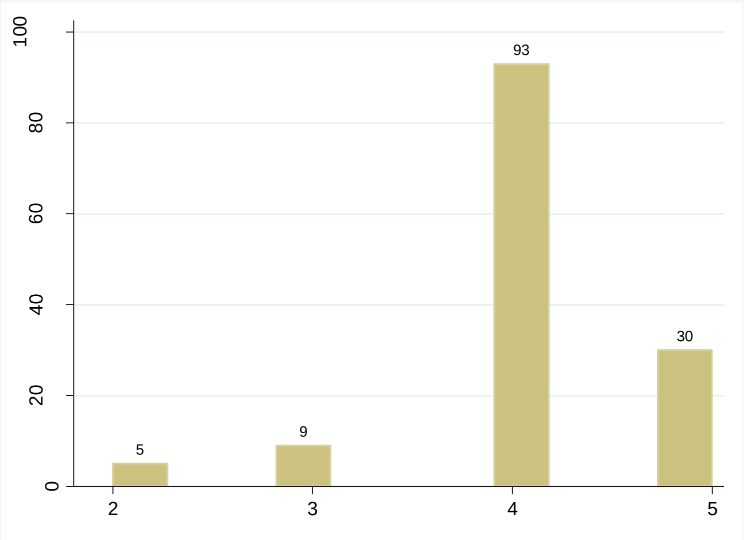


Note. Frequency of each answer shown inside the stacked column graph.

DBDW question 4 asked the participants whether or not they agreed with the statement: 'I liked seeing which topics are being covered at DBDW at the topic selection screen.' The participants reviewed the overview of topics present on the DBDW given to them through the DBDW event recommender system overwhelmingly positively. 90% (123/137) of the participants agreed or agreed strongly with the statement (Figure 12).

Figure 12

Answers to DBDW question 4: 'I liked seeing which topics are being covered at DBDW at the topic selection screen.'



Note. 1 = strongly disagree, 5 = strongly agree.

3.7. Likes and dislikes

82% of the participants left feedback when asked the question: 'What did you like about the DBDW recommendation app, what did you dislike?'. The complete list of answers given to this question can be seen in Appendix D. The current study manually went over all the answers, below frequent answers are described.

Comments made regularly, were that participants liked that the event recommender system was easy to use, and took little time to use. Some regularly mentioned dislikes, were that some of the topics in the topic selection screen were too vague. Participants suggested that if the topics had been grouped in categories, it would have made selecting the topics of their interest easier. Participants were divided on whether they liked the number of topics that they could choose from or not, some found that there were too many, while others liked the vast number of topics to choose from.

Another suggestion made often was that an overview of all events should be shown alongside the 5 events the participant got recommended. Participants made this suggestion regardless of whether they did or did not like the recommendations they got. Adding the overview of all events would give the participant more control over which event they eventually decide to visit.

Some final comments made, were that people did not like when events they got recommended were targeted at much younger audiences (10-12 years old). Multiple participants also mentioned that the visual side of the recommendation app should be improved. Finally, one participant also mentioned that the app could be more precise in understanding the interests of the user by analysing Twitter posts.

4. Discussion

Events are difficult to recommend to users because events are time-specific in nature and are one-and-only items. Recent studies have been researching multiple different approaches to solve the issues with event recommender systems. One of these ideas was to develop a content-based event recommender system which used social media for implicit preference elicitation (Horowitz et al., 2018).

The current study aimed to investigate the effects of using social media for enhancing the explicit preference elicitation method for an event recommender system on the user experience. It was hypothesised that using social media might have both positive and negative consequences for the user experience of the event recommender system. Although it might decrease the required effort the user needs to put into the system and potentially increase the recommendation quality, it might also increase the privacy concerns the users might have. This lead to the following research question: *'How does the use of social media for preference elicitation influence the user experience of an event recommender system?'*

4.1. Main findings

From the results, it can be concluded that the use of social media for preference elicitation in event recommender systems affects the user experience in two ways.

First of all, the user experience of an event recommender system is affected by using social media for preference elicitation through the privacy concern of the user. Results showed that using social media for preference elicitation significantly increases a person's privacy concern. In turn, privacy concern was shown to affect system effectiveness negatively. However, no significant difference of system effectiveness was found between the two experimental conditions. This meant that there were variables counteracting the negative effect of privacy concern on system effectiveness in the social media condition with a similar effect size. The structural equation model showed that the indirect effects of gender, expertise, and technology distrust through recommendation quality added up to counteract the negative effect of privacy concern on system effectiveness. However, it would be short-sighted to conclude that gender, expertise, technology distrust, and recommendation quality are truly the sole cause for counteracting the negative effect of privacy concern. There is the possibility that variables that could not be included in the structural equation model (such as system effort), also contribute to the positive effect on system effectiveness in the social media condition.

Aside from the experimental condition affecting privacy concern, no other significant effects of the experimental condition on other variables were found.

However, the findings described above might not be completely accurate. Something that could not be incorporated into the structural equation model was that relatively more participants quit the experiment in the social media condition than in the explicit condition. Most of the participants who quit in the social media condition did so when they were confronted with the question to insert their Twitter account name. Tufekci (2008), found that privacy-aware people were more reluctant to join online social network platforms. So in this

case, it was reasonable to assume that the cause for this high dropout rate in the social media condition was largely due to the participants not feeling comfortable with giving away their twitter name to the DBDW online recommendation app.
This meant that the privacy concern in the social media condition would likely have been larger in reality than was measured by the current study. And although moderate significant negative effect of privacy concern on system effectiveness was measured, this effect would likely have been stronger if participants had not quit the study after being asked for their Twitter account name.

In conclusion, although there was no significant net effect of the use of social media for preference elicitation on the user experience, this did not mean that an event recommender system using social media for preference elicitation would be received well by the public. The current study concluded that many potential users might refrain from using an event recommender system asking for access to the users' social media profile.

4.2. Exploratory research findings

Next to looking at the effects of privacy concern, the current study looked at the effect between recommendation quality and system effectiveness. The structural equation model shows a high correlation between recommendation quality and system effectiveness. Because there were indications that the recommendation quality and system effectiveness could have been one single variable, it was difficult to correctly interpret the effect of recommendation quality on system effectiveness. Clearly the two variables were very much intertwined. As mentioned earlier, one reason for this high correlation could be that the event recommender system used in the current study was somewhat simplistic. The system did not have much more to offer than just its recommendations. For this reason it was not strange that the user experience was dependent on the quality of the recommendations. Logically one would say that the quality of recommendations given by a recommender system predicts user experience. In the current study that would mean that recommendation quality was predicting system effectiveness.

The current study also looked into the effects of the PC variables in the structural equation model.
With the total effect of gender in the structural equation model being insignificant, and expertise only affecting another personal characteristic variable, the only PC variable of interest was technology distrust. Technology distrust had negative mediated effects on system effectiveness through both recommendation quality and privacy concern. Meaning that the more people distrusted technology, the worse their perceived system effectiveness of the event recommender system was. As technology distrust is a personal characteristic, it is not possible to alter this. However it might be possible to counteract the effects of technology distrust by improving the way people view the event recommender system. This phenomenon of global evaluations of a system affecting the evaluation of its attributes is known as the halo effect (Nisbett & Wilson, 1977). In case of the DBDW online recommendation app, the halo effect could be used to its advantage to increase the user experience in several ways. For example by improving the visual side of the event recommender system to make it more appealing to look at. Another way to improve people's

trust in a system is by associating it with a trusted authority (Beldad, De Jong, & Steehouder, 2011). In case of the DBDW the event recommender system could be associated with the municipality of Den Bosch. This line of reasoning is in accordance with the findings of Barth et al. (2019) mentioned earlier, which showed that the functionality, design, ratings, and reviews of an app outweigh the privacy concerns one may have. There are however some ethical concerns with using the halo effect to the advantage of an event recommender system. As effectively using the halo effect to the advantage of an event recommender system leads to people being less careful with their privacy sensitive data, it also increases the system's responsibility to make sure that the data is stored securely, and is not used beyond its intended scope (Jeckmans et al., 2013).

4.3.DBDW event recommendation suggestions

The current study was conducted in cooperation with the DBDW organization. The DBDW organization wanted to know whether there was a demand for an event recommender system from the point of view of the DBDW visitors. And if so, how this recommender system should be implemented. This lead to the following research question: *'What is the added value of a recommender system for events such as DBDW and how should it be implemented?*'.

Interpreting the results of DBDW questions 1 (Figure10) and 4 (Figure 12) was very difficult. DBDW question 1 was very clearly directed at visitors of the DBDW, who were not part of the participant pool. In case of DBDW question 4, for people who did not visit the DBDW, the topic list that was shown to them by the event recommender system was their only way of knowing what the contents of the DBDW events were. For this reason it could not be concluded whether visitors of the DBDW who had already gotten familiar with the contents of the events in other ways would also like to have such an overview of the topics or not. At best, from the results of DBDW questions 1 and 4, it could be concluded that the developed DBDW event recommender system was perceived positively by the vast majority of the participants, resulting in them agreeing to the statements. Answers to DBDW question 2 (Figure 10) and 3 (Figure 11) were more easily interpretable, as these questions were less directed at visitors of the DBDW.

Because the results showed that in general the event recommender system was perceived positively, it could be beneficial for the DBDW to implement such a system for the upcoming years to improve the event experience of the DBDW visitors. Based on the results of DBDW question 3, a good way this event recommender system could be implemented would be to have the event recommender system as an added functionality to a DBDW mobile app. This mobile app should at least contain a program of all the DBWD events, and an overview of the topics that will be discussed during these events. The added recommender system functionality could be a content-based recommender system based on these topics. Participants answered on the likes and dislikes question that they valued simplicity and immediacy in an event recommender system, which is exactly what a content-based recommender system could provide.

For the preference elicitation of the event recommender system it would be ill-advised to use social media for implicit preference elicitation. The current study showed that many people were turned off by having their social media information used for recommendations, even if this information was public. Instead, explicit preference elicitation should be used. This can be done in a similar way to the DBDW online recommendation app developed by the current study, where the user would select the topics they find interesting. If this approach were to be taken, it should be mentioned people indicated that the topics should be clear, distinct, and grouped in categories. This would make it easier for the user to review the list of topics, and find the ones they find interesting.

To further alleviate the privacy concerns people might experience when using an event recommender system, it might be helpful to make the mobile app visually appealing and have it officially associated with the municipality of Den Bosch. However the mobile app should be very mindful of the information it is gathering on its users, and make sure that this data is stored securely and is not used beyond its intended scope.

Finally, because the event recommender system should be simplistic, it should also produce fitting recommendations for its users as the user experience is largely dependent on the quality of the recommendations.

4.4. Limitations

One of the biggest problems the current study faced was that the participants weren't visitors of the DBDW. The current study hoped get insight into the attitudes towards event recommender systems of visitors of the DBWD, and the study was designed accordingly. With the participants being gathered through the JSF participant database from the TU/e and the Prolific participant database, especially the answers to the exploratory DBDW questions were more difficult to interpret.

Another issue was that despite best efforts, the division of participants was not equal among the experimental conditions. There were 41 participants in the social media condition and 96 participants in the explicit condition. The possibility of an unequal division among the experimental conditions was taken into account beforehand when doing the power analysis. A ratio of 35/65 was assumed, however with the achieved ratio of 30/70 and with 137 participants, this resulted in a lower power than was aimed for.

Another problem with the current study was that the selection confidence and system effort variables had measured issues. A reason for this could be that the amount of effort people had to put into the system was low by default, resulting in little difference in system effort between the two experimental conditions. Another reason could be that the implicit preference elicitation system through social media did not work well enough, and that the topics pre-selected for the participants in the social media condition did not reflect the participants' interests well enough. It was hypothesised that selection confidence and system effort might have been variables that positively influenced the system effectiveness. But unfortunately these hypotheses could not be tested. Although it was found that there was a positive effect counteracting the negative effect of privacy concern on system effectiveness, the current study was not able to identify what variable was causing this.

Finally the DBDW online recommendation app developed for the current study was a simplistic event recommender system. Not all events present at the DBDW were included in the event recommender system. For some events there was no description associated with them making it impossible to use the natural language processing tools for topic extraction, and for other events the natural language processing tools did not extract any topics describing the event correctly.

Some other functionalities were also lacking in the DBDW online recommendation app, which might be useful for the next version of the DBDW event recommendation app. Examples of lacking functionalities are functionalities that give the user some more control over the recommendations they get, such as selecting the dates for which they want event recommendations, or selecting the age group towards which the event is targeted.

5. Conclusion and future research

The current study showed that the perceived system effectiveness of the DBDW online recommendation app was not significantly different between the experimental conditions; the perceived system effectiveness was not different when using implicit preference data from social media profiles to enhance explicit preference elicitation compared to using an exclusively explicit preference elicitation method. However, the level of privacy concern was significantly higher in the social media condition compared to the explicit condition. Also the dropout rate of participants was significantly higher in the social media condition, most of these participants quit the experiment when they were asked to share their social media information. This indicates that the true effect of using social media for preference elicitation on users' privacy concern is larger in reality than was measured by the current study. For this reason the current study would advise not to use social media for preference elicitation for simplistic event recommender systems such as the DBDW online recommendation app. Further research is needed to investigate in which cases using social media in recommender systems leads to a better user experience. As indicated by earlier research it is important to the user of recommender systems that the system is transparent (Swearingen & Sinha, 2001). So it is possible that when the event recommender system is more transparent in how the data from the users' social media profile is used, people have less privacy concerns. Also if there are more obvious benefits associated with using one's social media profile, it may lead to a better user experience, and users might have less issues with giving access to their social media profile.

Although the current study found that privacy concerns negatively affected the perceived system effectiveness of the DBDW online recommendation app, and privacy concerns were higher in the social media condition, no difference in system effectiveness was found between the experimental conditions. This meant that there were variables positively affected by the social media condition, which in turn was positively affecting the perceived system effectiveness. It is likely that more variables aside from expertise, gender, technology distrust, and recommendation quality are responsible for this positive effect. To find out what variables are causing this effect, further research is needed.

Finally, for the DBDW organization, the current study found that the majority of the participants reacted positively to the DBDW online recommendation app. Most people indicated that their preferred way to decide which events to go to would be either by using a mobile DBDW app with the program of the DBDW, or by using a recommendation app similar to the DBWD online recommendation app. For this reason, the current study would suggest the DBDW organization to look into building a mobile app for the DBWD with the program, and have a simplistic content-based event recommender as an added functionality to this mobile app. Simplicity and immediacy were highly valued in the DBDW online recommendation app and should be taken into account.

However, it should be noted that the participants that partook in the current experiment did not visit, nor did they know about the DBDW. The participants of the current study were given an introduction into the DBDW and were asked to imagine visiting the DBDW. But the way actual visitors of the DBDW would perceive a DBDW event recommender system might differ from the way the participants of the current study perceived the DBDW online recommendation app. Future research may be needed to verify the results of the current study by repeating the current study with actual DBDW visitors.

Acknowledgements

The author would like give a special thanks to Yu Liang for her help with the implementation of the DBDW online recommendation app, and to Stephan Glerum for the opportunity to conduct DBDW related research.

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Appendix A

Programming code for creating the topic list

```
# Import and split DBDW program text
# File location of DBDW event text file = C:\Users\s148885\Documents\TUe\Msc HTI\HTI
jaar 2\Master thesis\Python stuff\programmaDBDW_opgeschoond.txt
program_DBDW  =  open(r"C:\Users\s148885\Documents\TUe\Msc  HTI\HTI  jaar  2\Master
thesis\Python stuff\programmaDBDW_opgeschoond.txt")

# The text file is edited in such a way that after each blank line a new event is
represented
text = program_DBDW.read().split("\n\n")
print(text)


# Translate text
from googletrans import Translator, constants

translator = Translator()
text_translation = []
for line in text:
    text_translation.append(translator.translate(str(line)))

for line in text_translation:
    print(line.text)




# TAGme API, annotate text
import tagme

MY_GCUBE_TOKEN = 'Your gcube token here'
tagme.GCUBE_TOKEN = MY_GCUBE_TOKEN

text_annotations = []
for line in text_translation:
    text_annotations.append(tagme.annotate(line.text))

# Print annotations with a score higher than 0.3, add annotations to a set and lists
topics_DBDW = []
set_topics_DBDW = set()
event_nr_topics_DBDW = []   # Save the topics per event
for i, line in enumerate(text_annotations):
    topics_DBDW_temp = []
    event_nr_topics_DBDW.append(topics_DBDW_temp)
    for ann in line.get_annotations(0.3):
        topics_DBDW_temp.append(ann.entity_title)
        set_topics_DBDW.add(ann.entity_title)
        topics_DBDW.append(ann.entity_title)

        print(ann)

print(topics_DBDW)
print(event_nr_topics_DBDW)
print(set_topics_DBDW)
```

```
# Save the set
import pickle
pickle.dump(topics_DBDW, open('topics_DBDW.dat', 'wb'))
pickle.dump(event_nr_topics_DBDW, open('event_nr_topics_BDDW', 'wb'))
pickle.dump(set_topics_DBDW, open('set_topics_DBDW.dat', 'wb'))
```

Programming code for the recommendation system

```
# Retrieve tweets
import re
import tweepy

# Twitter tokens for API access
bearer_token = 'your bearer token here'
access_token = 'your access token here'
access_token_secret = 'your access token secret here'
api_key = 'your api key here'
api_key_secret = 'your api key secret here'

# Get access to Twitter API
auth = tweepy.OAuthHandler(api_key, api_key_secret)
auth.set_access_token(access_token, access_token_secret)

api = tweepy.API(auth)


# Input Twitter screen name in order to get their tweets
print('Insert Twitter screen name (this is the name with the \'@\' in front of it)')
twitter_name = input()

# Get tweets if possible (User screen name might not exist, or tweets are not
publically availabe)
try:
    user = api.get_user(twitter_name)
except tweepy.error.TweepError:
    print('User does not exist.')
    exit()

print(user)
print('\nID:\n' + str(user.id) + '\n')
print('User description:\n' + user.description + '\n')

posted_tweets = []
print('Tweets:')

try:
    for tweet in tweepy.Cursor(api.user_timeline, user.id,
tweet_mode='extended').items(10):   # Set items to the number of tweets you want to
collect
        posted_tweets.append(tweet.full_text)
except tweepy.TweepError:
    print('No tweets available.')
    exit()

print(posted_tweets)
```

```
# Remove URL's from tweets
for i, tweet in enumerate(posted_tweets):
    tweet = re.sub(r'https?:\/\/.*[\r\n]*', '', tweet, flags=re.MULTILINE)
    posted_tweets[i] = tweet




# Translate dutch tweets
from googletrans import Translator, constants

translator = Translator()
tweet_translation = []
for tweet in posted_tweets:
    tweet_translation.append(translator.translate(str(tweet)))

print('\nTranslations tweets:\n')
for tweet in tweet_translation:
    print(tweet.text)




# TAGme API, annotate tweets
import tagme

MY_GCUBE_TOKEN = 'your gcube token here'   # Token to work with the TAGme API
tagme.GCUBE_TOKEN = MY_GCUBE_TOKEN

tweet_annotations = []  # Analyze tweets to get annotations (topics)
for tweet in tweet_translation:
    tweet_annotations.append(tagme.annotate(tweet.text))


# Print annotations with a score higher than 0.2, add annotations to a list
topics_tweets = []
print('\nAnnotations:\n')
mention_topic = dict()

for tweet in tweet_annotations:
    if tweet:
        for ann in tweet.get_annotations(0.2):  # Set score
            topics_tweets.append(ann.entity_title)
            mention_topic[ann.mention] = ann.entity_title
            print(ann)
            print(ann.entity_title)
            print(ann.mention)
print(mention_topic)



# Load topics_DBDW
import pickle
topics_DBDW = pickle.load(open('topics_DBDW.dat', 'rb'))
set_topics_DBDW = pickle.load(open('set_topics_DBDW.dat', 'rb'))
event_nr_topics_DBDW = pickle.load(open('event_nr_topics_BDDW', 'rb'))
print(topics_DBDW)  # List of all topics from the DBDW (including duplicates)
print(event_nr_topics_DBDW)     # Array of all topics PER EVENT from the DBDW
```

```
# Get relatedness per tweet topic - event topic pair
relatedness_pairs = ([])
for topic_tweet in topics_tweets:
    for topic_DBDW in set_topics_DBDW:
        relatedness_pairs.append((topic_tweet, topic_DBDW))

# Add relatedness scores of all tweet topics per event topic pair
topic_relatedness_score_dict = {key: 0 for(key) in set_topics_DBDW}
relatedness = tagme.relatedness_title(relatedness_pairs)
for rel in relatedness.relatedness:
    topic_relatedness_score_dict[rel.title2] += rel.rel

# Get average relatedness scores per topic (nr. between 0 and 1)
for topic in topic_relatedness_score_dict:
    topic_relatedness_score_dict[topic]  =  topic_relatedness_score_dict[topic]  /
len(topics_tweets)

# Set the top 5 topics to a binary 1, rest of the topics to a binary 0
sorted_topics_dict = {k: v for k, v in sorted(topic_relatedness_score_dict.items(),
key=lambda item: item[1], reverse=True)}
for key in list(sorted_topics_dict)[:5]:
    sorted_topics_dict[key] = 1
for key in list(sorted_topics_dict)[5:]:
    sorted_topics_dict[key] = 0

input_dict = {key: 0 for(key) in set_topics_DBDW}
print('Select a minimum of 5 topics that are interesting to you (1 = interesting,
0 = not interesting.')
for key, value in sorted_topics_dict.items():
    print(key + ' : ' + str(value))
    inp = input()

    if inp:
        input_dict[key] = inp
    else:
        input_dict[key] = sorted_topics_dict[key]

# Get relatedness score per event (add relatedness scores of topics present for
each event)
event_relatedness_score_dict = {key: 0 for(key) in
range(len(event_nr_topics_DBDW))}  # Create empty dictionary with len() equal to
amount of events
for i, event in enumerate(event_nr_topics_DBDW):
    for topic in event:
        event_relatedness_score_dict[i] += int(input_dict[topic])

# Delete pairs with relatedness == 0
delete = []
for key, val in event_relatedness_score_dict.items():
    if val == 0:
        delete.append(key)

for i in delete:
    del event_relatedness_score_dict[i]

for key, value in event_relatedness_score_dict.items():
    event_relatedness_score_dict[key] = value / len(event_nr_topics_DBDW[key])
```

```
# Sort on relatedness
sorted_events_dict = {k: v for k, v in sorted(event_relatedness_score_dict.items(),
key=lambda item: item[1], reverse=True)}
print(sorted_events_dict)

# print the top 5 recommendations (if 5 are available)
print('\nTop events you might enjoy:')
print(list(sorted_events_dict)[:5])
```

Appendix B

Informed consent page

JADS

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Welcome to the Den Bosch Data Week Online Recommendation App

Online informed consent

Introduction

Welcome to the Den Bosch Data Week online recommendation research! This app was developed for visitors of the Den Bosch Data Week (DBDW). The DBDW is a week-long event in Den Bosch, The Netherlands, a city in the south part of the country. Here all kinds of small events such as lectures, interviews, exhibitions and others talks are taking place throughout the city. These events are all on the topic of data science.
The goal of this study is to find out what visitors of the DBDW event think of using a recommendation tool in order to find interviews, lectures, activities, etc. at the DBDW event that they are interested in.
For this study, imagine yourself visiting the DBDW and trying to find out which events you would like to go to.

This research is a master thesis project by J.S.A. Verzuu under supervision of dr.ir. M.C. Willemsen, from Eindhoven University of Technology and JADS Den Bosch.

DBDW recommendation app

The app will show you a list of topics from DBDW events. From this list you will be asked to select at least 5 topics (more is also possible). After your topic selection you will be recommended 5 events from the DBDW that we think you might enjoy the most. The app will store your topic selection and recommended events securely for research purposes.

Procedure

Before making your topic selection , you will be asked a few demographics questions. After your topic selection you will be asked a couple of questions about your experience with the system so far. Then your 5 recommended events will show and you will be asked some final questions about your experience with the system. Your answers to these questions will be stored securely for research purposes.

Duration

Participating in the online recommendation research will take about 10 minutes.

Data storage

All research of Eindhoven University of Technology is performed in agreement with the ethical code of the NIP (Nederlands Instituut voor Psychologen). No personal information will be shared outside the research team. The information collected will be stored on a secured server of the HTI research group of the TU/e. The data will be used for writing scientific publications.

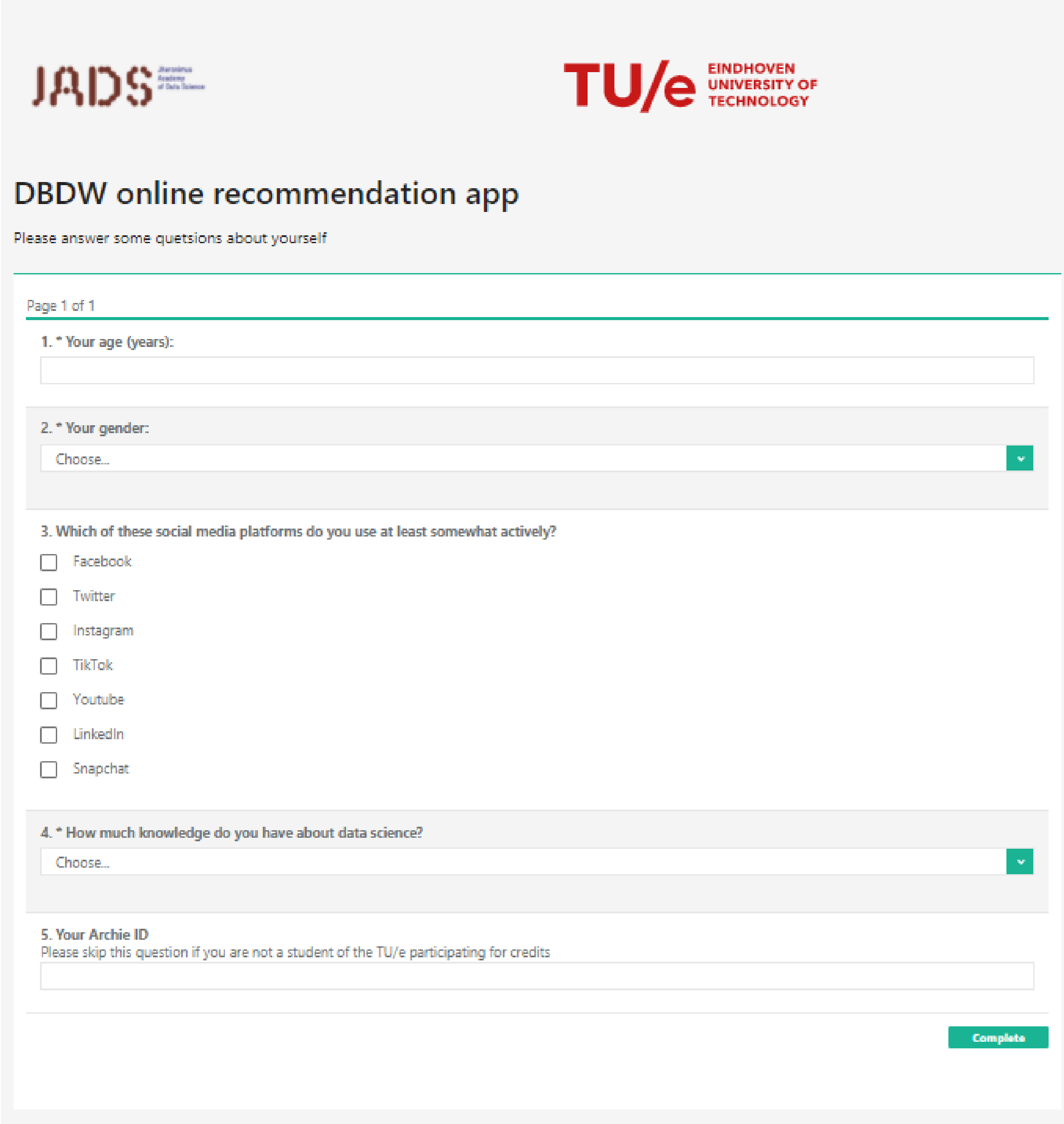
☐ **(optional) Other researchers from the HTI research group can use my data (after anonymization) for scientific research purposes.**

By pressing 'Continue', you indicate that you understood the information and agree to voluntarily participate to this research.

Continue →

**For questions about this study please contact J.S.A. Verzuu (email: j.s.a.verzuu@student.tue.nl). If you have any complaints about this study, please contact the supervisor, M.C. Willemsen (email: m.c.willemsen@tue.nl). You can report irregularities related to scientific integrity to confidential advisors of the TU/e.*

Demographics questions page



JADS Jheronimus Academy of Data Science

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

DBDW online recommendation app

Please answer some quetsions about yourself

Page 1 of 1

1. * Your age (years):

2. * Your gender:

Choose...

3. Which of these social media platforms do you use at least somewhat actively?

- [ ] Facebook
- [ ] Twitter
- [ ] Instagram
- [ ] TikTok
- [ ] Youtube
- [ ] LinkedIn
- [ ] Snapchat

4. * How much knowledge do you have about data science?

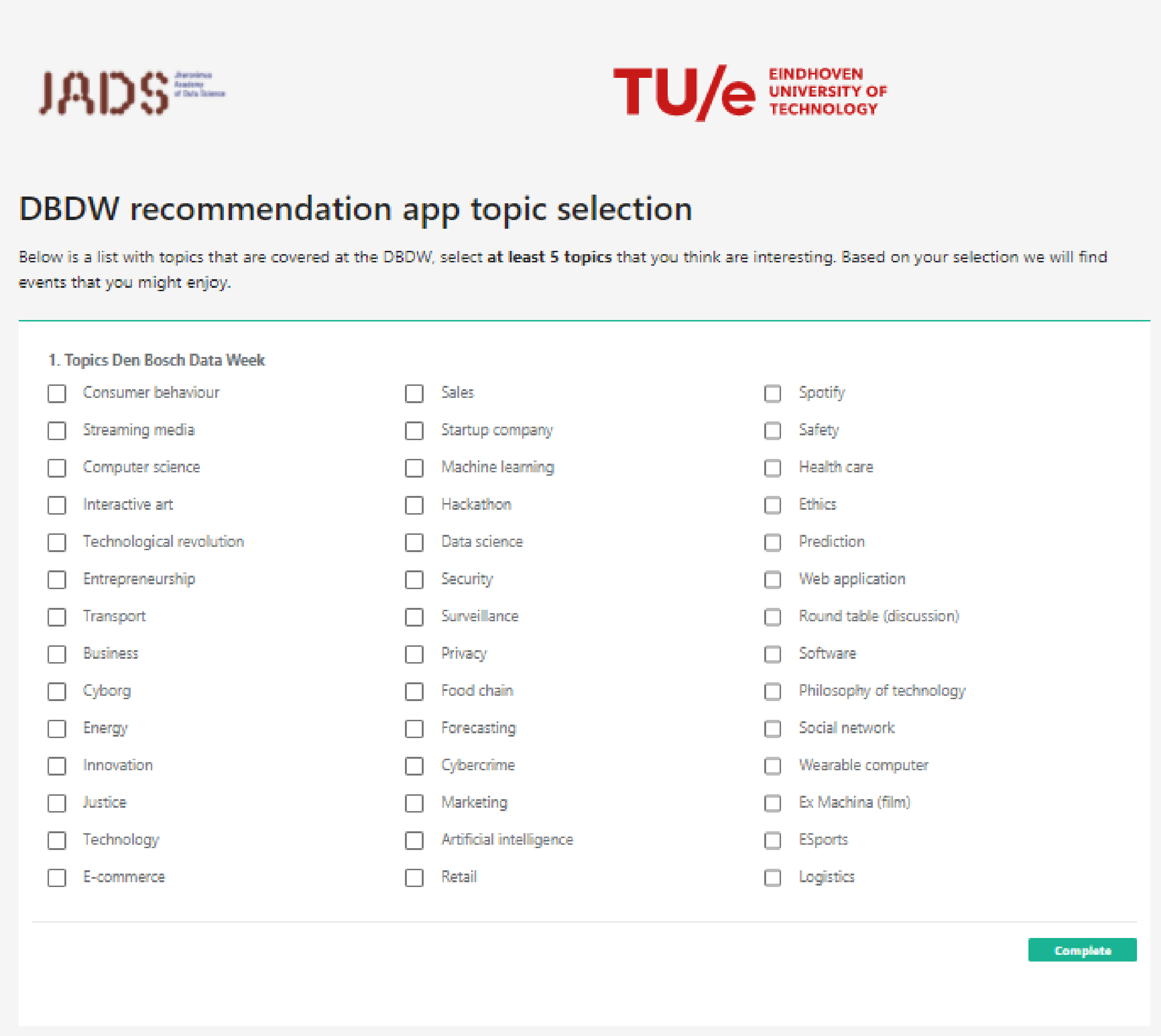
Choose...

5. Your Archie ID

Please skip this question if you are not a student of the TU/e participating for credits

Complete

Topic selection page, explicit condition



EINDHOVEN UNIVERSITY OF TECHNOLOGY

DBDW recommendation app topic selection

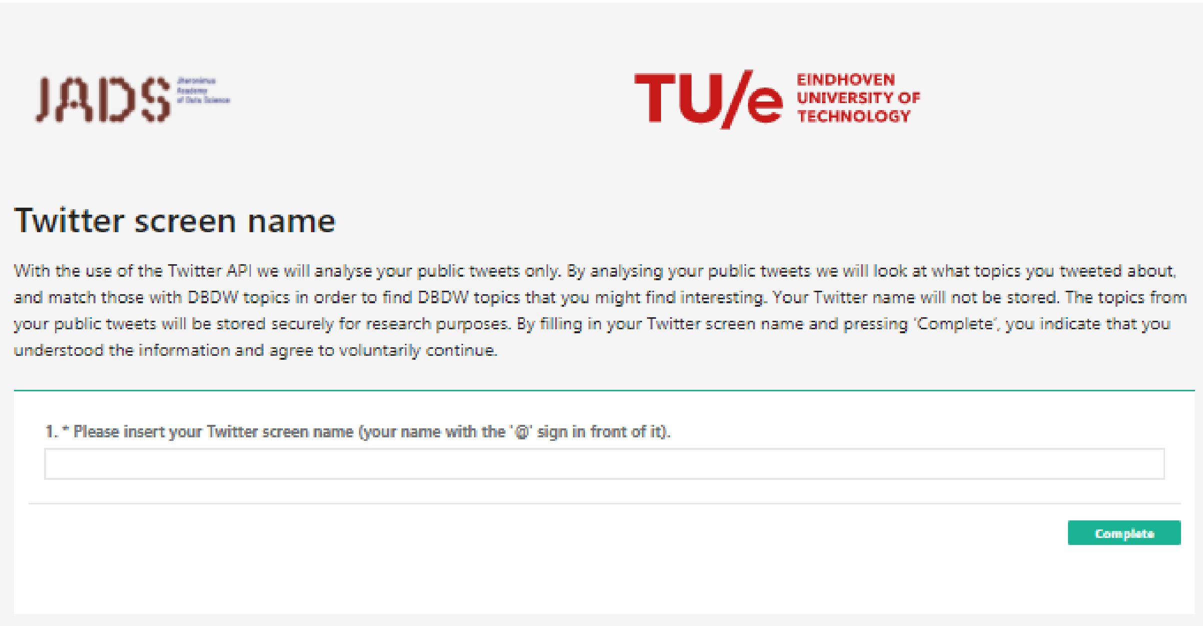
Below is a list with topics that are covered at the DBDW, select **at least 5 topics** that you think are interesting. Based on your selection we will find events that you might enjoy.

1. Topics Den Bosch Data Week

☐ Consumer behaviour	☐ Sales	☐ Spotify
☐ Streaming media	☐ Startup company	☐ Safety
☐ Computer science	☐ Machine learning	☐ Health care
☐ Interactive art	☐ Hackathon	☐ Ethics
☐ Technological revolution	☐ Data science	☐ Prediction
☐ Entrepreneurship	☐ Security	☐ Web application
☐ Transport	☐ Surveillance	☐ Round table (discussion)
☐ Business	☐ Privacy	☐ Software
☐ Cyborg	☐ Food chain	☐ Philosophy of technology
☐ Energy	☐ Forecasting	☐ Social network
☐ Innovation	☐ Cybercrime	☐ Wearable computer
☐ Justice	☐ Marketing	☐ Ex Machina (film)
☐ Technology	☐ Artificial intelligence	☐ ESports
☐ E-commerce	☐ Retail	☐ Logistics

Complete

Twitter screen name, social media condition



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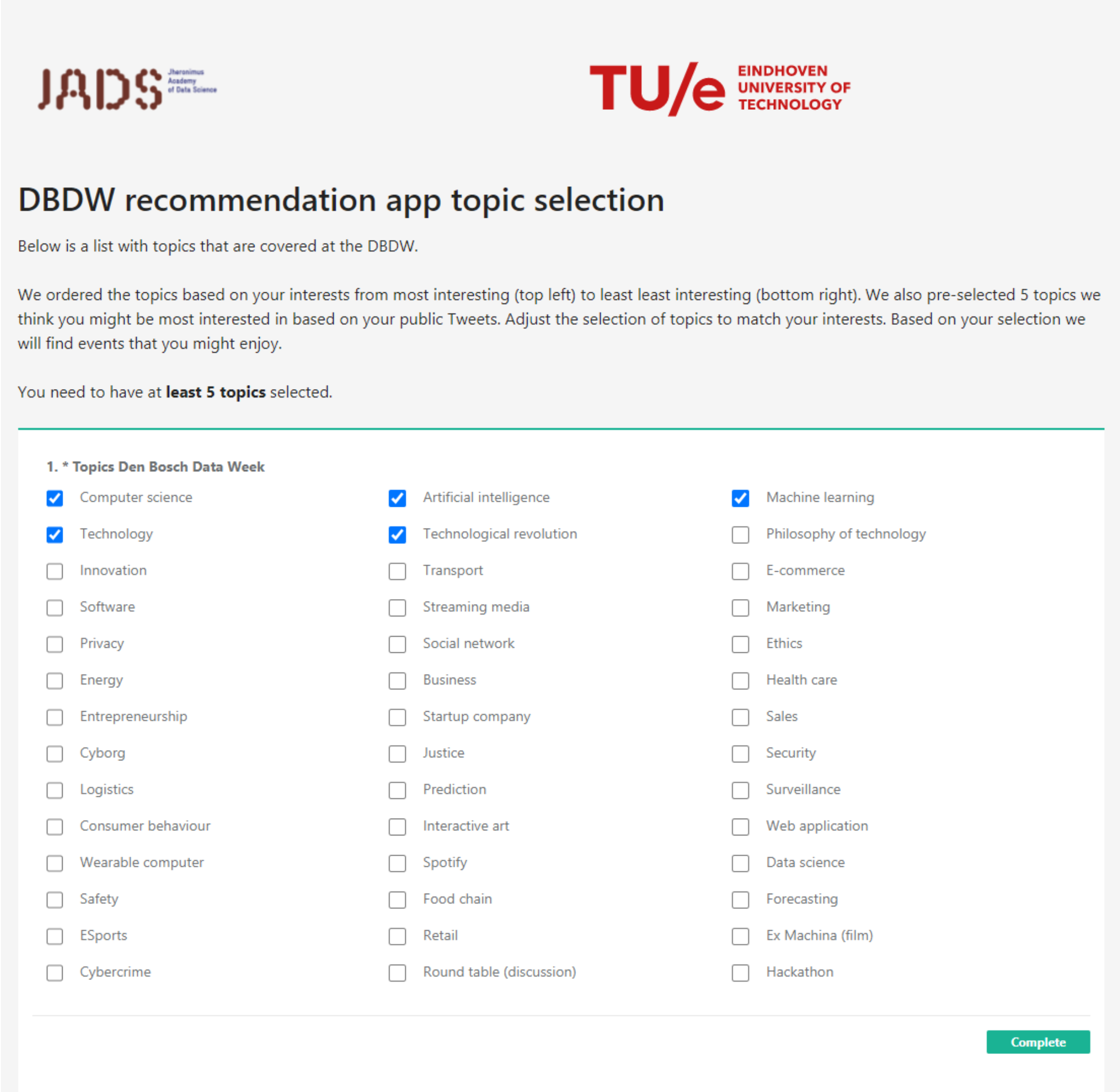
Twitter screen name

With the use of the Twitter API we will analyse your public tweets only. By analysing your public tweets we will look at what topics you tweeted about, and match those with DBDW topics in order to find DBDW topics that you might find interesting. Your Twitter name will not be stored. The topics from your public tweets will be stored securely for research purposes. By filling in your Twitter screen name and pressing 'Complete', you indicate that you understood the information and agree to voluntarily continue.

1. * Please insert your Twitter screen name (your name with the '@' sign in front of it).

Complete

Topic selection page, social media condition



JADS Jheronimus Academy of Data Science

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

DBDW recommendation app topic selection

Below is a list with topics that are covered at the DBDW.

We ordered the topics based on your interests from most interesting (top left) to least least interesting (bottom right). We also pre-selected 5 topics we think you might be most interested in based on your public Tweets. Adjust the selection of topics to match your interests. Based on your selection we will find events that you might enjoy.

You need to have at **least 5 topics** selected.

1. * Topics Den Bosch Data Week

[x] Computer science	[x] Artificial intelligence	[x] Machine learning
[x] Technology	[x] Technological revolution	[ ] Philosophy of technology
[ ] Innovation	[ ] Transport	[ ] E-commerce
[ ] Software	[ ] Streaming media	[ ] Marketing
[ ] Privacy	[ ] Social network	[ ] Ethics
[ ] Energy	[ ] Business	[ ] Health care
[ ] Entrepreneurship	[ ] Startup company	[ ] Sales
[ ] Cyborg	[ ] Justice	[ ] Security
[ ] Logistics	[ ] Prediction	[ ] Surveillance
[ ] Consumer behaviour	[ ] Interactive art	[ ] Web application
[ ] Wearable computer	[ ] Spotify	[ ] Data science
[ ] Safety	[ ] Food chain	[ ] Forecasting
[ ] ESports	[ ] Retail	[ ] Ex Machina (film)
[ ] Cybercrime	[ ] Round table (discussion)	[ ] Hackathon

Complete

Survey page 1

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Questions DBDW recommendation app

Your preferences have been collected, please answer the following questions and get your recommendation results.

Page 1 of 1

1. Below are some questions on your attitude towards technology. Please indicate to what extent you agree or disagree with each statement.

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Technology never works.	○	○	○	○	○
I'm less confident when I use technology.	○	○	○	○	○
The usefulness of technology is highly overrated.	○	○	○	○	○

2. Below are some questions on privacy. Please indicate to what extent you agree or disagree with each statement.

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I'm afraid the DBDW recommendation app discloses private information about me.	○	○	○	○	○
The DBDW recommendation app invades my privacy.	○	○	○	○	○
I feel confident that the DBDW recommendation app respects my privacy.	○	○	○	○	○

3. Below are some questions on your experience with the topic selection system you've just used. Please indicate to what extent you agree or disagree with each statement.

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The topic selection system is convenient.	○	○	○	○	○
I have to invest a lot of effort in the topic selection system.	○	○	○	○	○
It takes many mouse-clicks to use the topic selection system.	○	○	○	○	○

4. Below are some questions on the effort you had to put into working with the topic selection system. Please indicate to what extent you agree or disagree with each statement.

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I am confident that I selected the right topics.	○	○	○	○	○
I might have missed some interesting topics.	○	○	○	○	○
I changed my mind a lot while selecting the topics	○	○	○	○	○

Complete

Recommendations, survey page 2

Events you might like and some final questions

On the left are the events we think you might enjoy, take your time to check out these recommendations. Afterwards please fill out the final questions on the right.

Our event recommendations are:

Click the title to see more about the event!

THE BREAKTHROUGH OF AI - PROF.DR. ERIC POSTMA, PROFESSOR OF ARTIFICIAL INTELLIGENCE, TILBURG UNIVERSITY AND JADS

This presentation provides an overview of the development of artificial intelligence (AI) in an accessible and sober way. The following questions are answered: What is the state of affairs of AI? What are the strengths and weaknesses of the AI? Finally, the importance of AI for Den Bosch Datastad and the role of JADS in this is discussed.

Tuesday 27 October 2020

17.00 - 18.00

HACK DEN BOSCH BETTER

DATA & ETHICAL ISSUES: TALKING WITH YOUNG PEOPLE

PEOPLE ORIENTED ARTIFICIAL INTELLIGENCE

BLOCK DATA & ETHICAL ISSUES

Page 1 of 2

1. Below are some questions on your experience using the Den Bosch Data Week Online Recommendation App. Please indicate to what extent you agree or disagree with each statement.

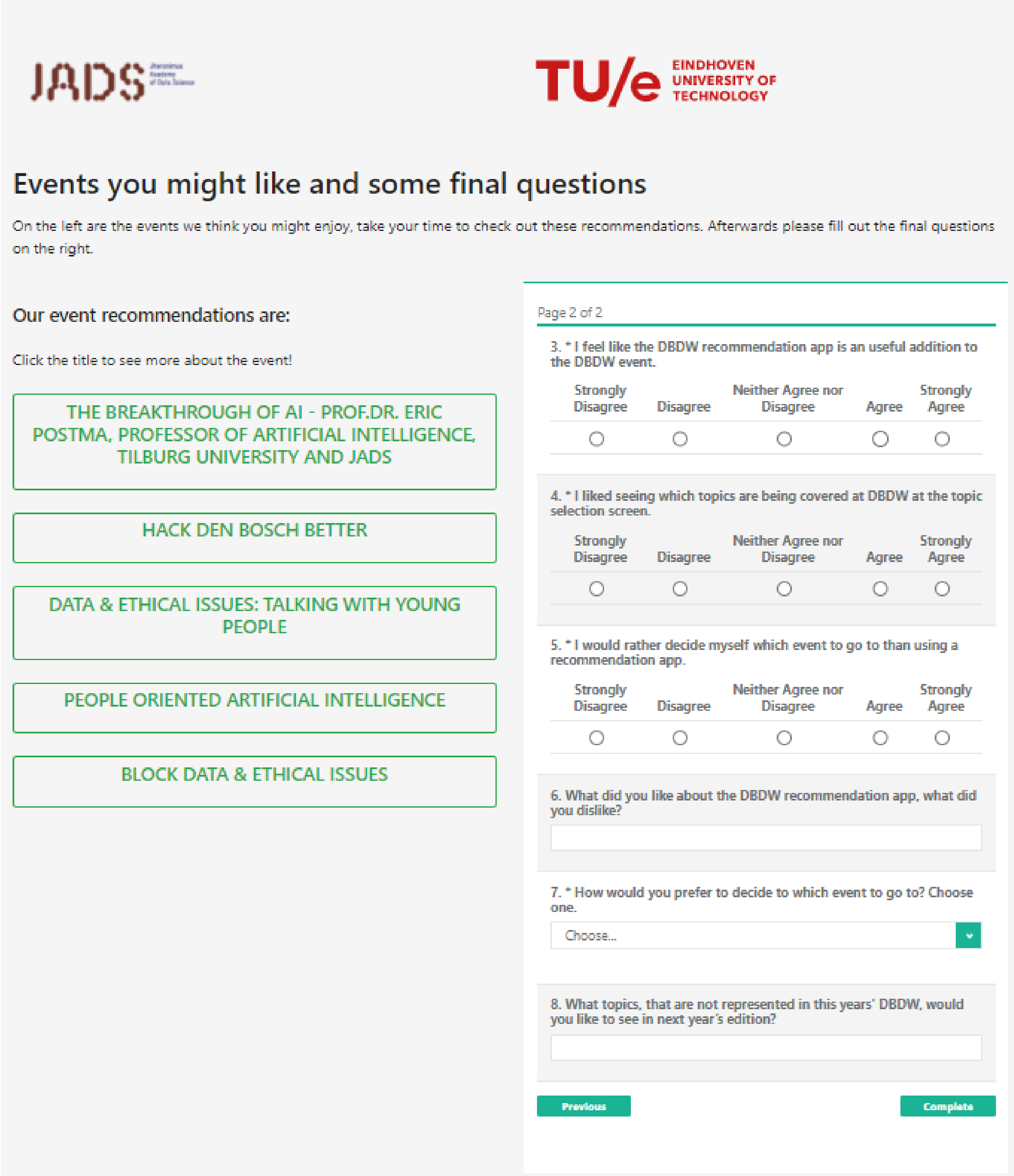
	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I would recommend the DBDW recommendation app to others.	○	○	○	○	○
The DBDW recommendation app is useless.	○	○	○	○	○
I can find better events using the DBDW recommendation app.	○	○	○	○	○

2. Below are some questions on what you think about the events you got recommended to you (recommendations on the left side). Please indicate to what extent you agree or disagree with each statement.

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I liked the recommendations provided by the DBDW recommendation app.	○	○	○	○	○
The recommended events fitted my preference	○	○	○	○	○
The recommended events were relevant.	○	○	○	○	○

Next

Recommendations, survey page 3



JADS Jheronimus Academy of Data Science

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Events you might like and some final questions

On the left are the events we think you might enjoy, take your time to check out these recommendations. Afterwards please fill out the final questions on the right.

Our event recommendations are:

Click the title to see more about the event!

THE BREAKTHROUGH OF AI - PROF.DR. ERIC POSTMA, PROFESSOR OF ARTIFICIAL INTELLIGENCE, TILBURG UNIVERSITY AND JADS

HACK DEN BOSCH BETTER

DATA & ETHICAL ISSUES: TALKING WITH YOUNG PEOPLE

PEOPLE ORIENTED ARTIFICIAL INTELLIGENCE

BLOCK DATA & ETHICAL ISSUES

Page 2 of 2

3. * I feel like the DBDW recommendation app is an useful addition to the DBDW event.

Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
○	○	○	○	○

4. * I liked seeing which topics are being covered at DBDW at the topic selection screen.

Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
○	○	○	○	○

5. * I would rather decide myself which event to go to than using a recommendation app.

Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
○	○	○	○	○

6. What did you like about the DBDW recommendation app, what did you dislike?

7. * How would you prefer to decide to which event to go to? Choose one.

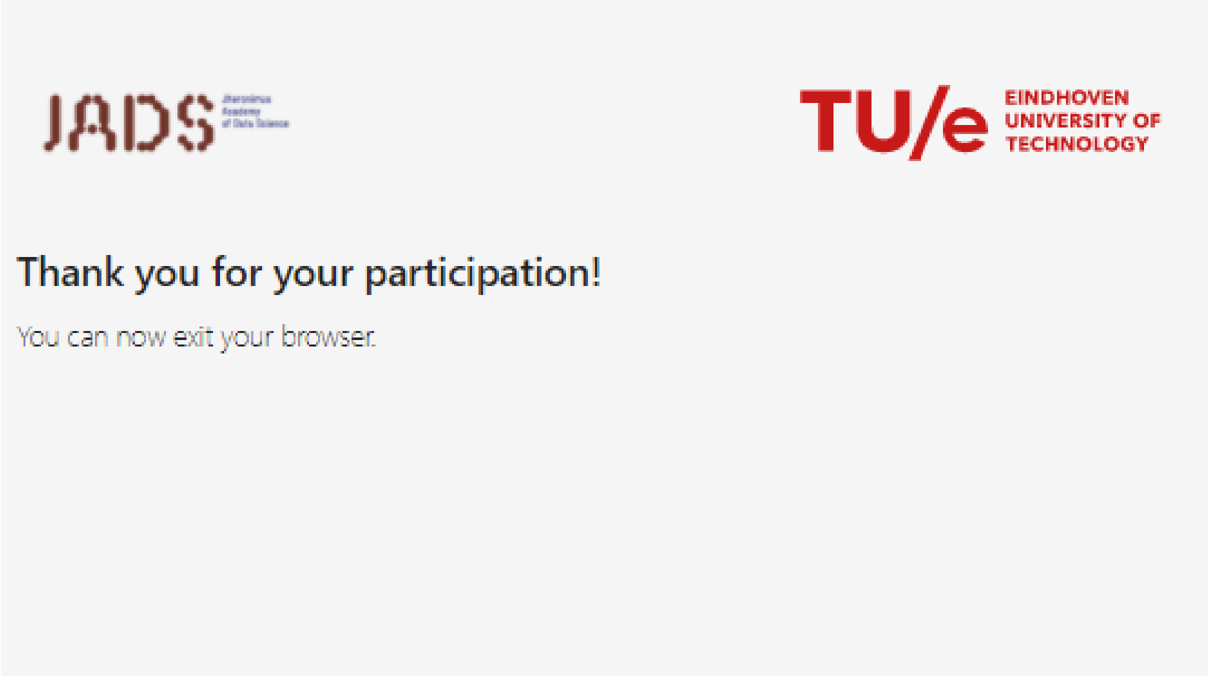
Choose...

8. What topics, that are not represented in this years' DBDW, would you like to see in next year's edition?

Previous

Complete

Final page


JADS
EINDHOVEN UNIVERSITY OF TECHNOLOGY
TU/e
Thank you for your participation!
You can now exit your browser.

Appendix C

Questions on technology distrust

Technology never works	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I'm less confident when I use technology	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The usefulness of technology is highly overrated	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Questions on privacy concern

I'm afraid the DBDW recommendation app discloses private information about me	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The DBDW recommendation app invades my privacy	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I feel confident that the DBDW recommendation app respects my privacy	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Questions on system effort

The topic selection system is convenient	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I have to invest a lot of effort in the topic selection system	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
It takes many mouse-clicks to use the topics selection system	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Questions on selection confidence

I am confident that I selected the right topics	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I might have missed some interesting topics	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I changed my mind a lot while selecting the topics	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Questions on perceived system effectiveness

I would recommend the DBDW recommendation app to others	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The DBDW recommendation app is useless	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I can find better events using the DBDW recommendation app	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Questions on recommendation quality

I liked the recommendations provided by the DBDW recommendation app	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The recommended events fitted my preference	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The recommended events were relevant	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Exploratory question for the DBDW

I feel like the DBDW recommendation app is an useful addition to the DBDW event	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I liked seeing which topics are being covered at DBDW at the topic selection screen	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I would rather decide myself which event to go to than using a recommendation app	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

What did you like about the DBDW recommendation app, what did you dislike?	(Open question)

How would you prefer to decide which event to go to? Choose one.	Options: brochure with the DBDW program, app with the DBDW program, DBDW webpage, through friends/family, recommendation app (such as this app), other

What topics, that are not represented in this years' DBDW, would you like to see in next year's edition?	(Open question)

Appendix D

Answers to the question: ‘What did you like about the DBDW recommendation app, what did you dislike?’

nice to receive recommendations
Its convenient and easy to use. I got four events that seem interesting.
Straightforward, but too many choices maybe
I liked the fact that you could fill in your preferred topics and recommendations were made. However, in addition to the recommendations I would also like to see the other events to makes sure I would not miss anything that I would perhaps find more interesting.
It gives you recommendation of events you otherwise would never have gone to.
You can see the overview of the topics of the event. I didn't really disliked something.
4 out of 5 events were not really interesting for me, but the app does give a clear overview of all events that are recommended
I liked the results, but would be better to see which ones there are as well. Just to be sure of the options given
It gives you a quick overview of interesting events but selecting yourself ofcourse can be never replaced. Maybe add something like see more
Depending on the amount of events, I would use this app.
I liked that first you are provided an overview of the topics presented and then later specific talks that fit your preferences. I did not like that there was no option to see an overview of all possible events.
I would like to also see all options
I like that I do not have to scan through all events to find some that fit my interest. I don't know how the whole app would look like but I would like to have the option to see an overview of all events, for example if I want to visit more than just the recommended events
First of all, it shows the relevant topics (after choosing the preferences) in a clear overview. Besides, I also like the fact that I am mostly interested in every topic, however, some of them aren't completely in my field so i would never click on them myself, but since it got recommended to me personally, I would give it at least a try.
I like that the recommendations were relevant to my preferences, recommender systems in general are great and this one seems to work fine, but some topics that I selected (e.g. esports) were not reflected in the recommendations. Also, no offence, but DBDW doesn't interest me too much, yet the events recommended to me seem interesting. It might be nice to take into account users' attitudes toward the topic of data science in a broader sense.
I liked the compact view of activities that it recommends. I dislike that it put in a children's college on data science. That does not suit me very well, as I am not 7 or 8 years old.
I really like how you get 5 recommendation (it's a nice number). I think an improvement would be to make the selection page of topics subdivided into main topics so it would be easier to find your interests
It recommended me 2 events aimed at younger children, one for group 7 and 8, the other for high school stuents.
Some of the recommendations were catered to people well below my age group.
It offered some suggestions which was nice, I missed an overview where I could skim through events myself
The topics were a bit off.
I like that i personifies recommendations, but there should be an overview containing all events.
An easy way to find recommendation
I liked the vastness of topics to select and the fact that recommendations based on my choices are relevant to my interests. What I disliked was the question about my Twitter name user, as I like to keep my account private, but at the end it wasn't such a big issue thanks to the option of selecting topics manually.

I liked the variety.
i dislike that it is not presented from the point of view of a person feels impersonal
that is makes it easier to choose programmes, and also i might miss out something manually that could interest me, and this recommendation app helps me not to see through it
nothing, all
The app could be more precise in understanding one's interests analyzing their social media public posts, I think.
I liked the vast selection of choices.
I liked the fact that it immediately reflected my preferences without asking me too many questions
I liked that it got some of event recommendations right, but some are not that relevant for me.
It could be a good app to find some interesting events but there are not enough topics to choose from
I think the topics I'm interested in (the ones I had to choose) should be grouped into cathegories or somehow better organized, as it was difficult to choose with so many options while i couldn't see ones that were similiar
i didn't like it recommending to me lecture for children
The events should be future ones.
it brought up topics i dont always think about, i dont like the titles of all the topics they are long
I liked that the app sugested me some events. It is really interesting. But I would prefer to have more choices.
I liked its simplicity, nothing I disliked
I liked that it made choosing topics way easier than if I had do choose them all by myself. I disliked the fact that it felt a bit like an invasion of my privacy even though I entered my username willingly and I was aware that it wasn't going to be stored anywhere.
I liked the amount of topics I could choose from but felt some of them were too vague
I liked the recommendations. Did not dislike anything
i felt insecure
simplicity and immediacy
I liked the precision, I did not dislike anything
I did like one of the events recommended and another might be interesting, the other two I would not go to
I liked to see the wide variety of themes presented and that it was able to recommend events based on my preferences.
It expanded on the area of expertise or topic matter but was not as relevant to my liking as expected
I liked how quick getting recommendation was and still mostly precise, but it could use more detailed option to get better results.
That I have to click to know more about the events instead of scrolling, but it's not that problematic also.
like - its a recommendation app, dislike - its a recommendation app
The topics recomended were useful and interesting. The layout / desing aesthetic of the form was a little dull.
I liked basically everything. I see something like this first time and not gonna lie i really like it already.
I liked to know that there are many events related to my tastes.
It selects one random topic for each subject, seeing more would be more practical.
Topics too broad - but very easy to use
I liked the way you recommended the topics
I liked that it recommended some events to attend. I think I would still take a look at the full program to make sure it didn't miss anything interesting (I'm a control freak). There wasn't anything I didn't like, it's a simple, useful tool.
I would attend all the recommendations that the app made because they seemed aligned with my preferences that i've selected earlier
Wrong Topics
The different topics i could choose, such variety! Can't point anything negative, it's a usefull app that help people think about what they like the most and learn even more from it.

I like the idea but It would be better for UI
I liked the topics and the events it recommended to me.
I really liked the Data Night.
I like that most of the topics are relevant. What i dislike about it is that some events have little description or no description at all.
I think the recommendations were not vast enough, I would have liked to see more on health related topics
It's easy to use, but I'd like to see the full list of events too
I liked how it's easy to use and doesn't require strong technological skills. It's also nicely designed and easy on the eye, even with as many choices as were present in the app.
I like that the program understood my preferences accurately. I don't have a dislike opinion in general.
It's choosing interesting and fitted events, but It should display more than five of them.
It shows relevant recommendations based on my preferences without me telling you what they are
It's useful
I like that it's a convenient way to be introduced to different topics. I don't like that there seems to be no organisation of the topics so it was easy to miis similar ones
I like the concept, but I would also like to have the option to manually see the topics myself. Having both options would be the preferable.
I liked the variety of the topics.
liked my options, disliked not being sure about my data care
Really easy to use and you get a better overview of which events you may like
although having my twitter profile analyzed made me slightly anxious, it was interesting to see what topics would the app extract from it. the process was pretty fast and choosing the topics was rather easy & convenient. overall it was exciting, just a bit underwhelming when I got the results but only because I chose so many topics and I assumed there would be more events to choose from. but the events that I got were still mostly interesting
I liked how simple it was to select the topics I'm interested in and I like that there were lots of topic options. All the recommendations were interesting and if I were going to the DBDW I would probably take part in all of them.
I don't have to go through everything when selecting recommendations were made and I selected
it's very useful
I think I would've missed some of the events recommended by the app if it didn't inform me of them so it's certainly very useful. I'd say some people may feel overwhelmed by the amount of topics in the app but personally, I didn't think it was a problem for me.
i like the fact that the DBDW recommendation knows what we like
nothing realy
I like the fact that the app is relevant and selects the best events.
I liked how easy it can find recommendations for my preferences
i like the topic selection in general, i only dislike for the privacity
I liked that it analyzed my twitter. But I disliked the fact that the recommendations are mostly connected to gathering data, it's not very interesting to me.
I didn´t dislike anything to be honest
I didn't like that those recommendation were very specific and they didn't really apply for the country i live in.
I like how it tries to pick something that might intererst you. I didnt like that it wasn't as accurate as i wanted
It was correct but this is just a recommendation app, not myself
it's easy to get a good recommendation
Maybe make more visually appealing?
I liked how it fitted my preferences. I dislike the short number of recommendations
I like the overall layout and UI, nice colours and big letters help me see what is important

I liked the recommendations, they were accurate.
good overview
handy
You couldn't receive more information on the topics whilst choosing them so I did not know what to expect from each topic and I coulnd't find the appropriate information and it would have been nice if they were categorized in some way. I liked that you could see all of the topics at once without having to click through a list.
It was easy to use, but an improvement might be that you can select if you dont like the recommended topics and then the app shows more alternatives.
it was a nice way to get a quick view on which events would be interesting. On the other hand, you only get events that are inside my interest, recommending some events that are outside the scope would also be iiteresting
I like that it narrows down the possible events for you when there are a lot of them. However, I think that if I would've selected some other boxes as well I would have maybe gotten more and better recommendations. I think the ones I got now are somewhat too similar.
could improve on recommendations
There were a lot of options upfront without further explanation so I didn't know what many of them entailed.
easy to use
I liked that it didnt take much time
I like that it is quick and easy to see the events and see the information
It recommended some interesting sounding events.
I liked that it was accurate and helped me to narrow down which topics I was interested in quicker. There was nothing I disliked.
Liked that it was very quick and easy. But do not know to what extent that it can really indicate good events with just clicking some topics.
I liked seeing the suggestions, but I have a feeling that I may have missed events that I would have liked
it only gave me 3 useful recommendations