Contributions to
Chatbots and Digital Analytics in Industry

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Abstract

This cumulative dissertation includes ten scientific papers contributing to the knowledge of digital analytics, technology acceptance measurement, and chatbots. The papers aim to simplify and support the development, implementation, and management of technologies by developing frameworks that describe the most important steps, e.g., listing important related questions, naming the stakeholders to be involved, and presenting the appropriate tools to be considered. Taxonomies are developed and presented that show the range of design options that currently exist, while the identified archetypes present design combinations that can be observed and adapted. Identifying the most common reasons for the failure and development of critical success factors also contributes to the objective of facilitating the development and management process. As end-users decide the acceptance, and usage and, consequently, the success of a technology, the approaches demonstrate how user acceptance of technologies can be measured and how users can be involved in the development process at an early stage.

Keywords: Digital Analytics, Chatbots, Technology Acceptance, User-oriented Design, Customer Service, Business-to-Business, Human–Computer Interaction

Zusammenfassung

Diese kumulative Dissertation umfasst zehn wissenschaftliche Artikel, die zur Forschung digitaler Analytik, Messung von Technologieakzeptanz und Chatbots beitragen. Ziel der Artikel ist es, die Entwicklung, Implementierung und Verwaltung von Technologien zu vereinfachen und zu unterstützen. Modelle werden entwickelt, welche die wichtigsten Schritte beschreiben und unter anderem relevante damit zusammenhängende Fragen auflisten, die zu beteiligenden Interessengruppen benennen und geeignete Tools vorstellen, welche berücksichtigt werden sollten. Es werden Chatbot Taxonomien entwickelt und vorgestellt, welche die Bandbreite der derzeit bestehenden Gestaltungsmöglichkeiten aufzeigen, während identifizierte Archetypen zu beobachtende Kombinationen aufzeigen. Die Identifizierung der häufigsten Gründe für Misserfolge und die Entwicklung kritischer Erfolgsfaktoren tragen ebenfalls zu dem Ziel bei, den Entwicklungs- und Managementprozess zu erleichtern. Da die Endnutzer über die Akzeptanz und Nutzung und damit über den Erfolg einer Technologie entscheiden, werden Ansätze genutzt, wie die Nutzerakzeptanz von Technologien gemessen werden kann und wie Nutzer frühzeitig in den Entwicklungsprozess eingebunden werden können.

Schlagworte: Digital Analytics, Chatbots, Technologieakzeptanz, Nutzerorientiertes Design, Kundenservice, Business-to-Business, Mensch-Computer Interaktion

Management Summary

In the age of digital transformation, several companies are seeking for new digital communication techniques that can enable them to reach customers in a more efficient manner by providing 24/7 support and minimizing call center costs by automating manual processes. More and more B2B companies are deploying chatbots, known as one of the fastest-growing communication services (Kushwaha et al. 2021). Chatbots are software programs that automatically interact with humans within a simulated conversation to fulfill tasks or provide information (Bittner et al. 2019). For enterprises, one of the major challenges is to develop, deploy, and manage these tools in a way that provides value to the end-user as well as the organization. For this reason, the chatbots must meet the requirements and tasks of the users so that they can trust these chatbots to fulfil their needs.

On the other hand, users leave a digital footprint when browsing the internet, and digital analytics tools enable to capture this data to analyze the behavior of website visitors (Booth & Jansen 2009; Palomino et al. 2021). Used wisely, these tools can be essential to assess consumer needs. However, employees are inundated with ever-increasing amounts of data, sourced from a variety of tools (Du et al. 2021; Morgan & Lurie 2021). Thus, approaches outlining how target-group-specific information about the company's stakeholders can be provided on various channels are required to ensure that interpretations can be derived and appropriate actions are undertaken.

Contributing to the knowledge of digital analytics, technology acceptance measurement, chatbots, and user involvement, this cumulative dissertation is based on ten scientific papers. The papers aim to simplify the development, deployment, and management of technologies. This is done in the form of chatbots and web analytics reports, by building and applying frameworks, presenting possibilities for involving end-users, developing taxonomies, identifying archetypes, and measuring technology acceptance. To address the research needs, qualitative research, taxonomy development, and quantitative research approaches were applied, which are described in Chapter 2.

Chapter 3, "Digital Analytics and Technology Acceptance" focuses on presenting approaches to analyzing (potential) customer behavior on different digital channels and measuring technology acceptance. Frameworks are developed and applied in two papers to analyze the users' behavior on corporate websites and to predict the

personality traits of Twitter users. These frameworks can be used by practice as a basis to monitor and improve communication activities.

Web analytics tools for analyzing website visitors' behavior have become common in digital analytics (Harb et al. 2020). However, this data not only is relevant for the marketing department, which usually manages these tools, but also provides valuable information for the various business units in companies, such as the press department, product management and human resources. To this end, Janssen et al. (2019) developed a reusable and transferable web analytics model for individual web traffic report development based on a literature review and expert interviews. By applying participatory design (PD) methods, the model enables the development of target-group-specific reports in an industrial context by involving future users from different business units within the development process. Figure 1 (p. IV) presents the final model for web traffic report development in which stakeholders participate within the whole development process.

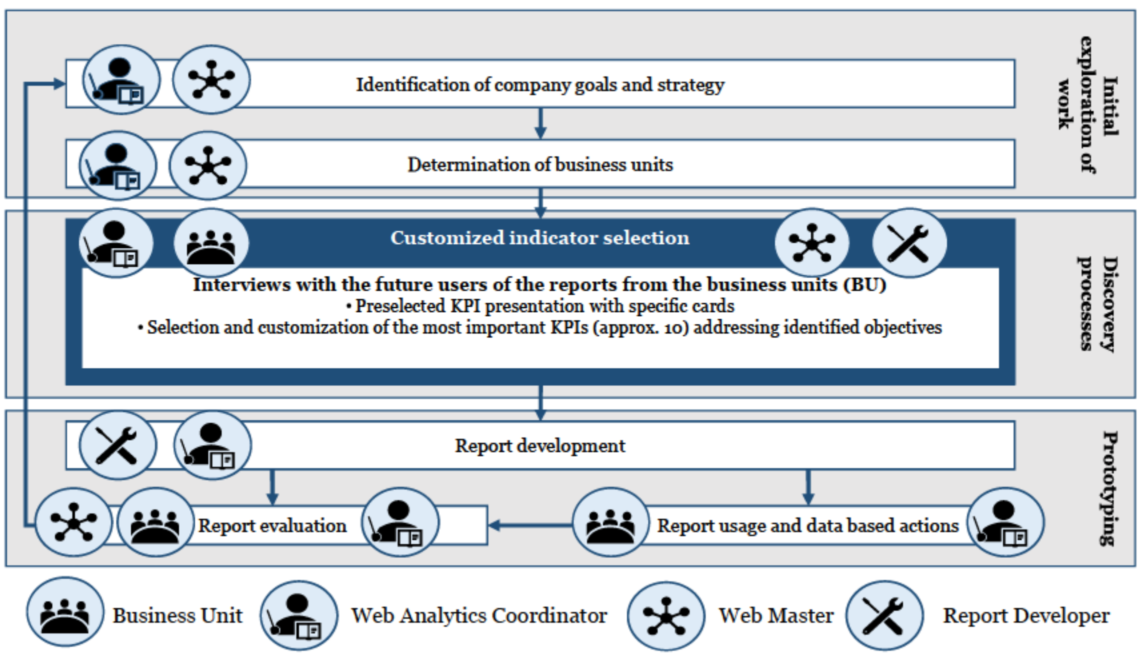

Figure 1: Participatory Design Model for Web Analytics Report Development (Janssen et al. 2019 p. 7)

The first step concentrates on detecting the overall goals and strategy of a company and identifying the relevant business units. This step is followed by the customized indicator selection process in which employees of the business units describe the main purposes of the business unit before identifying and customizing appropriate indicators. The process is supported by using a PD gamification card method, helping to easily select and prioritize the relevant indicators. In the subsequent steps, the report with relevant indicators is developed, evaluated, and released so that the business units can use the reports to draw conclusions. As part of an applicability check, the model was applied in an industrial automation company leading to a greater adoption and higher interest demonstrated by the involved users when the reports were individually tailored to their needs. We conclude that a comprehensive and early involvement of future users by applying PD methods is an effective way that can be adopted in other fields. This model further provides suitable indicators without losing focus on the actual goals of the business units and the organization.

By publishing posts about their own experiences, feelings, and opinions, Twitter users disclose a wealth of personal information about themselves (Carducci et al. 2018). The ever-growing dataset of Twitter posts enables a variety of automated analyses such as the prediction of personality traits, that is, information that can be used for marketing, healthcare, or recruitment purposes. In this regard, Klebansky et al. (2021) provide a framework to predict OCEAN (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) personality traits based on the tweets of Twitter users. This approach allows the analysis of target audiences without directly involving and interviewing users, which can minimize bias in the results, compared to the traditional questionnaire-based approaches. The framework was tested through an applicability check, demonstrating how the model can be applied to gain in-depth insights into the personality profiles of Twitter's active users which can be used, e.g., for product recommendations (Buettner 2017).

The acceptance of a technology by a target group is crucial for its success. In addition to analyzing usage and behavior statistics by monitoring actual users, gaining insights into intentions, concerns, and reasons for use is feasible by surveying potential and current users on acceptance, which is done in two papers. First, Rodríguez Cardona et al. (2020) investigated the technology acceptance of robo-advisor systems in the German finance sector. Robo-advisor chatbots are intelligent interfaces that automatically provide professional financial advice to private users based on a previously conducted dialogue (Adam et al. 2019; Hildebrand & Bergner 2021). To investigate acceptance in form of the behavioral intention to use robo-advisor chatbots, the unified theory of acceptance and the use of technology 2 (UTAUT2) model of Venkatesh et al. (2012) were applied in an online survey with 250 respondents. The results indicate that the expected performance and the degree of automation are the most decisive factors for the intention to use robo-advisor chatbots in Germany, even though socio-economic factors also have a certain impact. Further, Rodríguez Cardona et al. (2021) conducted an online survey-based study to investigate the impact of the trust and technology acceptance aspects on the intention to use insurance chatbots. To investigate the intention to use insurance chatbots by testing hypotheses, the technology acceptance model (TAM) (Davis 1989) was extended to include trust and privacy concerns and was applied in an online survey involving 215 participants. The findings reveal that while trust has a significant positive influence on the intention to communicate with an insurance chatbot, perceived usefulness has a stronger positive influence on the intention to use it. Thus, the functional features of an insurance chatbot that provide a practical added value to the customer experience are most decisive in the intention to use the chatbot. Consequently, this implies that functional features should be carefully selected and developed by involving future users in strengthening their perceived usefulness. Furthermore, the functionalities should be promoted by the companies. Due to the circumstance that both finance and insurance firms promote services that may need further explanation in a conservative industry, the results could also be useful for B2B companies whose industries are considered similarly conservative while selling complex products and services.

Chatbots have been developed in recent years for application in a wide variety of areas such as education, health, and customer service. They can automatically fulfill specific tasks on websites, social media channels, and apps by using natural language processing (Zierau et al. 2020; Diederich et al. 2019b). However, little is known from a practical and scientific perspective about what design features characterize chatbots in the global market of domain-specific chatbots. Therefore, Chapter 4, "Chatbot Taxonomies, Archetypes, and Design Implications" contributes to the chatbot field in human–computer interaction and information systems (IS). Three taxonomies are developed to understand conceptually grounded and empirically validated chatbot design elements and their availability across chatbots from different application domains.

In the paper of Janssen et al. (2020), the literature on chatbots, as well as 103 chatbots from six application domains, is classified using an iterative approach to develop a design elements taxonomy of domain-specific chatbots. The final taxonomy, which can be seen in Table 1 (p. VII), contains 17 dimensions and 49 characteristics ordered into the three perspectives: intelligence, interaction, and context. The columns contain the percentage distribution values of the 103 domain-specific real-world chatbots across the various characteristics and large differences can be seen in terms of frequency. This classification indicates that in 2019, most of the analyzed chatbots were far from offering all technical capabilities from an intelligence and interaction perspective. Five archetypes (i.e., goal-oriented daily chatbots, non-goal-oriented daily chatbots, utility facilitating chatbots, utility expert chatbots, and relationship-oriented chatbots) were identified. These archetypes will help support practitioners in identifying appropriate characteristics, depending on the task and application area.

Table 1: Final Taxonomy of Design Elements for Chatbots (Adapted from Janssen et al. 2020, p. 217)

Layer 1: Perspective	Layer 2: Dimensions D_i	Layer 3: Characteristics $C_{i,j}$ (% distribution)		
Intelligence	D_1 Intelligence framework	$C_{1,1}$ Rule-based system (73%)	$C_{1,2}$ Utility-based system (17%)	$C_{1,3}$ Model-based system (6%)
		$C_{1,4}$ Goal-based system (2%)	$C_{1,5}$ Self-learning system (2%)	
	D_2 Intelligence quotient	$C_{2,1}$ Only rule-based knowledge (41%)	$C_{2,2}$ Text understanding (42%)	$C_{2,3}$ Text understanding and further abilities (17%)
	D_3 Personality processing	$C_{3,1}$ Principal self (96%)	$C_{3,2}$ Adaptive self (4%)	
	D_4 Socio-emotional behavior	$C_{4,1}$ Not present (88%)	$C_{4,2}$ Present (4%)	
	D_5 Service integration	$C_{5,1}$ None (22%)	$C_{5,2}$ Single integration (59%)	$C_{5,3}$ Multiple integration (18%)
Interaction	D_6 Multimodality	$C_{6,1}$ Unidirectional (91%)	$C_{6,2}$ Bidirectional (9%)	
	D_7 Interaction classification	$C_{7,1}$ Graphical (23%)	$C_{7,2}$ Interactive (77%)	
	D_8 Interface personification	$C_{8,1}$ Disembodied (71%)	$C_{8,2}$ Embodied (29%)	
	D_9 User assistance design	$C_{9,1}$ Reactive assistance (79%)	$C_{9,2}$ Proactive assistance (21%)	
	D_{10} Number of participants	$C_{10,1}$ Individual human participant (96%)	$C_{10,2}$ Two or more human participants (4%)	
	D_{11} Additional human support	$C_{11,1}$ No (80%)	$C_{11,2}$ Yes (20%)	
	D_{12} Front-end user interface channel	$C_{12,1}$ App (7%)	$C_{12,2}$ Collaboration and communication tools (7%)	$C_{12,3}$ Social media (34%)
		$C_{12,4}$ Website (39%)	$C_{12,5}$ Multiple (14%)	
Context	D_{13} Chatbot role	$C_{13,1}$ Facilitator (39%)	$C_{13,2}$ Peer (3%)	$C_{13,3}$ Expert (58%)
	D_{14} Relation duration	$C_{14,1}$ Short-term relation (84%)	$C_{14,2}$ Long-term relation (16%)	
	D_{15} Application domain	$C_{15,1}$ E-customer service (21%)	$C_{15,2}$ Daily life (47%)	$C_{15,3}$ E-commerce (9%)
		$C_{15,4}$ E-learning (4%)	$C_{15,5}$ Finance (13%)	$C_{15,6}$ Work and career (7%)
	D_{16} Collaboration goal	$C_{16,1}$ Non goal-oriented (23%)	$C_{16,2}$ Goal-oriented (77%)	
	D_{17} Motivation for chatbot use	$C_{17,1}$ Productivity (19%)	$C_{17,2}$ Entertainment (29%)	
		$C_{17,3}$ Social/relational (7%)	$C_{17,4}$ Utility (45%)	

Depending on the use case, chatbots are contacted by a user once (e.g., dialogue to complain about a product) or multiple, recurring times over a long period (e.g., tutoring dialogues throughout the school year). This frequency and duration of use necessitate different requirements for the design of the chatbot. Nißen et al. (2022) concentrated on identifying design elements that characterize and distinguish short-, medium-, and long-term chatbots across diverse application domains. Within seven iterations, in which 120 real-world chatbots and scientific literature were investigated, a design taxonomy for chatbots with different temporal profiles was developed. The final taxonomy contains in total 61 characteristics within 22 dimensions, which are clustered into the perspectives temporal profile, appearance, intelligence, interaction, and context. By applying a time-dependent chatbot archetype formula, three archetypes were identified: ad-hoc supporters, temporary advisors, and persistent companions. By analyzing the chatbot–user relationship across several time horizons, significant differences can be observed across the archetypes. Ad-hoc supporter chatbots primarily fulfill tasks in a short-time horizon without inserting gamification elements, while persistent companion chatbots, which communicate with a user over a long period, are more socially oriented and show socio-emotional behavior within a personalized dialogue.

Especially in customer service, chatbots are employed to guarantee 24/7 assistance, automate frequently repeated manual processes, and minimize call center costs. In the B2B sector, companies increasingly use chatbots for customer communication purposes too. In the scientific literature, the B2B chatbot area has hardly been researched yet, though there is demand for it, because, in the B2B sector, the products and services that are marketed are often complex and require explanation. Face-to-face contact is considered essential, and various people of a buying center are often involved in the long purchasing processes. To classify the prevailing B2B customer service chatbots, Janssen et al. (2021a) developed a design elements taxonomy for B2B customer service chatbots. Relevant scientific literature and 40 B2B customer service chatbots were classified resulting in a final taxonomy with 17 dimensions and 45 characteristics. Based on a cluster analysis, whose results are presented in Table 2 (p. IX), three archetypes (i.e., lead generation chatbots, aftersales facilitator chatbots, and advertising FAQ chatbots) were identified. According to the results, B2B customer service chatbots are predominantly used for FAQ and lead generation purposes, as well as in aftersales. Table 2 illustrates which characteristics are present in these archetypes, visualized by a color intensity code. In comparison to the other two taxonomies, which included chatbots from diverse application areas, it becomes apparent that additional human support in the B2B area is extremely important and that there is still a lot of undiscovered potential in terms of intelligence.

Table 2: Final B2B Customer Services Chatbot Taxonomy with Identified Archetypes (Janssen et al. 2021a, p. 184)

	Label	Lead generation chatbot	Aftersales facilitator chatbot	Advertising FAQ chatbot
	Archetype	1	2	3
	n	8	10	22
Industry classification	Financial services industry	0%	10%	5%
	Manufacturing industry	0%	50%	18%
	Marketing industry	0%	10%	14%
	Software industry	100%	30%	64%
Business integration	No	75%	40%	77%
	Yes	25%	60%	23%
Access to business data	No	88%	70%	100%
	Yes	13%	30%	0%
Dialogue structure	Predefined	88%	20%	45%
	Open	0%	40%	9%
	Both	13%	40%	45%
Data policy	Not provided	38%	60%	77%
	Provided	63%	40%	23%
Handoff to human agent	Not possible	0%	20%	14%
	Possible	100%	80%	86%
Small talk	Not possible	100%	60%	82%
	Possible	0%	40%	18%
Human-like avatar	No	100%	70%	95%
	Yes	0%	30%	5%
Content related service	Content advertisement	75%	0%	100%
	Content consumption	25%	100%	0%
Account authentication	Not required	50%	60%	68%
	Optional	0%	20%	14%
	Required	50%	20%	18%
Question personalization	None	50%	0%	5%
	FAQ	0%	20%	82%
	Personalized account questions	38%	70%	9%
	Highly personalized questions	13%	10%	5%
Customer service orientation	Knowledge-oriented	0%	0%	95%
	Task-oriented	100%	100%	5%
Company information	No	100%	60%	64%
	Yes	0%	40%	36%
Service/product information	No	38%	10%	9%
	Yes	63%	90%	91%
Pricing	No	100%	60%	82%
	Yes	0%	40%	18%
Action request	Book/show a demo	25%	0%	5%
	Callback request	25%	40%	32%
	Both	50%	20%	36%
	None	0%	40%	27%
Service request	Support question/ticket	13%	40%	36%
	Billing details	0%	0%	5%
	User management	0%	10%	0%
	Multiple	0%	40%	0%
	None	88%	10%	59%

The three developed taxonomies and the identified archetypes help researchers and practitioners in selecting design options when developing chatbots and provide support in determining which characteristics are typical for a particular use case. Even though the identified design elements offer an overview of the design possibilities of chatbots, this does not mean that chatbots will actually be used and accepted. However, more aspects need to be considered while developing, deploying, and managing chatbots successfully, which is illustrated in two more papers.

Several chatbots fail in practice because they fail to understand the user's intent, do not respond, or become undetectable. This is annoying not only for the end-user but also for the company providing the chatbot whose reputation may suffer and which has invested a lot of time and money in the development. Even from a global perspective, the failure of chatbots is problematic because the reputation of chatbots, in general, might get affected. To avoid chatbot failure in the future, Janssen et al. (2021c) focused on investigating the main reasons for the failure of chatbots by analyzing real-world chatbots, performing a literature review, and conducting 20 expert interviews. To explore the extent to which chatbot failure is an issue in practice, 103 chatbots from the dataset of Janssen et al. (2020) were revisited, revealing that 53% could not be found after 15 months. Through the expert interviews, six main reasons for chatbot failure were identified: insufficient resources in the form of the human, organizational, or technical capacity to continually manage the chatbot, the lack of a business case, ignorance of user expectations, poor conversation design, poor content, and the provision of false, incomplete, or outdated information. To avoid future failure of chatbots, twelve critical success factors (CSFs) were developed based on the findings evaluated in a focus group discussion (FGD). The design implications of the CSFs and the knowledge of failure risks may help researchers and practitioners continually improve chatbots.

When developing a chatbot, it seems obvious to focus on the technical functionalities or the dialogue tree construction. However, as outlined based on the previous paper, several chatbots fail because of organizational issues in the team or because the wrong use case was chosen. Janssen et al. (2022) concentrated on developing a user-oriented eight-step model for developing a chatbot, which is presented in Figure 2 (p. XI). By interviewing 15 experts, 102 questions were identified which were clustered into the four elements people, activity, context, technology (PACT) (Benyon et al. 2005) and ordered into eight steps. The model was evaluated through interviews, a FGD, and a case study application. The chatbot implementation model starts with of focusing on business-context-related questions to find out, before identifying an appropriate use case, whether a chatbot is the appropriate communication tool. The eight-step model, as well as the list of 102 questions to be asked in the chatbot implementation process, help and guide practitioners and researchers in structurally developing and managing chatbots under the consideration of the most important questions. It also includes the step of asking whether chatbot technology is appropriate for the use case to be realized.

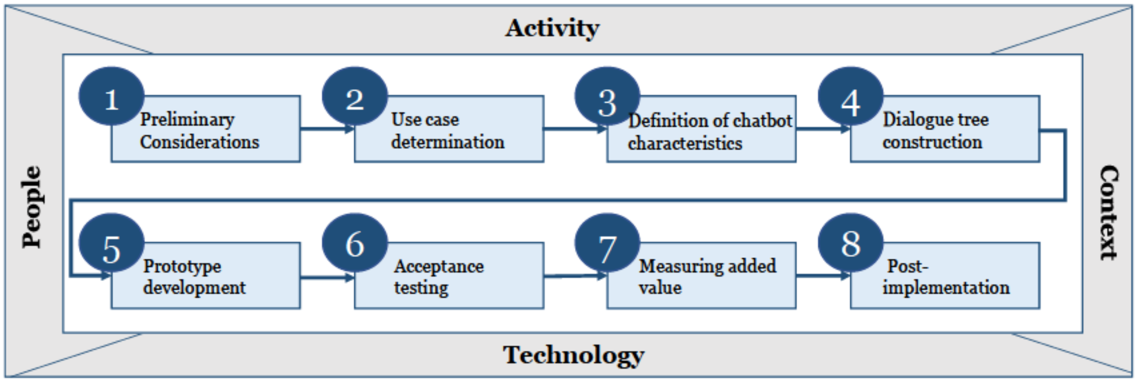

Figure 2: Chatbot Implementation Model (Janssen et al. 2022)

In summary, this cumulative dissertation contributes to the field of digital analytics and chatbots. The guidance provided simplifies the development, deployment, and management of technologies by developing and applying frameworks and reference models, presenting methods for involving end-users, building taxonomies, deriving archetypes, and measuring technology acceptance. To move from a micro perspective to a more general view, communication channels should essentially fit into the overall corporate strategy and fulfill an added value for both the provider and the end-user. Many companies aim to be pioneers in the use of new technologies to demonstrate their innovative prowess to the public. However, apparently the mere use of a technology does not add value but can lead to reputational losses if users become frustrated. Eventually, the benefit and acceptance of the end-user determine whether the use of a technology, such as a chatbot or a digital analytics tool, is successful, as it is the users who decide whether they will use a chatbot again and whether the dialogue will lead to success or even to reputational damage. Therefore, the research papers included in this dissertation provide user-centered design, instead of company-centered design. The papers also indicate the existence of a variety of behavioral analytics options that do not directly involve users. The multitude of analysis options can lead to a flood of data. It is, therefore, essential to question what users really need to be able to target and to efficiently control their decisions.

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