Journal of Business Research 137 (2021) 222–232

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

The effect of customer-perceived value when paying for a product with personal data: A real-life experimental study

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ARTICLE INFO

Keywords:
Consumers' privacy valuation
Willingness to sell data
Reverse auction
Privacy calculus

ABSTRACT

This study delves into consumers' privacy valuation, modeling the privacy calculus as a mediating construct and aiming to investigate the factors that possibly influence the perceived costs and benefits thereof. A reverse auction was conducted within a real-life experimental field setting, which enabled the researchers to control the consumer decision-making process for customer-perceived value. The results highly support the conceptualization of the cost–benefit calculus as a mediating construct. The findings indicate that consumers distinguish between the positive and negative consequences of personalization when they determine the value of their data. Furthermore, the findings prove the important relationship between customer-perceived value and consumers' data valuation. The findings show that negative elasticity of the suggested bid amounts to a change in usage intensity. This study substantially enhances the academic understanding of consumers' decision-making processes when exchanging data for benefits.

1. Introduction

How much money would you sell your location data for? Would it be 1 EUR, 10 EUR, or 100 EUR, or would you even say it is unsellable for you? In the last case, you should consider that you trade this data almost every day. You trade your mobile location data with your mobile service provider, your navigation system provider, and your location-based dating application. Furthermore, you trade your address when you order a product online, sign into a loyalty program, or create a social network profile. In recent years, there have even been examples of companies (such as 23andMe.com and Ancestry.com) that enable users to trade their DNA data from a saliva sample for valuable medical or genealogical information. In this line, within the COVID-19 pandemic situation, many governments have offered citizens services to trade their location data for information related to a possible infectious outbreak. Consequently, privacy and personal data trade-offs have again been called into question and highlighted as a research priority (Cho, Ippolito, & Yu, 2020; Lenca & Vayena, 2020; Lenert & McSwain, 2020; Leslie, 2020; Pantano, Pizzi, Scarpi, & Dennis, 2020).

These examples show that we typically trade data not for money but for benefits in the form of value, considering personal data as a tradable asset (Spiekermann, Acquisti, Böhme, & Hui, 2015; Zeng, Ye, Li, & Yang, 2021). In marketing, the exchange processes resulting in value for consumers can be described by the concept of customer value (Zeithaml, 1988). Traditionally, the concept of customer value has focused on the exchange of products or services and a cost component—mainly, but not exclusively, monetary price (Gutman, 1982; Kumar & Reinartz, 2016; Zeithaml, 1988). However, with the development of online connections, markets have evolved, and monetary price no longer seems to be a cost component for consumers. In so-called free online markets, consumers exchange their data for free (at the point of use) services (Arrieta-Ibarra, Goff, Jiménez-Hernandez, Lanier, & Weyl, 2018; Martin, 2020; Martin & Palmatier, 2020). The data are then monetized in a second step, in most cases through the online advertising market. In recent years, a number of companies have emerged (such as Google and Facebook) for which data are their primary source of value in order to secure positive stock market performance (Martin & Murphy, 2017). Consequently, customer value might be better described as a dual concept, in which companies first create value for their customer bases and second extract some of the customer value in the form of profit, which results in value for the company (Kumar & Reinartz, 2016).

A company's estimation of customer value often entails applying the same metrics as those already used in traditional markets. Based on income parameters, such as advertising revenue, variables such as

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https://doi.org/10.1016/j.jbusres.2021.08.029
Received 12 March 2020; Received in revised form 11 August 2021; Accepted 15 August 2021
Available online 25 August 2021

customer lifetime value can be estimated (e.g., Zeithaml, Lemon, & Rust, 2001). In a similar vein, according to the *privacy paradox*, which is the discrepancy between privacy concerns and actual data-sharing behavior (Acquisti, Brandimarte, & Loewenstein, 2015; Awad & Krishnan, 2006; Martin, 2020; Okazaki, Eisend, Plangger, de Ruyter, & Grewal, 2020), the risk–benefit trade-off of disclosing personal information shows that private data are shared in exchange for personalization value (Thomaz, Salge, Karahanna, & Hulland, 2020; Zeng et al., 2021).

Previous research concerning privacy valuation has offered consumers the opportunity to trade their data in exchange for monetary value (Benndorf & Normann, 2018; Carrascal, Riederer, Erramilli, Cherubini, & de Oliveira, 2013; Huberman, Adar, & Fine, 2005), whereas consumers are usually excluded from this opportunity (Acquisti, Taylor, & Wagman, 2016; Culnan & Bies, 2003). However, when consumers exchange their data for money, it is difficult to consider perceived value in the form of a product or service within the experimental setting.

Beside the large amount of research in the context of consumers' attitudes toward the collection and sharing of data (see review by Kolotylo-Kulkarni, Xia, & Dhillon, 2021), there is little knowledge about the value that consumers assign to data and how they trade off this value within the digital economy. Thus, several authors have called for more research in this area (Bélanger & Crossler, 2011; Gabisch & Milne, 2014; Kumar & Reinartz, 2016; Martin, 2020). A high level of interest among practitioners in this field is assumed, mainly due to the negative impact of customer data vulnerability on firm performance (Martin, Borah, & Palmatier, 2017).

Consequently, the Marketing Science Institute (MSI) emphasized the importance of the topic in its 2020–2022 research priorities by posing the questions: "In the age of GDPR and the increasing importance of preserving customers' privacy, what is the appropriate tradeoff between privacy and personalization, and what are the ethical ramifications of customer data collection and use? How will regulation/compliance affect marketing?" (MSI, 2020, p. 7). This study aims to answer these questions by analyzing how online consumers value personal data sharing with respect to "selling" their data and "receiving" value in two-sided online markets. Usage intensity has been harnessed as a satisfaction indicator in terms of customer value in service research (Bolton & Lemon, 1999). The higher the perceived value of a service, the higher its usage intensity. Hence, the research question of this study is: *How does consumer-perceived value, measured as usage intensity, impact the trade-off decision?*

To answer this research question, this study proposes an original means by which to measure consumers' valuation of data. This research created an experimental setting that can be best described as a "beyond 'free'" market simulation (Arrieta-Ibarra et al., 2018). With the purpose of collecting data for this research, a real search engine was launched in order to simulate a typical data-versus-value exchange of a free online service. Additionally, users of the search engine were offered a *compensation price* that they could use if the perceived value of the service was lower than their perceived value for the data they had to disclose. This experimental study contributes to existing research on privacy valuation by introducing a measurement model of consumers' data valuation that incorporates the value of a service, exploring the role of customer-perceived value within the privacy calculus.

2. Theoretical background: The privacy valuation framework

Consumers' attitudes towards their data have become a widely discussed topic in marketing (Li, 2011; Martin & Murphy, 2017; Okazaki et al., 2020). Particularly, personal private information disclosure is still being highlighted as a research priority (Kolotylo-Kulkarni et al., 2021; Swani, Milne, & Slepchuk, 2021). Research on consumers' valuation of data has focused on furthering the understanding of consumers' decision-making processes when disclosing data in today's online environment. Stricter regulations, such as the European Union (EU) General Data Protection Regulation (GDPR) (May 25, 2018), reflect the increasing awareness of the value of data among the public and have forced practitioners to rethink their practices related to customer data. Specifically, in the privacy literature, the trade-off between the benefits and costs of sharing personal data has been theorized through the *privacy calculus* (Gabisch & Milne, 2014; Gutierrez, O'Leary, Rana, Dwivedi, & Calle, 2019; Krafft, Arden, & Verhoef, 2017; Schumann, Wangenheim, & Groene, 2014). Herein, the costs of sharing data refer to the fact that consumers positively value their privacy; this means that they may not be willing to share information about themselves due to *privacy concerns* (Culnan, 2000). These privacy concerns can be summarized according to four dimensions: collection, unauthorized secondary use, improper access, and errors contained within the personal data (Malhotra, Kim, & Agarwal, 2004; Smith, Milberg, & Burke, 1996). While the concept has been theoretically established in the literature, with several mediating effects found regarding the validity of the privacy calculus, the question of how to conceptualize and measure the trade-off empirically has not yet been answered. This is mainly due to three effects affecting privacy research: a discrepancy between intentions to protect personal data and actual disclosure behavior (known as the *privacy paradox*); a missing data market that includes the consumer; and a missing metric to measure the value of data. The privacy paradox concept helps in understanding the contradiction between privacy concerns and the careless disclosure of personal information (Acquisti et al., 2015; Awad & Krishnan, 2006; Kokolakis, 2017; Martin, 2020; Norberg, Horne, & Horne, 2007). Within the privacy paradox, consumers who value information transparency are less willing to share information in exchange for online personalization (Awad & Krishnan, 2006). However, consumers with high privacy expectations continue to show these expectations after disclosing information (Martin, 2020). Thus, there is a balance between concerns and rewards (Hallam & Zanella, 2017), where private personal information is shared in exchange for personalization (Thomaz et al., 2020).

The valuation of data is highly related to the concept of privacy. Generally, privacy is an interdisciplinary topic, discussed in the psychology, management, information systems, and marketing literature (Bélanger & Crossler, 2011; Li, 2011; Martin & Murphy, 2017; Pavlou, 2011). In the broadest sense, Clarke (1999a) proposed four privacy dimensions: privacy of the person, which refers to the integrity of the individual's body; privacy of personal behavior, which refers to sensitive matters, such as the use of sex toys; privacy of personal communication; and privacy of personal data, which means that data about an individual should not be automatically available to other individuals and organizations. Similar to most literature in marketing, the present work mainly focuses on two dimensions: privacy of personal communication and privacy of personal data (Martin & Murphy, 2017). This combination is named "information privacy" and is defined as "the interest an individual has in controlling, or at least significantly influencing, the handling of data about themselves" (Clarke, 1999b, p. 60).

At the beginning of the twenty-first century, the micro-economic modeling of privacy trade-offs started to appear (Hann, Hui, Lee, & Png, 2008; Taylor, 2004). Therein, privacy calculus modeling was proposed as a remedy for describing the complicated nature of privacy (Dinev & Hart, 2006; Smith, Dinev, & Xu, 2011). To date, the concept of the privacy calculus has provided the framework for many empirical works in this area (Gabisch & Milne, 2014; Gutierrez et al., 2019; Krafft et al., 2017; Schumann et al., 2014). Thereby, the concept of the privacy calculus can be described by the idea that consumers "disclose [information] if benefits of disclosure exceed risks" (Culnan & Armstrong, 1999, p. 108). Based on previous works (Smith et al., 2011; Xu, Teo, Tan, & Agarwal, 2010; Zeng et al., 2021), in this study the privacy calculus refers to the risk–benefit analysis that users perform to assess whether to disclose personal information in exchange for personalization value. Thus, the privacy calculus is often connected to social exchange theory, implying "a two-sided, mutually contingent, and mutually rewarding process involving 'transactions' or simply 'exchange'" (Emerson, 1976,

p. 336).

However, in today's data disclosure environment within the digital economy, consumers' trade-off is often between "giving" data and "getting" online services in return, which are often free in terms of monetary cost. Hence, the trade-off can be expressed as being more utilitarian in the form of the cost–benefit calculus. The cost–benefit calculus refers to consumers' anticipation and comparison of the benefits, costs, and other consequences associated with the protection or disclosure of private information (Acquisti, John, & Loewenstein, 2013). In the context of direct marketing, Krafft et al. (2017) demonstrated that permission decisions are primarily based on a consumer-side cost–benefit calculus. This research follows this cost–benefit expression of the privacy calculus, assuming a consumer trade-off between data as a cost factor and perceived value as a beneficial factor. Therefore, the consumer-side trade-off in two-sided markets shows high similarities to customer-perceived value, described as a trade-off between "give" and "get" elements (Kumar & Reinartz, 2016).

Customers' "get" elements are the benefits that customers receive in connection to a product or service. These include the attributes of the product or service, as well as the more abstract benefits linked to these attributes, such as psychosocial consequences and personal values (Gutman, 1982). A consequence of "paying with data instead of money" is that this can lead to additional benefits, increasing the customer-perceived value of a product or service. These benefits can include personalized products, recommendations, price discounts, and more-relevant marketing content (Martin & Murphy, 2017; Miltgen, Henseler, Gelhard, & Popovič, 2016). This increases the complexity of the decision-making process for the consumer, especially in situations where data disclosure is needed to receive the main benefits of a service. For example, not giving location data to a navigation service provider would enormously decrease the perceived benefits of the service.

To investigate consumers' data valuation in two-sided markets, this research adopts the cost–benefit calculus as a theoretical framework, as follows. In line with previous research in this area, it is assumed that consumers are rational, informed agents with stable privacy preferences (Martin & Murphy, 2017). Thus, it is also assumed that consumers are cognitively able to predict and consider the consequences of data sharing, negative as well as positive, in their trade-off decisions. Users regularly share their personal data in exchange for personalization value (Jackson, 2018; Zeng et al., 2021). Even though some users might not notice that they are sharing their data, according to the EU GDPR all digital privacy–related information must be visible and provided. A recent study conducted in the EU and the United States confirmed that the visibility of a cookies notice impacts perceived risk (Bornschein, Schmidt, & Maier, 2020). Bornschein et al. (2020) stated that perceived risk can be reduced if users have more choice over their data, providing more power to users. Thus, our research considers users as informed agents, with digital privacy information always at their disposal.

3. Literature review and hypothesis development

Previous research has typically observed the economic value of privacy in an experimental setting (Benndorf & Normann, 2018; Cvrcek, Kumpost, Matyas, & Danezis, 2006; Staiano et al., 2014). In such studies, it has been found that individual-related variables, such as sociodemographics, culture, and behavior, can influence consumers' valuation of data (Cvrcek et al., 2006; Danezis, Lewis, & Anderson, 2005). Moreover, factors related to the data type—for example, the information's sensitivity or the amount of information—have been found to influence consumers' valuation of data (Carrascal et al., 2013; Staiano et al., 2014). Likewise, there is evidence that contextual factors influence privacy valuation, such as the circumstances and the usage of the data (Danezis et al., 2005; Staiano et al., 2014). Hence, it seems reasonable to assume that consumers' trade-off decisions are context-related, which means that consumers will choose to protect their data in some situations but not in others in which protection is seen as too costly or not efficient (Acquisti et al., 2016).

Nevertheless, context-related research on privacy valuation has mainly focused on consumers' purchase decisions (e.g., Hann, Hui, Lee, & Png, 2007; McCole, Ramsey, & Williams, 2010; Sánchez & Urbano, 2019; Tsai, Egelman, Cranor, & Acquisti, 2011; Wang & Herrando, 2019). However, as there are companies that consider data as their primary source of value, purchase intention is often not the relevant outcome of interest in privacy trade-offs (Martin & Murphy, 2017). The present study investigates two-sided markets, where consumers' relationships with a company are driven by the company's interest in the users' data disclosure. Thereby, companies such as Google or Facebook are positioned as intermediaries between online users and advertisers. These companies aim to provide advertisers with detailed market segmentation tools, which are gained from the storage and analysis of user data. Hence, a peculiarity in these markets is that the value an online user provides to an intermediary is solely data; more specifically, data containing information that the company, and therefore also the advertisers, have about online users' demographics; current or past browsing or purchase behavior; preferences; and geographic locations (Banerjee, Xu, & Johnson, 2021; Krishen, Raschke, Close, & Kachroo, 2017; Palos-Sanchez, Saura, & Martin-Velicia, 2019; Schumann et al., 2014). There is little evidence from previous empirical work concerning data valuation in the context of disclosing data and receiving "free" value in return. Consequently, a research design is proposed that considers the idea that consumers trade data not in exchange for monetary rewards but in order to receive benefits in the form of customer value. This research approach allows the investigation of context-related influences in two-sided markets while controlling broad aspects of the privacy calculus.

Consumers' usage of a service has been described as an antecedent and consequence of their satisfaction with the service (Bolton & Lemon, 1999). The more consumers use a service, the more satisfied they are with it, and the more they will use the same service in the future. Therefore, the usage level of a particular consumer is an "observed indicator of the unobserved perceived value of usage" that the customer derives from service usage (Bolton & Lemon, 1999, p. 177). When trading off between the perceived value of a service and the perceived cost of data disclosure, rational consumers should be more willing to disclose data when the perceived value is high. This is also supported by findings in the context of social exchange theory, showing that consumers have a feeling of reciprocity and are willing to reward the value offered by a free service provider (Schumann et al., 2014). Therefore, consumers should be more willing to sell their data when they receive high customer-perceived value in return. That is, considering that customer value can be expressed according to higher usage intensity (Bolton & Lemon, 1999), in this case a higher number of searches will express customer value. For this reason, it is hypothesized that:

H1: High usage intensity decreases the price for which consumers are willing to sell their data.

4. Methodology

4.1. Experimental design

Even though economists such as Laudon (1996) have called for a (regulated) market for data, today's market for data is business-to-business (B2B) driven, generally excluding consumers from participation (Acquisti et al., 2016). Arrieta-Ibarra et al. (2018) proposed the idea of treating data as labor and including consumers, as creators of the data, in its capitalization. Almost no existing business model gives consumers the facility to reap rewards from the revenue generated by their data; thus, in this study we created a situation where consumers could trade their data for such compensation. Selected from all possible two-sided online markets, a search engine business was used to implement the proposed market model. Designing a specific search engine for this experiment allowed us to improve the experiment's realism and to offer a service/value via the same platform on which the auction was taking place, therefore enabling data to be collected easily. In addition, participants of this real-life experiment were not aware that they were taking part in an academic study. With the sole purpose of conducting this research as a field experiment, the search engine WALLETSEARCH was designed. WALLETSEARCH enables users to register, to get consent form information, to disclose or not disclose their personal data, to bid on data, etc. Thus, all data could be collected through this platform, again boosting its realism.

The experiment was conducted in a real-life atmosphere to avoid any bias issues that might have impacted users' behavior (Benndorf & Normann, 2018). The experiment aimed to observe whether, in line with the privacy paradox, there was a discrepancy gap between individuals' intentions to protect their personal data and their actual disclosure behavior. To do this, usage intensity was harnessed as a measure to observe usage service satisfaction (Bolton & Lemon, 1999), in terms of number of searches a day (see Section 4.2 for details on the operationalization of this variable). In this vein, the participants were able to engage in disclosure behavior for different types of personal data through the bid options of the auction. The real-life atmosphere pursued through the design of the search engine precisely aimed to offer an environment that was as similar to reality as possible. Moreover, the participants were randomly assigned to three different scenarios, which were simply three different auction presentation options intended to reflect current practices. These three options consisted of presenting the auction directly, offering information about the possibility of using the data for targeted advertising, and offering information about third parties. Thus, the presentation scenario was considered the control variable of this study. WALLETSEARCH was designed solely for this study and was online for the data-collection period of two and a half months.

Using pinball communication on social networks, Internet users received the information that a new search engine was being launched that affords users the benefit of earning advertising revenue by giving them 80% of the generated profit. When Internet users visited the homepage of the website, they were able to test the search engine and see the results of their searches, observing the invitation to sign in and receive the advertising revenue generated through their use of the search engine.

After a user had successfully created an account, they could collect one *Coin* every time they searched for something on the Internet using WALLETSEARCH. In a second step, the Coins were multiplied by an *Exchange Rate*, resulting in an amount in euros shown in the *Deposit*. To create an account and thereby accept the storage of their search requests, the user received an initial Exchange Rate of 0.005 EUR per Coin. After pretesting WALLETSEARCH, a missing relation to the values was claimed; thus, it was decided that information would be added about the approximate amount per year a user could potentially earn (see snapshot of the search engine in Fig. 1). This amount was calculated by multiplying the user's Exchange Rate by 2,000—the approximate number of search requests per user per year. This estimated number might be rather low compared with illustrative numbers (Pash, 2011); however, no statistical data could be found concerning a more specific number, and the main purpose of this value was for illustrative purposes only.

The design of WALLETSEARCH focused on showing realism to avoid participants realizing that there were academic purposes behind its creation. In this way, the data offered by the participants were real; consequently, the participant responses were not biased by the knowledge that they were participating in a research experiment. Technically, the search results of WALLETSEARCH were displayed using the "S2 Tier BING Search" application programming interface (API) provided by Microsoft (Microsoft, 2017). Nevertheless, in order to conduct the project, an element of deception was necessary: the Internet users were told that WALLETSEARCH shows advertising next to the search results, which was not in fact the case due to the non-existence of open APIs. Deception is a frequently used tactic in experimental psychology (e.g., Cvrcek et al., 2006), and because the action did not negatively affect the users there were no ethical considerations in adopting this procedure. Interestingly, none of the participants reported the missing advertising.

4.2. Measurement and procedures for consumers' data valuation

This research assumed that consumers' valuation of data could be examined by the metrical variable of their demanded compensation price. This price can be measured as consumers' willingness to sell their data. As in previous research on consumers' willingness to sell their data, this study used a reverse-auction methodology to examine these aspects (Carrascal et al., 2013; Cvrcek et al., 2006; Danezis et al., 2005;

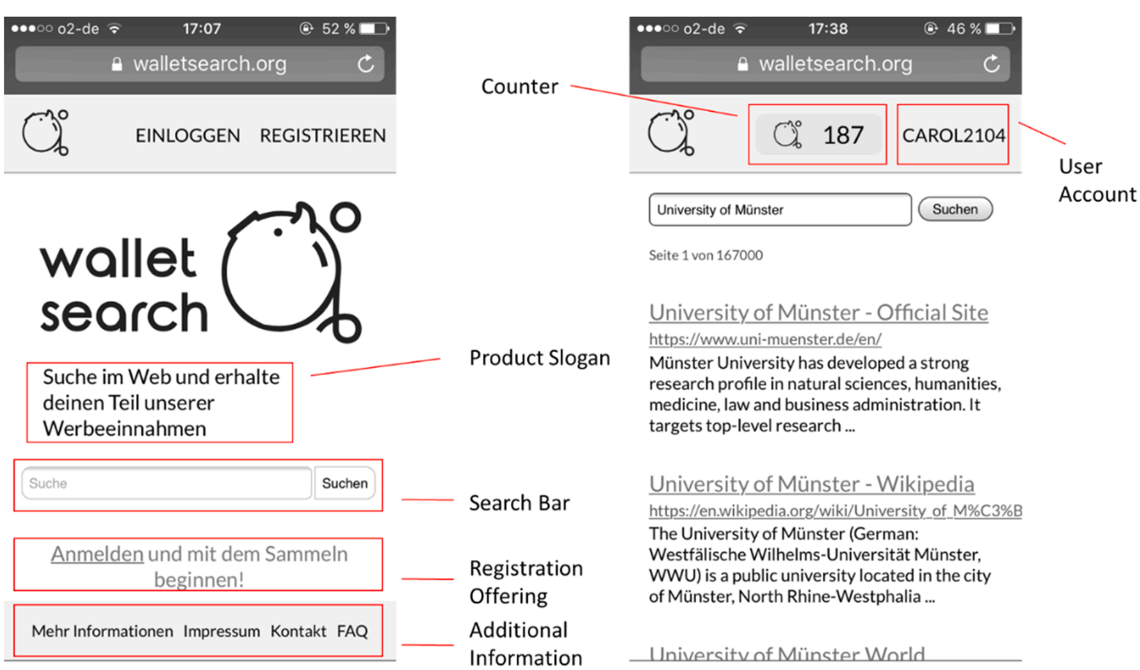

Fig. 1. Snapshot of the search engine.

Huberman et al., 2005). The term "reverse" refers to the fact that consumers are asked about their willingness to sell a specific item, which implies that the lowest (not the highest) price wins. This means that sellers compete to win an auction by trying to underbid each other.

The main idea behind an auction methodology is to create incentives for participants to show their true valuation of an offer (Cvrcek et al., 2006). This results from the design of the auction, which motivates users to maximize their outcomes under the consideration that not everyone can receive an outcome at all. On the upper bound, utility-maximizing consumers aim to achieve the highest prices possible. On the lower bound, consumers aim to win the auction and therefore must anticipate the behavior of other participants in their decisions. Consequently, the best strategy for participants is to bid exactly the value they ascribe to their data in this context (Lusk & Shogren, 2007). Therefore, this price can also be defined as consumers' reservation price (Benndorf & Normann, 2018; Carrascal et al., 2013). The winner of the auction—that is, the person with the lowest bid—is paid the bid amount of the second-lowest bidder (if there are multiple winners, the bid amount of the last participant not chosen). A desirable side effect of this methodology is that it overcomes consumers' overemphasis of their privacy valuation, as described in the literature concerning the privacy paradox (Benndorf & Normann, 2018).

The auction was placed in the user profiles of WALLETSEARCH. Users received the information that WALLETSEARCH was in a beta stage and that some users would achieve more possibilities to increase their Exchange Rates and receive more money per search request. Users were free to bid in all available auctions (see Table 1) or to choose the ones they preferred. Further, they were told that a reverse auction was being developed to choose the winner for this Exchange Rate increase. Therefore, they had to suggest their demanded Exchange Rate increase for which they would disclose the requested data in return. Next, they were told that participants demanding the lowest 25% of the bids would be chosen and would have to disclose the data in the next step. The approach of defining multiple winners was chosen to ensure that bidders were motivated to participate in the auction (Danezis et al., 2005).

The set of data items for the auction was selected to reflect a holistic overview of the different data types under consideration based on previous research results, as it has been found that the type of data influences data valuation (Carrascal et al., 2013; Huberman et al., 2005; Tsai et al., 2011). The data type, the wording used in the auction, the data character, and related concepts in the literature are provided in Table 1.

The variable *usage_intensity* was calculated from several observations. First, the number of search requests a user conducted on WALLETSEARCH, equal to the user's Coins, was stored. This number was seen as equal to the user's frequency of use. Users were able to use WALLETSEARCH any day of the observation period. Therefore, the number of search requests was combined with the length of time the user had held a user profile on WALLETSEARCH. Hence, the date a user joined WALLETSEARCH (*t_joined*), as well as the date of the last action on WALLETSEARCH (*t_last_login*), were collected. By subtracting *t_last_login* from *t_joined*, the variable *t_usage* was created, which was equal to the number of days a user had used WALLETSEARCH. Therefore, *usage_intensity* was defined as Coins divided by *t_usage*. However, it could be that users participated in an auction at the beginning, during, or at the very end of their usage period. Consequently, it was assumed that consumers' perceived value of WALLETSEARCH was constant over the usage time. This assumption was supported by the finding from previous research that consumers anticipate their future usage when comparing prices (Bolton & Lemon, 1999).

When users accessed their profile pages, they were offered the opportunity to increase their Exchange Rates by 0.002 EUR by providing demographic information in the form of gender, age, current occupation, and highest level of education. The main reason for the take-it-or-leave-it offer was to use the data as control variables in the analysis (e.g., of control variables used here: gender, age, occupation, usage of ad blockers, etc.). Previous research has identified the influences of gender

Table 1
Auction offerings and question wordings.

Auction (i)	Item/Question Wording	Character	Usage and Related Concepts in the Literature
name	First name and surname	Identifier	"Contact Data for a mean of 14.88 EUR, in GER" (Benndorf & Normann, 2018, p. 5)
address	Street number and postcode		
telephone_no	Mobile or landline number		
sex_toy	What sex toy(s) do you own?	Product	"Privacy matters in settings with sensitive information (sex toy) more than in settings without sensitive information" (Tsai et al., 2011, p. 266)
phone_type	What mobile phone do you own?		Non-sensitive treatment (to sex toy)
body	What is your size and weight?	Demographic	"74.06 USD for weight" (Huberman et al., 2005, p. 12)
nationality	What is your nationality?		Non-sensitive treatment (to weight) and as comparison values for the three types of demographic information requested (with real exchange)
marital_stat	Are you married, divorced, or unmarried?		
household_size	How many people live in your household?		
political_party	Which political party do you feel closest to?	Preference	Political preference is considered "secret" in Germany and therefore more sensitive
chocolate	What is your favorite chocolate brand?		"Preferences (Bundle) for a mean of 8.32 EUR, in GER" (Benndorf & Normann, 2018, p. 7)
shoes	What is your favorite shoe brand?		
income	What is your monthly net income?	Financial	"Demanded price exceeded 100 USD in 48%, in US " (Huberman et al., 2005, p. 5)
account_balance	Send a digital copy of your current bank account balance to WALLETSEARCH		"Demanded price exceeded 100 USD in 38% of the cases, in US " (Huberman et al., 2005, p. 5)
location	Install a plug-in and permit WALLETSEARCH to identify your location	Location data	"27.40 EUR for 28 days, in EU" (Danezis et al., 2005, p. 12); "43 EUR for 30 days, in EU" (Cvrcek et al. 2006, p. 117); "1 day location 3 EUR, in living lab ITL" (Staiano et al., 2014, p. 7)
browsing_hist	Install a plug-in and permit WALLETSEARCH to access your browsing history	Online data	"Median of 7.00 EUR, in ESP" (Carrascal et al., 2013, p. 191)
facebook	Give WALLETSEARCH access to your public Facebook profile	Social media information	"Facebook about page for a mean of 17.67 EUR, in GER" (Benndorf & Normann, 2018, p. 7)

(Cvrcek et al., 2006) and age (Carrascal et al., 2013; Huberman et al., 2005) on data valuation. Further, the procedure of collecting the demographic information aimed to increase users' understanding of the underlying decision model of the trade-off. Users disclosed the demographic data in return for a monetary reward. However, this approach led to a situation where not everybody who provided demographic data participated in the auction, and vice versa.

Regardless, the procedure of collecting this information aimed to overcome another issue. It was assumed that a large proportion of online consumers are unaware of the fact that they pay for free Internet services with their data (Carrascal et al., 2013; Cvrcek et al., 2006; Staiano et al., 2014). Hence, it was assumed that some users who created accounts were not aware of the fact that they would be paid for disclosing data (in the form of their search requests) when using WALLETSEARCH. Nevertheless, the majority of Internet users are aware of their countries' data protection and privacy rules (Statista, 2020).

5. Data analysis and results

5.1. Sample description

In total, 130 out of the 285 WALLETSEARCH users participated in the auction, generating 1,444 bids. This dataset was cleaned for bid suggestions, which seemed to be an error caused by technical or human failure (nine observations), and for all observations with a bid amount of zero (68 observations), reducing the dataset to 1,367 bids from 122 users. Descriptive information about the dataset can be found in Table 2. In total, 136 users (47.72%) sold their demographic information for an Exchange Rate increase of 0.002 EUR per search request. Of the 122 users who successfully participated in the auction, more than half (66%) also disclosed their demographic data. The design of the study is illustrated in the flow diagram in Fig. 2.

5.2. Regression analysis

The data collected through the experiment yielded a dataset with multiple bid amounts per user. These data can be described as having a panel structure, with some of the variance explained by influences related to the data type and to the users. However, users were not forced to bid for all data types, which resulted in an unbalanced dataset. Therefore, the variable *auction_id*, which describes the data type (i) a user (u) bid for, functions as the panel variable. The model was conducted in Stata 13 using the xtreg command with *auction_id* (StataCorp., 2013). The Hausman test shows that the unobserved heterogeneity in the model was correlated with the dataset (chi-square = 97.29; p-value = 0.000). This indicates that the random effects were probably correlated with the explanatory variables, which in turn suggests the application of a fixed-effects model.

The bid amount distribution per auction shows that the mean always exceeded the median. This indicates a non-normal distribution, which has also been found in previous research using reverse auctions for data (Cvrcek et al., 2006). A Shapiro–Wilk normality test confirmed the non-normal distribution ($z = 16.72$; p-value = 0.000). The structure of the distribution indicated positive skewness, for which Mosteller and Tukey (1977) recommended log transformation as a remedy. An analysis of the log-transformed bid prices shows that the mean and median were closer after this transformation. However, the log transformation did not ultimately cure the non-normal distribution, but it improved it. Consequently, the logged variable was used with the assurance that it met the assumption of normality (Hair, 2009). In order to enable interpretation for different data types, the full model was adapted for log–log regression using the natural logarithm ln(x). The variable *ln_usage_intensity* was created by using ln(x + 1)-transformation to avoid zero values (Mosteller & Tukey, 1977).

Based on the hypothesis raised and the discussed possibility of using panel data regressions, the following model was estimated:

$$\begin{aligned} ln\text{BidAmount}_{ui} = \alpha_1 + \beta_3 ln\text{Usage}_{\text{Intensity}_{ui}} + \beta_1\text{Scenario}_{ui} + \beta_2\text{Adblocker}_{ui} \\ + \beta_4 ln\text{Age}_{ui} + \beta_5\text{Gender}_{ui} + \beta_5\text{Occupation}_{ui} + \vartheta_u + u_i + \varepsilon_{ui} \end{aligned} \tag{1}$$

where *ln*BidAmount represents the natural logarithm of the bid amount of user u for data type i. In the model, α is a random intercept; ϑ_u represents user fixed effects; u_i controls for the unobserved heterogeneity

Table 2
Descriptive statistics.

		WALLETSEARCH User (*N*)	Full sample size *N* = 285	Auction Participants (*N*)	Auction sample size *N* = 122
Variable	Responses	Value	%	Value	%
AdBlocker	False	230	81	94	77
	True	55	19	28	23
Usage Intensity	(in searches/day)	Mean: 25.24		Mean: 27.67	
		With Demographics	*N* = 136	With Demographics	*N* = 80
Variable	**Responses**	**Value**	**%**	**Value**	**%**
Gender	man	91	67	59	74
	not_specified	2	1	2	3
	woman	43	32	19	24
Highest Education	bachelor	35	26	25	31
	main school	21	15	12	15
	matriculation_standard	12	9	6	8
	no_graduation	6	4	5	6
	other	2	1	2	3
	middle school	27	20	12	15
	technical_school	33	24	18	23
Current Occupation	apprentice	8	6	5	6
	employee	60	44	40	50
	other	19	14	8	10
	pensioners	2	1	0	0
	pupil	5	4	5	6
	self-employed	20	15	7	9
	student	22	16	15	19
Age		*Mean:* 32.73		*Mean:* 31.71	

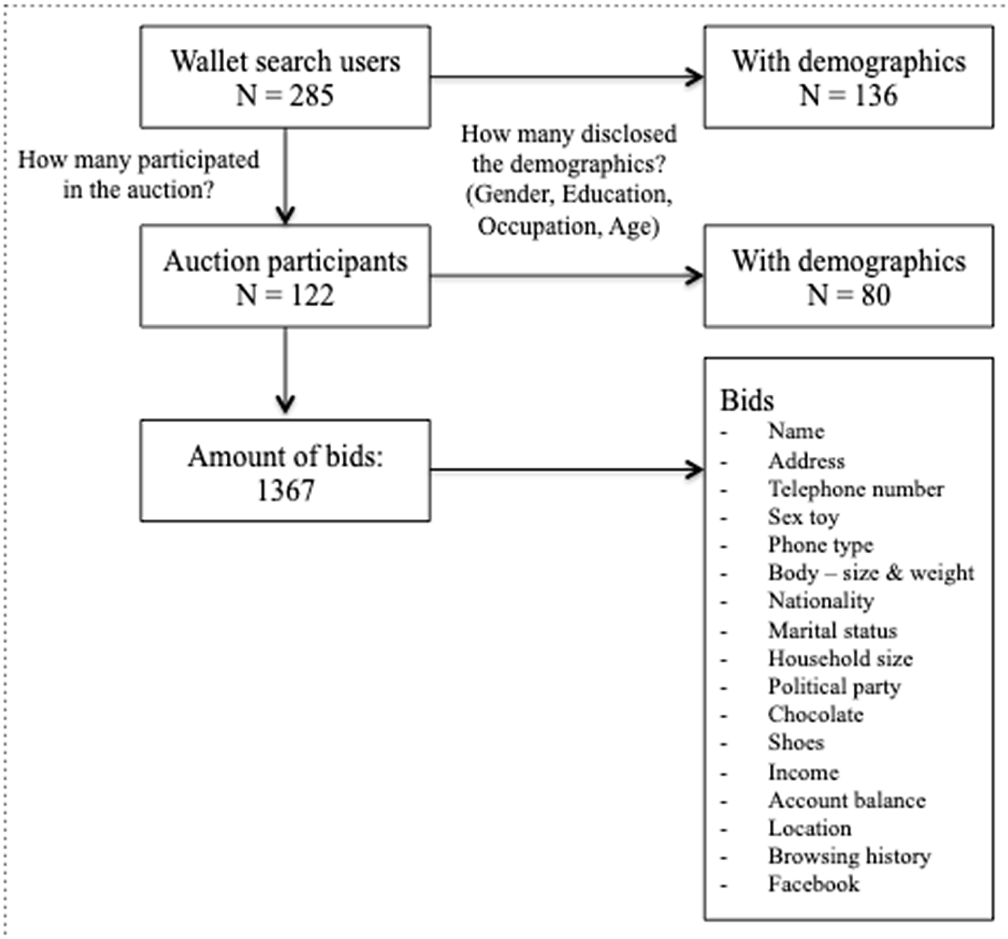

Fig. 2. Study design flow diagram.

between data types; and ε_{ui} is the error term, which is independent and identically spread over u and i. All other variables are detailed in Table 3. Pearson's coefficients show that there were significant correlations (p-value ≤ 0.01) between Bid_Amount and *ln*_Usage_Intensity (-0.20), between Bid_Amount and *ln*_Age (0.14), and between *ln*_Usage_Intensity and *ln*_Age (−0.11).

Table 3
Variable operationalization in the fixed-effects model.

Variable	Description and measure
User (ID)	User identification *u,* chosen by the user when they created an account.
Ln_Usage_Intensity	Natural logarithm of (*Coins/t_usage*)
ln_amount	Natural logarithm of the amount a user *u* bid for the auction *i* (expressed as course increase in euros)
Coins	Number of search requests of user *u*.
t_usage	Days for which user *u* used WALLETSEARCH (1 + day of last login – day joined)
Control Variables	
Auction (ID)	Auction/data type *i* for which user *u* placed a bid.
ln_Age	Natural logarithm of the age of user *u*.
Gender	Gender of user *u*.
Occupation	Current occupation of user '.
Scenario	Personal data scenario to which user *u* was randomly assigned.
AdBlocker	Variable indicating whether user *u* uses ad blocking software (False, True). The use of an ad blocker was detected by a computer script placed in the website.

5.3. Empirical results

In the model, 94.67% of the original data were retained (see Table 4). The model was significant (Prob. > F = 0.000) and explained 18.87% of the variance in the dataset. The coefficients of the (quasi) metric variable could be directly compared, and all represented (shifts in) elasticities. The categorical variables *Scenario*, *AdBlocker*, *Gender*, and *Occupation* expressed differences in the bid amounts relative to their base in percentage terms. The hypothesis was tested on a 0.05 level.

The results show that if usage intensity increased by 1%, the suggested bid prices decreased by 0.55%, on average. Therefore, H1 was supported, as high usage intensity decreased the price for which consumers were willing to sell their data.

The variable *ln*Age was found to be significant, implying that a 1% increase in participant age resulted in a 0.95% increase of the suggested bid amounts. Further, users who utilized an ad blocker offered 197% lower bid prices compared to users who did not use such software. This indicates that participants who used ad blocker software were willing to sell their data for lower prices compared to the participants who did not use such software. There were also significant differences between genders: Women had lower bid amounts than did men, and the results indicate that the participants who did not provide gender information also had lower bid prices compared to men. Regarding occupation, students and the self-employed suggested lower prices for their data compared to employees, while trainees and others suggested higher prices compared to employees. The empirical results are further discussed in the next section and are contrasted with previous privacy valuation research.

Table 4
Estimated parameters (FE).

	Coefficient	t
Dependent variable	*ln_BidAmount*	
ln_usage_intensity H1: (–)✓	**−0.5490*** **	−14.29
Control variables		
ln_age	**0.9530** **	2.75
Gender (Base: Male)		
Females	**−0.7557*** **	−4.74
Not specified	**1.9230*** **	4.89
Not filled	**−0.3792* **	−2.31
Occupation (Base: Employees)		
Pupil	0.2154	0.60
Trainee	**2.2149** **	3.47
Student	**−2.0714*** **	−10.28
Self-employee	**−1.2850** **	−3.01
Other	**0.5154* **	2.67
Not completed		
AdBlocker (Base: False)		
True	**−1.9743*** **	−12.57
Scenario (Base: B – Rel. ads)		
A – Control	−0.0755	−0.66
C – Rel. content	**−0.9107** **	−3.68
D – Data partners	**−0.8056*** **	−5.91
Constant	**−3.9270** **	−3.04
sigma_u (u)	0.9143	
sigma_e (ui)	3.0565	
rho	0.0821	
Statistics		
Observation (N)	1367	
No. of individuals (auction sample)	122	
F(14,60)	1722.99	
Prob > F	0.0000	
R-square (overall)	0.1887	
Within	0.2001	
Between	0.0299	
Corr(u_i, Xb)	0.0024	
AIC	6930.66	
BIC	7003.74	

6. Discussion and conclusions

The aim of this study was to investigate consumers' behavior with regard to disclosing data in a real-life situation. Research in this field is still scarce and typically has not focused on consumers' trade-off between the costs of data disclosure (*privacy concerns*) and the benefits of data disclosure (*customer-perceived value*) as is present in free online services. Nevertheless, in such a trade-off, consumers' valuation of data is difficult to examine. Inspired by the proposal of "radical markets" (Arrieta-Ibarra et al., 2018), where consumers are paid when their data is monetized, the search engine WALLETSEARCH was designed for the purpose of conducting this experiment. The search engine was configured so that Internet users collected a micro-payment every time they used this search engine to search the Internet. Via their profiles, users were offered the option to increase their micro-payment amount by disclosing more data in a reverse-auction scenario. Thereby, it was possible to examine a metrical variable in the form of the demanded bid price, which served as the reservation price and an indicator of the users' data valuation. A feature of this experimental design was that it enabled us to measure how consumers anticipate and consider the consequences of their data sharing on perceived service value (which will change based on their data) in their trade-off decisions. This approach is unique in data valuation research and enabled us to measure four specific effects, contributing to the understanding of consumers' data valuation.

In order to answer the research question, the role of usage intensity as an indicator of customer-perceived value was observed. Hence, it was found that a 1% increase in usage intensity led to a 0.55% decrease in consumers' demanded price for disclosing data. This indicates that users consider the perceived value they receive from the company in their trade-off decisions. This finding concurs with indications of previous research that consumers are willing to disclose their data as a gesture of reciprocity in return for free content (Schumann et al., 2014). However, this finding extends the results of previous research by empirically proving the relationship between usage intensity—proposed as an indicator of customer-perceived value by Bolton and Lemon (1999)—and consumers' valuation of data. This indicates that the higher the consumer-perceived value of a service, the more willing consumers are to sell their data in return. Therefore, this finding highly supports the theory of the privacy calculus as a cost–benefit analysis.

7. Theoretical implications

This study has addressed several research gaps concerning the privacy valuation literature. First, a measurement model of consumers' data valuation was proposed, which enables the observation of consumers' privacy calculus in real-life decisions. Second, the importance of the company's data usage in consumers' data valuation was examined. Third, it was empirically proven that consumers consider the perceived value in their data valuation, which highly supports the existence of a cost–benefit trade-off when disclosing data.

This study has answered the call for more research on the value that consumers assign to data and how they trade off this value within the digital economy (Gabisch & Milne, 2014; Kumar & Reinartz, 2016). Moreover, this study directly responds to the MSI's research priorities for 2020–2022 by further increasing the academic understanding of consumers' privacy trade-offs. Hereby, the richness of the proposed measurement of consumers' data valuation is underlined. While consumers' valuation of data has been measured according to their willingness to sell their data in previous studies, this investigation has reinforced this approach by assessing it in a real market scenario. Considering the fact that disclosing data typically affects both the perceived benefits (e.g., a free service) and the perceived costs (e.g., privacy concerns), including the value of a product or service in the model enables richer implications and a more detailed fragmentation of consumers' trade-off decisions when disclosing data. Consumers are more willing to provide their data if they expect additional benefits—for example, personalized recommendations—which can increase consumers' valuation of the services (Martin & Murphy, 2017). Finally, the proposed experimental setting overcomes the issue of the privacy paradox affecting survey methodologies (Benndorf & Normann, 2018), because consumers faced real trade-off decisions in this setting.

Furthermore, this study empirically measured the negative relationship between usage intensity (as an indicator of customer value) and consumers' data valuation. The reported negative elasticity indicates that users treat the value of their data similar to monetary value. It is conceivable that if the perceived value is high, the willingness to pay with data will be higher. On the one hand, this finding indicates that social exchange theory, which has often been proposed in this context (Gabisch & Milne, 2014; Hann et al., 2007; Schumann et al., 2014), is a well-suited theory to the topic. Consumers consider perceived value in their trade-off decisions, which explains why consumers disclose data based on their intention to reciprocate the perceived benefits. On the other hand, it indicates a structural problem in current privacy research, which has mainly assumed that consumers' decision-making processes are binary (disclose data or not). While this assumption is in line with current business practice, the present research has indicated that when consumers are given the opportunity to assign value to their data, they treat their data as a valuable good and trade it according to the perceived costs and benefits.

8. Managerial implications

The understanding of consumers' data valuation is of high interest in practice. As greater numbers of people become more aware of the collection, storage, and aggregation of data, data practices will become more important (Martin, 2018). This is especially true for companies acting under GDPR. GDPR aims to enable users to control their personal information; consequently, companies are forced to inform consumers in more transparent and detailed ways as to how their data are collected and used. Hence, companies are required to institutionalize the practice of obtaining consent statements or permission from users to meet regulatory requirements. The way this information is stated and presented must be comprehensible to users, who must also be properly informed about how the data are processed and traded. This study suggests that companies can easily create mechanisms to recognize which types of data are disclosed more often, as well as add a certain average value to this data.

The research shows that consumers' perceived value affects their valuation of data. While it is well-known that perceived value is individualistic and personal (Zeithaml, 1988), currently, practitioners design their offers mainly as a take-it-or-leave-it offering. The problem with this practice can be illustrated using a brief example. A free online service asking customers for their name, address, and age to sign in might seem like a fair deal to Customer A; however, the "price" in terms of data might be considered too high by Customer B in exchange for the perceived benefits of the service. As a result, Customer B might not sign in. Yet, if age is deleted from the list, both Customers A and B might take the deal. Therefore, this research highly recommends that companies treat the relationship between required data (e.g., to sign in) and demand (e.g., number of users) as responsive, just as the common practice for monetary price has been for decades (e.g., Tellis, 1988). In other words, companies should develop "pricing" strategies when defining what data they ask for. Particularly, companies could formulate pricing strategies focused on the additional benefits gained from personalization, rather than placing emphasis on more-relevant advertising. Existing research in this area has proposed two strategies to increase users' acceptance of targeted advertising and thereby increase their willingness to share data. The first strategy highlights how targeting increases the relevance of the advertising that users see (the *relevance argument*) (Milne & Gordon, 1993). This strategy is used by some of the main players in the market, such as Facebook, which even allow users to decide on which data their advertising is selected. The second strategy highlights how the provision of personal data helps the provider to finance its free offer (the *reciprocity argument*) (Schumann et al., 2014). For instance, free news websites are likely to use this strategy when users with active ad blocker software enter. Schumann et al. (2014) showed that reciprocity arguments are more appealing to online users than relevance arguments are. In Schumann et al.'s research, participants assigned lower value to their data when they expected to see more relevant content based on the disclosed data, compared with when they expected more relevant advertising. Therefore, it is recommended that companies highlight and communicate the (additional) benefits that users can gain from disclosing data.

Likewise, the presented results are in line with approaches to privacy as a form of strategy (Martin, 2018; Martin et al., 2017; Martin & Palmatier, 2020; Okazaki et al., 2020) and illustrate how privacy could be a basis of competitive advantage. Specifically, the idea is to treat consumers' data disclosure as a kind of labor, which is later monetized in cooperation with the company (Arrieta-Ibarra et al., 2018). This research showed that there are consumers who are willing to sell their data and accept micro-payments as a form of transaction. The experiment further demonstrated that there are consumers who will accept micro-payments in line with current market values for their data (e.g. 0.005 EUR per search request). If consumers are willing to sell their data, firms are able to gain additional revenue generated via the monetization of these data, such as through targeted advertising, and then compensate consumers with parts of this revenue. This might offer the opportunity to create new business models by creating "beyond 'free'" markets where customers participate in the generation of revenue. The major argument against such business models typically pertains to "how one would cheat, spoof, phish, or spam such a system" (Lanier, 2014, p. 262). However, as a qualitative but motivating insight of this study, the majority of WALLETSEARCH users followed the rules of the website, and for the minority who cheated, most of the cheating attempts (except two) were quickly stopped by simple algorithms. With cryptocurrency approaches gaining ground (Klein & Stummer, 2021), business strategies can look at the use of fee-less micro-payments as a way of implementing similar platforms.

9. Limitations and further lines of research

This study had some limitations that must be acknowledged. In the following, these limitations are identified and proposals for further research are provided. First, the results were based on a field experiment in a specific business setting. Hence, possible differences between markets, industries, and business models are expected. How people decide what their data are worth depends heavily on the context in which they are asked and how the problem is framed (Acquisti et al., 2013). Further research should attempt to replicate the study and validate whether the results are consistent across different markets. In this context, it has to be clarified that all WALLETSEARCH users had one underlying characteristic: they were willing to sell their data. Therefore, the generalizability is limited; however, this is a general and accepted limitation of conducting field studies, as it is similar to using company data. Unfortunately, in the context of WALLETSEARCH, the number of consumers who visited the website and did not create accounts and the number of consumers who dropped out of the sign-up process were not logged or tracked. Therefore, it is highly recommended for further research to track these numbers in order to gain a more holistic view of participation. Likewise, there will be people who are so concerned about their privacy that they would never be willing to participate in a personal data market. In our research, we assumed that customer decision-making is rational; nevertheless, privacy decision-making is often irrational and more complex, so further research is needed in this regard.

Finally, the approach of measuring Exchange Rate increases rather than measuring direct amounts must be evaluated by future research. On the one hand, this approach is optimal to observe consumer behavior over a longer period and to include perceived value in the experimental setting. On the other hand, there might be effects influencing this amount, such as an overestimation of future usage, a lower motivation to participate, or even an intention to cheat the system. Furthermore, in the market simulation, the compensation price can be viewed not only as compensation for disclosing data but also as compensation for the value not received from competitors. For instance, WALLETSEARCH only offered users Web search results. This means that other types of search results (e.g. images, news, or videos) that might be shown by competing search engines were not shown. Users who missed these additional benefits might have perceived a lower level of service when using WALLETSEARCH, and for this reason these users might have "compensated themselves" by selecting higher bid prices. Future research is advised to control this effect, for example by including instrumental variables. Likewise, it would be interesting to study the existence of moderating effects directly related to consumers' user experience, not only demographic data but also personality cues.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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