Is transparency the new green? How business model transparency influences digital service adoption

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ABSTRACT

The proliferation of data-driven business models raises privacy concerns, as users often perceive a lack of transparency in how companies use their data. This study explores how business model transparency (and the absence of it) influences users' decisions to adopt a digital service. We propose a model grounded in rational choice theory, tested through multigroup structural equation modeling. Data were collected through a field experiment that exposed users to two different mock-ups characterized by varying levels of transparency related to data usage. The results show that the level of transparency does not directly influence users' willingness to adopt the service. Switching from a transparent to an opaque data-driven business model negatively affects users' willingness to adopt a service. Such findings remark on the users' service adoption decision-making process criteria, which are highly influenced by perceived data usage transparency. Consequently, this study introduces a user perspective on data-driven business models. It conveys to managers the importance of transparency when business models are grounded in data-driven strategies and data exploitation.

1. Introduction

Scott Goodson, a well-known marketer, said in 2012, "*If you are not paying for it, you become the product.*" Business models based on users' data have grown over the years, thus revealing an underlying truth: data constitute the new gold, which is often why we enjoy services for free (Trabucchi et al., 2017).

While the increasing availability of data fuels the diffusion of data-driven business models (Hartmann et al., 2016; Kiel et al., 2017; Sestino et al., 2020; Sorescu, 2017), it also leads to a paradoxical scenario. On the one hand, the widespread recognition of the value of embedded data makes it a primary lever of business model innovation in service domains (Ostrom et al., 2015). On the other hand, the indiscriminate use of users' generated data leads to several privacy concerns. The Cambridge Analytica scandal is a salient example of these concerns. In 2018, Cambridge Analytica, a British data mining and analysis consulting firm, used a personality test to harvest personal data from 87 million Facebook users. These data were used to generate psychographic user profiles to stratify advertisements that effectively persuade users to fall into a specific profile. Such a scandal led Mark Zuckerberg to testify in front

of the US Congress in April 2018, followed by an apology and revision of Facebook's privacy policy (Confessore, 2018).

Scholars are increasingly paying attention to the fast growth of data-driven business models (DDBMs) as they represent a new frontier for scholars in the business field (Delgosha et al., 2021; Gligor et al., 2021; Hartmann et al., 2016). There has been extensive research on the potential of data use in various fields (Ciampi et al., 2020, 2021; McAfee and Brynjolfsson, 2012), even though previous scandals have driven scholars to take a user-centric perspective exploring privacy concerns regarding data exploitation models (Acquisti et al., 2013; Martin et al., 2017). The current diffusion of Big Data analytics has also raised ethical concerns over data acquisition and use (Hajli et al., 2020) and, more broadly, over DDBMs (Guzdial and Landau, 2018; Palmaccio et al., 2020). Public opinion is increasingly hostile toward the power of big tech, negatively reacting to data-related scandals (e.g., the #LeaveFacebook movement immediately following the Cambridge Analytica scandal). However, while users seem to respond in the short term, they do not change their behavior regarding the company involved in such scandals. Observing Facebook users over the years reveals how this trend continued even after the Cambridge Analytica scandal (Statista,

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2021). Therefore, reaction to scandals are mainly related to the lack of awareness of what companies can do with data.

In recent years, there has been an increasing focus on data transparency from firms and governments. From a business perspective, data transparency can help build trust with customers and stakeholders (Palmaccio et al., 2020). By being transparent about how they collect, use, and share data, companies can demonstrate their commitment to ethical business practices. This can also help mitigate potential risks associated with data breaches or the misuse of personal information. Many companies have implemented policies and practices to improve data transparency (Martin et al., 2017). For example, some companies have adopted privacy-by-design principles that prioritize the protection of personal information throughout the entire lifecycle of a product or service. Others have implemented clear privacy policies that outline how they collect and use customer data (Barth et al., 2022).

Governments also play a crucial role in promoting data transparency. Many governments have implemented open data initiatives that make government datasets publicly available to citizens, researchers, and businesses (Bandara et al., 2021). These initiatives can help promote accountability and transparency in government decision-making. In addition to open data initiatives, governments can implement regulations requiring companies to be more transparent about their data practices. For example, the European Union's General Data Protection Regulation (GDPR) requires companies to provide transparent information about collecting and using personal information.

Despite these efforts to improve data transparency from both firms and governments, challenges still need to be addressed (Bandara et al., 2021). One challenge is ensuring that individuals understand how their personal information is used. While many companies provide privacy policies or terms of service agreements outlining their data practices, these documents are often lengthy and challenging for individuals to understand.

As privacy can be studied from multiple perspectives, this study focuses on the impact of users' awareness of how digital companies use their data and how disclosure about data usage influences the users' willingness to use a service.

Therefore, we define the concept of "business model transparency" as the extent to which end-users are informed (in simple and understandable language) regarding the kind of data that companies collect and how such data may be used to generate revenue streams. This study explores the paradox mentioned above from the end-user perspective through the following research question:

Does the degree of data transparency in the business model influence users' willingness to adopt a service?

To answer this question, we designed a conceptual model—grounded in rational choice theory—and tested it via multigroup structural equation modeling (SEM). We collected data through a field experiment in which users were exposed to two mock-ups related to digital services with different degrees of data transparency.

The findings suggest that companies should design DDBMs' value propositions by valuing users as co-creators. The findings also demonstrate that business model transparency should be central to the value proposition. Business model transparency does not directly impact the users' willingness to adopt a digital service, and users tend to avoid opaque business models when they perceive different degrees of transparency. Such findings have relevant implications for the research field on DDBMs and for developing related transparency policies, thereby suggesting that (business model) transparency can be the new "green," becoming a differentiation factor in DDBMs.

2. Theoretical background

This study is grounded on DDBMs and the end user perception of data usage. We propose an analysis of the literature at the intersection of these two pillars and present the theoretical background supporting our study.

2.1. Data-Driven business models

Hartmann et al. (2016) conceptualized DDBMs, focused on companies that use data as a critical resource in their business model, and demonstrated that DDBMs are not limited to companies that conduct analytics but also include companies that aggregate or collect data. Similarly, Spiekermann et al. (2015) viewed data usage as a strategic asset to improve the decision-making process and existing operations. Schroeder (2016) defined the concept of big-data business models as companies that gather data through various digital technologies and leverage them as a core resource of their entire business model. Consequently, for this study, we combined these three definitions to explore the broad concept of DDBM.

According to Xie et al. (2016), users can generate data differently: by using a service, designing something, or completing a transaction, among the various modes. Companies can use these data internally to improve their business model and seize market opportunities. Taking advantage of user-generated data may lead to different innovation opportunities and allow companies to exploit the value of these data (e.g., Del Vecchio et al., 2018; Troilo et al., 2017). For example, the recent open innovation 2.0 strategy suggests the creation of a public–private roadmap to foster innovation relying on data-gathering opportunities (European Commission and Directorate-General for Research and Innovation, 2016) . Accordingly, data (both inbound and outbound feeds) may be considered a new resource to be leveraged to implement open innovation strategies. Open innovation based on data may involve gathering insights, ideas, and opportunities and exploiting them internally by implementing screening algorithms or other data mining techniques (Christensen et al., 2018). Similarly, they may be used to scan the market for lead users or additional innovation opportunities (Somoza Sánchez et al., 2018). From an outbound perspective, this process may mean finding new markets for the data (Trabucchi et al., 2018).

The current body of literature has classified DDBMs into different types (e.g., Schoreder, 2016; Van Rijmenam et al., 2019; Wiener et al., 2020): (1) data users (companies using data for internal purposes); (2) data suppliers (companies marketing the data); and (3) data facilitators (companies providing users' data). While most studies have primarily focused on data users, a few studies have been conducted on data suppliers (Wiener et al., 2020), which are central to this study. Data suppliers are an interesting unit of analysis as they comprise two sets of a company's customers: users who generate data through service usage and those who generate data on a two-sided platform.

A two-sided platform serves at least two groups of customers linked through cross-side network externalities (Evans, 2003; Rochet and Tirole, 2003; Trabucchi and Buganza, 2022). Traditional examples are the credit card market (with cardholders and merchants) and videogame consoles (with gamers and developers). This model has been adopted by numerous growing businesses, such as Airbnb, Uber, Deliveroo, and Etsy. The two main types of two-sided platforms are transactional (i.e., when the platform provider enables a direct transaction between the parties, such as Airbnb) and non-transactional (i.e., when the platform provider does not enable a transaction, such as newspapers, which have both readers and advertisers as customers (Filistrucchi et al., 2014)). Non-transactional two-sided platforms are particularly interesting for their subsidizing mechanisms. In this regard, the first side (e.g., the readers of a newspaper) can be heavily subsidized by the second side (e. g., the advertisers) and aim to exploit the value embedded in data from numerous users (Ihlström Eriksson et al., 2016). This model has been revised through the opportunities unveiled by data, defining a client-as-a-source strategy, thus allowing the rise of DDBMs, which Scott Goodson (2012) provocatively criticized as "*If you are not paying for it, you become the product*" (Kathuria, 2019; Trabucchi et al., 2017). Consequently, digital services can exploit the value of the user-generated data by finding a group of customers interested in those data, thereby enabling a revenue flow that may sustain a free (or almost

free) service offered from the first side (Farrelly and Chew, 2019; Trabucchi and Buganza, 2019). This fact is particularly relevant for mobile apps and digital services, which are frequently freely used by end users.

2.2. End users' perspective on data usage

The diffusion of DDBMs opened up new opportunities for companies while creating threats to privacy and security for users (Del Vecchio et al., 2018). Privacy management and its impact on brand reputation can contribute to increasing or decreasing business opportunities (West and Gallagher, 2006). In recent years, privacy has become a new element of the marketing mix, with the potential to create (or destroy) value for end users (Weinberg et al., 2015). Therefore, companies must understand the magnitude of data breaches and privacy issues on their reputation, value creation mechanism, and performance (Martin et al., 2017). Privacy management literature has examined the relationship between personalization and privacy and commented on the trade-off between service personalization and the information disclosure requirements that users must fulfill to procure the service. It leads to the personalization–privacy paradox, which "[…] *refers to a situation where consumers give out their private information with subjective expectations that the service provider will provide personalized services based on their profiles and trust that the provider will not indiscriminately share their personal information*" (Li and Unger, 2012, p. 625). However, as online personalization services belong to industrial goods with no free disposal (NFD) property, users only sometimes wish for more personalized services because of privacy concerns (Chellappa and Shivendu, 2010). Although personalization has clear benefits in fulfilling customer needs and increasing customer loyalty, it is intrinsically related to hidden privacy costs that prevent users' adoption (Chellappa and Shivendu, 2010). In this context, recent studies have shown how personality traits influence privacy concerns (Spiekermann et al., 2015) and have demonstrated diverse user profiles, from privacy guardians to convenience seekers (Hann et al., 2007).

Along with personality traits, context influences privacy concerns and the trust between users and service providers (Bansal et al., 2016). For example, Acquisti et al. (2013) noted the importance of understanding the value individuals attribute to protecting their personal information. Understanding the value of data protection helps companies deliver more effective DDBMs (Acquisti et al., 2013). When using a digital service, users accept the extent to which personal data are collected and processed, thus interpreting it as a price they are willing to pay in exchange for the benefits of using the service. This scenario is representative of the paradox mentioned above. On the one hand, users lack awareness of how companies use their personal data (Trabucchi et al., 2017, 2018). On the other hand, they are often more concerned about privacy issues (Acquisti et al., 2013; Hann et al., 2007).

Recent research has explored the impact of a fair approach to data usage. Different theories have been applied to explore users' perceptions of companies leveraging their data for purposes other than service delivery. Scholars have approached data usage by companies through the lens of cognitive theory (Turel, 2015), social capital theory (Ellison et al., 2007; Maksl and Young, 2013; Valenzuela et al., 2009), and gratification theory (Chiu and Huang, 2015; Sutanto et al., 2013). Such theories share a common starting point: individuals' attitudes toward data usage result from a cost–benefit analysis assessment. Wagner et al. (2021) proposed a slightly different viewpoint: the relationship between the two parties—those who generate data and those who use them—-should evolve in a service-like perspective, creating a fairer environment.

In summary, extant literature framed the theoretical reasoning on the privacy paradox, thus attempting to understand the relationship between privacy concerns and the co-existing willingness to enjoy a data-based service. Recent studies have explored a broader perspective in which companies and users interact and bargain for data usage, transparency, and protection.

3. Research model and hypotheses development

According to existing literature, combining the growing opportunities for providing new, personalized services to users by leveraging their data with the growing concern among users regarding their privacy and how these data are being used is essential.

3.1. Privacy paradox and the rational choice theory

Previous studies defined the privacy paradox as follows: "*[…] privacy is a primary concern for citizens in the digital age. On the other hand, individuals reveal personal information for relatively small rewards, often just for drawing the attention of peers in an online social network*" (Kokolakis, 2017, p. 122).

Following those studies that considered the willingness to use a service to be a rational decision born of a cost–benefit analysis, we adopt the lens of the rational choice theory. Such a theory stems from the neoclassical economic approach attempting to explain how individuals make decisions (Becker, 1968). The rational choice theory assumes that an individual first recognizes alternative actions and considers the likely outcomes of each possible decision (Bulgurcu et al., 2010; McCarthy, 2002; Paternoster and Pogarsky, 2009). Possible outcomes can be perceived in association with costs and benefits according to individual utility functions (McCarthy, 2002). Therefore, individuals' preferences have influenced the perceptions associated with costs and benefits (Becker, 2009), which are subjective and not necessarily monetary (Paternoster and Pogarsky, 2009; Paternoster and Simpson, 1996).

The privacy paradox (Li and Unger, 2012; Kokolakis, 2017) mirrors the dimensions of rational choice theory. Given different utility functions, everyone perceives a different value associated with digital service usage. As in many cases, the services are free (as they are paid back through user-generated data), so the value perceived is equal to saving avoided cost of buying a service. Simultaneously, individuals perceive a cost when sharing their data in terms of losing control and, therefore, a possible privacy issue. Quantifying such a cost might be difficult without transparent information about the users' data usage.

By mirroring the rational choice theory into the privacy paradox, we theorize a baseline model (Fig. 1) explaining users' behavior based on their attitudes (Bulgurcu et al., 2010; McCarthy, 2002; Paternoster and Pogarsky, 2009). The users' utility function is modeled considering perceived benefits and perceived costs. In our baseline model, benefits are related to what users perceive as valuable in the service experience. To measure such benefits, we drown in the construct of personal innovativeness (Mun et al., 2006). In a setting where the privacy paradox is diffused, personal innovativeness measures the relevance of the perceived benefit. It emphasizes the user's willingness to try, adopt, and enjoy a new service.

Similarly, privacy attitude (Chellappa and Sin, 2005) is an efficient proxy to predict the intensity of perceived costs by individuals (in terms of their utility function). DDBMs require users to trade their privacy by sharing personal information for personalized service (Buganza et al., 2019). Individuals with a higher privacy attitude would have perceived such a high cost (Chellappa and Shivendu, 2010; Spiekermann et al.,
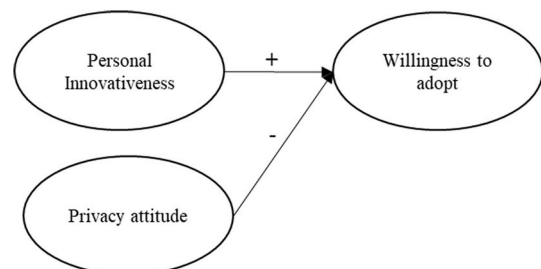
Fig. 1. Research model: Traditional perspective.

2015).

By applying the rational choice theory to the privacy paradox, we theorize that individuals with high personal innovativeness and a low privacy attitude would be more willing to adopt new and innovative services as they perceive the high benefits and low costs associated with service use. Meanwhile, the willingness to adopt the service will decline when personal innovativeness is low and/or the privacy attitude is high. Combining these two effects will drive the individual to avoid adopting the new service.

3.2. The moderating role of business model transparency in DDBMs

To comply with data regulations, companies in many countries must declare the types of data they gather and how they use and treat them in their privacy statement. Despite increasing data policy statements, most users need better awareness of how companies leverage their data. In a recent study by Ogury (2019), only 8% of consumers declared that they had a better understanding of data one year after the delivery of general data protection regulation (GDPR) laws.[1]

In this context, the companies' decisions regarding the level of transparency are crucial as they may significantly influence the perception of the services offered by users, thus allowing a better evaluation of perceived costs and benefits (Betzing et al., 2020; Gimpel et al., 2018). Willis et al. (2021) demonstrated that companies applying GDPR are perceived as more sucre and trustworthy by users, including those not based in Europe. The increase in transparency, thanks to regulation, also appears positive for countries that do not request data transparency regulations for business operations (Strzelecki and Rizun, 2020).

In this context, companies are increasingly taking measures to ensure business model transparency by publicly disclosing what user-generated data they use and how. For example, Uber has set up a platform, *Uber Movement*, where rides are anonymized so the public can access data to improve town mobility services. Strava, the fitness tracking app, has taken a similar approach with Strava Metro to let municipalities access the aggregate and anonymous data of bikers and runners in their cities. Skyscanner has developed the Skyscanner Partners Service to share data with airports. These services are advertised and easily findable by end users, showing a good level of transparency.

As a result, we incorporate in our theoretical model the level of business model transparency in DDBMs. We define the concept of business model transparency in DDBMs as the extent to which users are informed (in an accessible and understandable manner) about what data are collected and how they are used, including how they are employed to generate value for third parties. In our theoretical model, a DDBM is defined as "transparent" if (1) it openly communicates what data are being retrieved and how they will be used, (2) it communicates the benefits that customers will receive by accepting the usage of their data by third parties, and (3) it communicates which third parties are involved in the process.

However, we acknowledge the existence of an opaque business model that does not report to users one or more of the dimensions mentioned above in the privacy policy statement (Schaub et al., 2017). Data transparency is not a data security feature. Data security deals with the protection of databases. It is managed by specific regulations that force companies to report data breaches (e.g., the European GDPR, art. 33 about mandatory notification of data breaches). While transparent and opaque business models can correspond regarding what is declared in the privacy policies, the critical aspect is how "transparently" the company showcases such a business model (and its data usage) to the end users outside the privacy policies.

By relying on information transparency (Awad and Krishnan, 2006)

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[1] The general data protection regulation (EU) 2016/679 (GDPR) is a regulation in European Union (EU) concerning the data protection and privacy for EU and the European Economic Area (EEA) citizens.

to measure customer awareness of how companies deal with the gathered data (Malhotra et al., 2004), this study explores the impact of different degrees of DDBMs' transparency on the privacy paradox. Consequently, we theorize that providing clear information about how data are collected and used will influence the users' willingness to adopt the service, thus positively impacting the perceived benefits and the perceived cost. In particular, we hypothesize that irrespective of the prevailing perception of benefit or cost in the rational choice, a more transparent view of the business model strengthens the relationship between the DDBMs-based companies and users. In line with rational choice theory, greater business model transparency strengthens rational choice, given that transparency provides users with additional information to ground their evaluations (Bulgurcu et al., 2010; McCarthy, 2002; Paternoster and Pogarsky, 2009). We, therefore, hypothesize that business model transparency in DDBMs moderates the influence of the decision to adopt a service (Fig. 2) and propose the following hypotheses:

H1. Personal innovativeness is positively associated with the willingness to adopt a digital service. Such a relationship is stronger when users are exposed to transparent business models.

H2. Privacy attitude is negatively associated with the willingness to adopt a digital service. Such a relationship is stronger when users are exposed to transparent business models.

3.3. Business model transparency in DDBMs

Traditionally, users have had limited awareness of how companies use their data. However, in recent years, newspapers have reported several actions and protests against technology giants, given the growing concerns about user data use (Guzdial and Landau, 2018). Consequently, companies now face the dilemma of whether they should invest in moving from an opaque to a transparent business model or vice versa.

Recent scandals highlight a growing interest among users in understanding how companies use their data. Previous studies explored the different strategies companies can adopt to improve the users' awareness and positive perceptions about data usage (Slepchuk et al., 2022; Wagner et al., 2021), thus highlighting the central role of psychological and ethical facets (Saura et al., 2021). This study also explores how shifting to a transparent business model can impact the willingness to adopt the service. Consequently, we investigate whether a variation in business model transparency in the DDBMs (moving from a transparent to an opaque business model or vice versa) impacts users' willingness to adopt a digital service. Therefore, we formulate the following hypotheses (Fig. 3):

H3a. The willingness to adopt a digital service increases with an improvement in business model transparency.
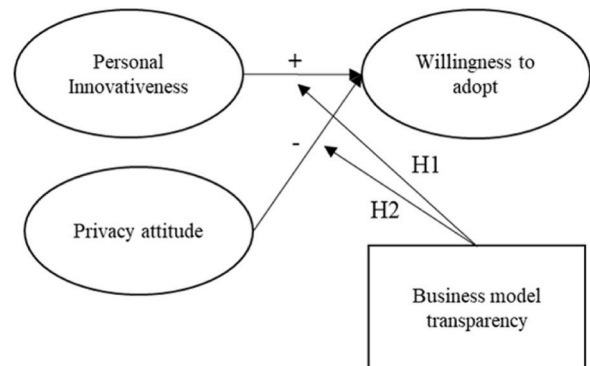

Fig. 2. The research model: The moderating effect of business model transparency.
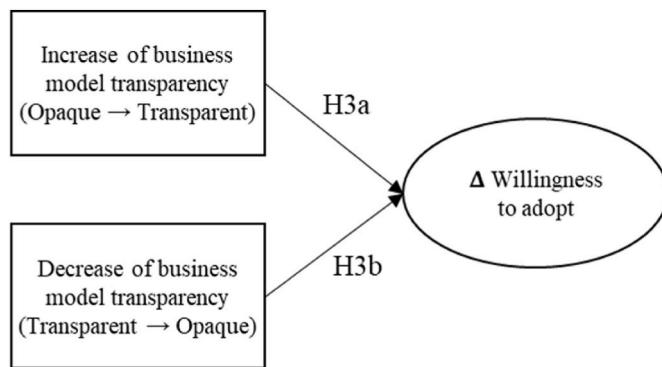
Fig. 3. The effects of a change in business model transparency.

H3b. The willingness to adopt a digital service decreases with a deterioration of business model transparency.

4. Research design and methodology

We select an experimental approach to test our theoretical model. In this regard, "*experiments have been used to quantify value creation, test customers' willingness to pay, understand an unfamiliar technology in use, design ways of shaping user behavior, measure channel effectiveness, quantify costs of providing a service, and test the effectiveness of new partnerships*" (Ganguly and Euchner, 2018). The increasing use of experiments as a methodology for innovation studies focusing on individuals (e.g., Eliëns et al., 2018; Hofstetter et al., 2018; Xiao et al., 2018) allows us to better justify the use of our method to test an expected behavior in a controlled context (Kokolakis, 2017). Experiments bring respondents into a reality-like environment, stimulating a specific behavior rather than relying on retrospective perceptions (Kokolakis, 2017).

4.1. Experiment design

Given the topic under study, we opt for a web-based experiment. As researchers manipulate the moderating variable (business model transparency), the participants are randomly assigned to various conditions, while the researchers have no control over the experimental setting (Podsakoff and Podsakoff, 2019). Following Carpenter et al. (2005) recommendation, we classify our experiment as a "framed field experiment," as it includes a non-standard subject pool and gives the participants a frame to evaluate services.

We designed two service mock-ups named *FitYou* and *Weights*. The two experimental sets belong to the health and fitness category (one of the most studied categories in this type of data collection; e.g., Pellizzoni et al., 2019; Trabucchi et al., 2017). To guarantee the neutrality of the experimental sets, the mock-ups have the same functionalities. In both cases, the application accesses users' locations to monitor their activities, which may vary among the following three categories: walking, running, or cycling. The mock-ups also access the health information the smartphone records to gain information related to steps taken during the day. Additional data have been collected depending on the different devices paired by the users, such as diet and calories, sleeping activities, and heart rate. By aggregating such information with the ones provided by the accelerometer devices, *FitYou,* and *Weights* can build personalized dashboards showing users information about daily activities over time. Both applications offer additional functionalities, such as training videos and challenges, to create a gamified experience to motivate users toward fitness.

In both mock-ups, collected data are aggregated, anonymized, and sold to the departments of transportation and municipalities in charge of delivering transportation services to citizens. Both mock-ups are accompanied by *FitYou for Cities* and *Weights for Cities* sections and sell information regarding the areas of the city mainly used for fitness activities to government entities. In both experiments, data selling should help municipalities improve infrastructures for cyclists and pedestrians.

Both mock-ups have been designed in two different versions. One is with a transparent business model reveals how providers leverage the gathered data per the privacy policies and the service presentation. Two ad hoc screens are presented to users that answer the questions "*What will we do with your data?*" and explain data usage. Two additional screens present the partners—the department of transportation—demonstrating that the service is free owing to the benefits reaped by the service providers. The final screen highlights how the data are kept private. Instead, the opaque version of the mock-up declares the usage of the data only in the privacy policies, with no additional information for users and no disclosure about the partners involved.

Having two services with the same functionalities enables us to work in a within-subject design experiment and gather the respondents' perceptions on both the transparent and opaque versions.

The experiment begins with a general study presentation without reference to the dependent variable. The experiment follows a two-step process (see Fig. 4). In the first step (designed to test H1 and H2), each participant is randomly assigned to one of the two versions of *Weights*. The first exposure randomly shows one scenario - 'opaque' or 'transparent' - measuring willingness to adopt the app.

In the second step, participants are exposed to *Fit You* using the following criteria: those who have seen the opaque business model during the first step are assigned to the transparent in the second step, and vice-versa. The second step has been designed to gather the data to test H3a and H3b. It records the user's reaction to positive or negative perceptions when changing data exploitation transparency.

The experiment concludes with some demographic questions and a thank you for participating. In detail, the 'opaque scenario' has only four screens presenting the main functionalities of the service, with no direct reference to the use of data except in the privacy policy.

On the other hand, the 'transparent scenario' has 8 screens presenting the service but explaining in detail that the service is free thanks to aggregated and anonymized user data offered to third parties. The 'transparent scenario' explains the privacy policy in non-technical, simple, and direct language.

They have two experiments to avoid the replication bias, where responses are replicated for the same service. Therefore, using two mock-ups, respondents can quickly notice the differences in the information given on how the companies use the data.

4.2. Survey design and operationalization of constructs

The survey we employ to gather the data for this study has been validated and pre-tested by five independent researchers and ten potential respondents. We make minimal adjustments to the texts within the mock-ups, thus enriching the explanation of the services proposed by the mock-ups.

The final structure of the survey comprises four different sections: (1) the respondents are asked to provide demographic information (i.e., age, education, and gender); (2) they are exposed to an introductory framing (searching for an app to track health and fitness activities); (3) they are exposed to the two services; and iv) they are asked to report their willingness to adopt the service, their privacy attitude, and personal innovativeness. The organization of sections aims to reduce common method bias in the responses.

The measurement tool encompasses constructs and items validated in the available literature. In line with Venkatesh et al.'s (2012) proposed approach, the *willingness to adopt the service (WA)* construct reflects the extent to which consumers are likely to use the service in the future, the frequency with which they would use the service, and the reason for using the service. *Personal innovativeness (PI)* evaluates the tendency of the consumer to be an early adopter of the proposed service. It follows Mun et al.'s (2006) approach, which measures the users'
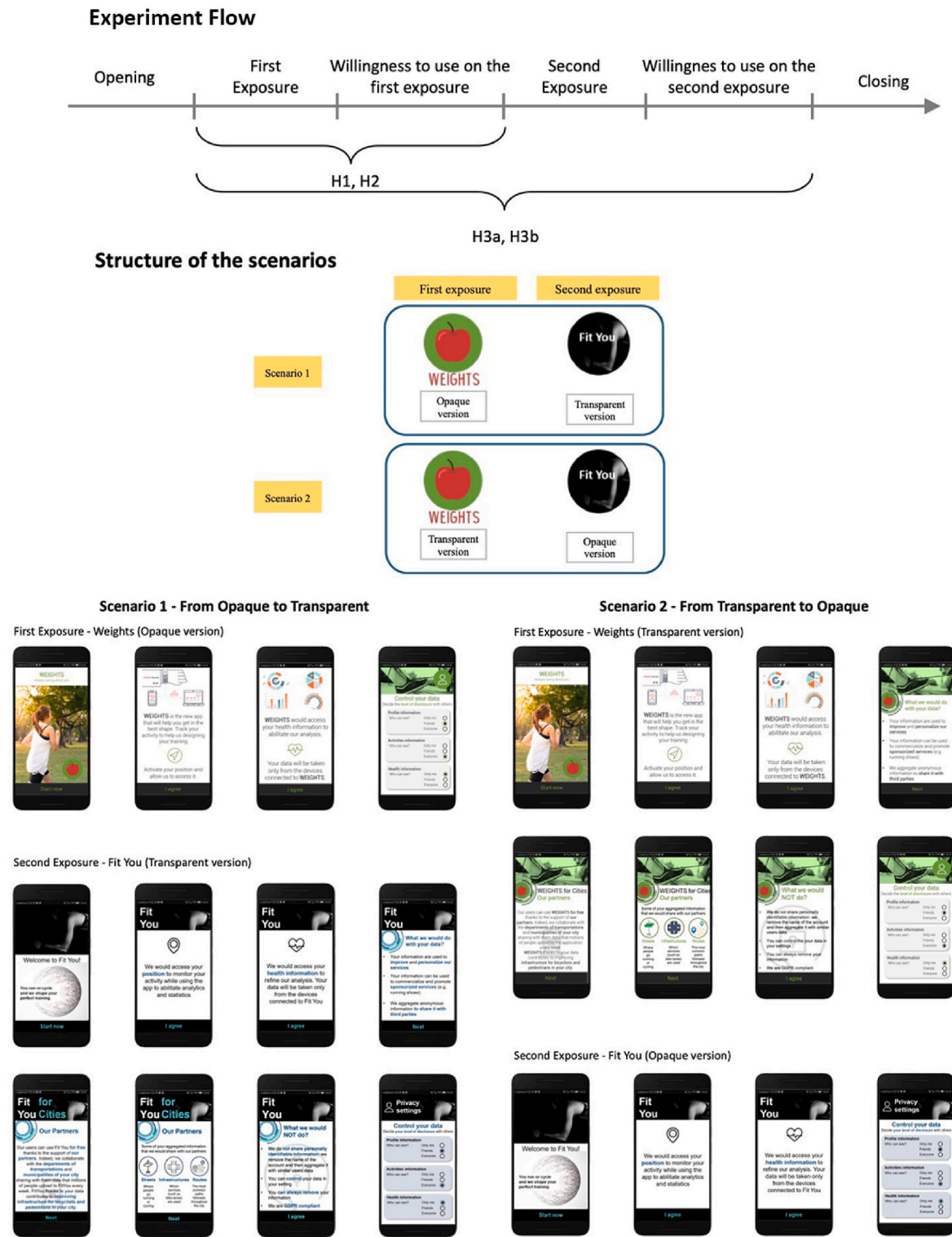
Experiment Flow

Structure of the scenarios

Fig. 4. Flow of the experiment and structure of the scenarios.

willingness to take risks and try innovations. *Privacy attitude (PA)* is grounded in Chellappa and Sin's (2005) research, which defined it as the cost of joining a digital service. PA measures people's concerns about collecting and using different types of personal information. PA encompasses respondent sensitivity and concern regarding sharing information related to choices, mobile app navigation, and other personal information.

Table 1 presents the main items included in the questionnaire. The survey also includes additional descriptive and behavioral variables (e. g., gender, age, and education of the respondent) as well as respondents' attention checker to the privacy policy statement displayed at the beginning of the experiment.

4.3. Data collection and sample characteristics

Before the final distribution phase, the survey was pre-tested with a

Table 1
Items included in the questionnaire.

Variable		Item	Scale
Gender		The gender of the respondent	1=Male 2=Female
Age		The age of the respondent	Age class from 1 (18–24 years) to 6 (>64)
Education		The level of education of the respondent	Education level class from 1 (less than high school) to 5 (Doctorate)
Privacy policy read		Do you agree to read the privacy policy statement?	0=No 1=Yes
Privacy policy agreement		Do you agree with the privacy policy statement?	0=No 1=Yes
Privacy attitude (PA)	PA1	I am sensitive about sharing information regarding my preferences or choices while using mobile apps	Likert scale 1 (Strongly disagree) – 5 (Strongly agree)
	PA2	I am concerned about sharing anonymous information in mobile apps	
	PA3	I am concerned about how personal unidentifiable information like sex and age will be used by mobile app providers	
	PA4	I am concerned about how personal identifiable information like name, email, and geographical location will be used by mobile app providers	
Personal innovativeness (PI)	PI1	I tend to try out an innovative digital service once I hear of it	
	PI2	I tend to be one of the first to try out innovative digital services compared to friends and colleagues	
	PI3	I tend to experiment with innovative digital services	
Willingness to adopt the service (WA)	WA1	I am willing to adopt the service in the future	
	WA2	I am willing to adopt the service in daily life	
	WA3	I am willing to adopt the service frequently	

Table 2
Sample description.

	Frequency
Scenario exposure	
Scenario 1	262 *(52%)*
Scenario 2	246 *(48%)*
Gender	
Male	280 *(55%)*
Female	228 *(45%)*
Age	
18-24	286 *(56%)*
25-34	179 *(35%)*
35-44	11 *(2%)*
45-54	21 *(4%)*
55-64	10 *(2%)*
>64	1 *(1%)*
Education	
Lower than high school	5 *(1%)*
High School	38 *(7%)*
Bachelor's degree	225 *(44%)*
Master's degree	231 *(45%)*
Doctorate/PhD	9 *(2%)*
Privacy policy consultation	
No	317 *(62%)*
Yes	191 *(38%)*
Privacy policy agreement	
Not read	307 *(60%)*
Not agree	56 *(11%)*
Agree	145 *(29%)*

on privacy and business model transparency (e.g., Bhattacharya et al., 2022; Chen et al., 2022)

4.4. Bias control

Potential biases are considered in the experiment, questionnaire design, and data analysis. To check non-response bias, we adopt the "continuum of resistance" model (Kypri et al., 2004), comparing early and late respondents. T-tests are performed on the early and late waves of the model's variables, which indicate no statistically significant differences between the groups. Social desirability bias in the overall experiment was reduced via the assurance of confidentiality and the wording of questions in a neutral fashion.

Finally, the experimental setting controls common method biases (Conway and Lance, 2010). First, the experiment is labeled a comprehensive study to explore the perception of different digital service interfaces; hence, no reference to the data-driven model was provided. Second, the experiment and questions are organized to separate the items clearly. This helps prevent respondents from developing theories regarding the possible cause–effect relationships shown in the model. Third, we statistically address common method bias using the common latent factor technique (Craighead et al., 2011). We find that the common latent variable has a linear estimate of 0.383. This value indicates a variance of 0.146, below the threshold of 0.50. It indicates that common variance does not represent a problem in our study.

4.5. Statistical approaches for model testing

Our research is theory-driven, and our research objective is theory testing and confirmation. The relationships in the research models in Figs. 1 and 2 are tested using covariance-based structural equation modeling (CB-SEM), which is the preferred method employed for this type of research (as opposed to variance-based SEM, which is more beneficial for exploratory and predictive purposes; Hair et al., 2017).

First, to check the reliability of the hypothesized constructs, we perform a confirmatory factor analysis (Brown, 2014). In line with Byrne (2013), we also use the average variance explained (AVE), composite reliability (CR), Cronbach's alpha (CA), and McDonald's omega (MO) to assess construct validity. Acceptable values of CR, CA, and MO are above

small sample of possible respondents to receive feedback on the overall structure of the survey and pre-test manipulation checks (Belle and Cantarelli, 2021; Kane and Barabas, 2019). Therefore, we include a specific question on the respondents' perceptions of the two mock-ups to measure perceived transparency and perform a manipulation check. The perceived level of transparency in the two cases differs significantly, thus confirming the experimental design's validity.

The survey has been distributed online via three personal profiles on LinkedIn, searching for voluntary participation. In recent years, this has been a popular method of gathering data on digital services (e.g., Toni et al., 2018; Wu et al., 2017). Online experiments have also been used in the innovation literature (e.g., Hofstetter et al., 2018; Xiao et al., 2018).

Using such a distribution approach, we collected 744 responses between January and April 2019. Subsequently, we perform a data cleaning to have a sample with 1) complete responses; 2) responses that show that the respondents completed the questionnaire by accurately reading and answering the questions. Consequently, all the responses with missing data on critical questions and/or unusual response patterns (e.g., the same response to all the questions) are removed. The removal of incomplete and low-quality answers yields a final sample of 508 useable responses.

Table 2 reports the main sample description. Both the size and the characteristics of the sample are in line with recent B2C research focused

0.7, while AVE should be higher than 50% (Hayes and Coutts, 2020). Subsequently, the model is tested using the maximum likelihood (ML) estimation method because ML provides more realistic indices of overall fit and less biased parameter values for paths that overlap with the actual model relative to other methods, such as generalized least squares and weighted least squares (Enders and Bandalos, 2001). The ML estimation assumes that the variables in the model are conditionally multivariate normal, which is valid for our dataset according to the Doornik–Hansen ($p > \chi^2 = 0.117$) and Henze–Zirkler ($p > \chi^2 = 0.108$) tests. To evaluate the model fit, we use a combination of the chi-square goodness-of-fit statistic and other absolute or relative fit indices (Hu and Bentler, 1999). Some studies (e.g., Cangur and Ercan, 2015) suggest various indices' presentation strategies, including the comparative fit index (CFI), the Tucker–Lewis index (TLI), and the root mean square error of approximation (RMSEA). A satisfactory threshold for CFI and TLI is >0.90 (with a value >0.95 showing excellent fit), whereas RMSEA is supposed to be < 0.07.

As the intent is also to evaluate the moderating effect of business model transparency on the relationships in the model (hypotheses H1 and H2), a multigroup analysis of structural invariance across respondents in the sample characterized by the exposure to business models with different characteristics is performed (Yuan and Chan, 2016). The moderator is treated as a categorical variable to separate respondents exposed to an opaque business model and those exposed to the transparent version.

Following similar procedures previously adopted (e.g., Bianchi et al., 2016), we first test the model on the whole sample (Fig. 1). Subsequently, to test the model with the moderator (Fig. 2), three invariance tests are performed: configural invariance, measurement invariance, and structural coefficient invariance (Bollen, 1989; Byrne, 2013; Cheung and Rensvold, 1999; Steenkamp and Baumgartner, 1998). To verify the evidence of invariance, we evaluate the χ_2 differences between the unconstrained (configurational) model and the constrained models (Byrne, 2013). An adequate fit should complement these variations with the data of the multigroup model and a negligible difference between the goodness of fit indicators (e.g., CFI; Byrne, 2013; Cheung and Rensvold, 2002).

To test the third hypothesis (Fig. 3), we use analysis of variance (ANOVA; Hair et al., 2007). Once the respondents were exposed to the alternative business model, new values for the *willingness to adopt* items were recorded. Thus, ANOVA allows us to capture changes in this construct and spot potential differences between the two groups.

5. Results

We use Stata 17.0 to perform the data analysis. The main statistical results are reported in the following sections.

5.1. Validity and reliability of the survey constructs

Table 3 presents the results of the CFA. All the measurement model indicators are satisfactory (χ^2/d.f. = 1.06; CFI = 0.988; TLI = 0.982;

RMSEA = 0.012). In addition, convergent validity is assessed through significant loadings from all scale items on the hypothesized constructs and through the AVE, CR, CA, and MO. AVE ranges are between 50% and 68% (higher or near the 0.5 thresholds), and CR, CA, and MO are higher than 0.7 for all three constructs.

As an additional test for discriminant validity, in Table 4, we report the squared correlation of the two latent constructs to their AVE estimates (Fornell and Larcker, 1981). According to this test, the AVE for each construct should be higher than the squared correlation between each pair of constructs, which is valid for our case.

5.2. Model testing

When testing the relationship for the model in Fig. 1, the postulated path model produces an excellent fit to the data (χ^2/d.f. = 1.051; RMSEA = 0.013; CFI = 0.989; TLI = 0.987).

Table 5 summarizes the results. The structural model shows a highly positive and significant relationship between *PI* and the *WA* ($p < 0.001$), while no negative association is observed between *PA* and the *WA*. These results provide an interesting perspective as, in our sample, the relationships of the traditional model (Fig. 1) still need to be fully confirmed. As shown in Table 5, no control variable significantly affects the *WA*.

To run a multigroup analysis, it is crucial to meet the following three essential preconditions (e.g., Bollen, 1989; Steenkamp and Baumgartner, 1998):

1) The items and several underlying constructs are the same across groups.
2) Comparable sample size.
3) Separate CFAs models have been estimated for each group, and no estimation problems occurred.

All these conditions are valid for our sample (see Table 6).

Subsequently, we perform two-group invariance tests across the two independent survey samples to establish whether the willingness to adopt is impacted differently if exposed to an opaque or transparent business model. Table 7 reports the results.

5.3. Configural invariance

To perform the configural invariance test, we compare the two-group model test (the opaque and transparent business models' baseline models) without imposing equality constraints.

Table 4
Correlation matrix.

	Mean	*St. dev.*	1	2	3
1. PI	*3.13*	*1.17*	1		
2. PA	*3.09*	*1.30*	0.052	1	
3. WA	*2.94*	*1.02*	0.432***	0.101**	1

Table 3
Constructs' validity and reliability.

	Mean	St. dev.	Loading	Composite reliability	Cronbach	McDonald omega	Average variance explained
PA1	3.11	1.27	0.719	0.798	0.793	0.801	50%
PA2	2.99	1.29	0.715				
PA3	2.89	1.34	0.666				
PA4	3.37	1.29	0.717				
PI1	3.13	1.17	0.841	0.852	0.852	0.864	66%
PI2	2.82	1.16	0.738				
PI3	3.45	1.18	0.849				
WA1	3.24	0.97	0.771	0.863	0.893	0.899	68%
WA2	2.75	1.04	0.86				
WA3	2.84	1.04	0.836				

Table 5
Path analysis.

	WA
Independent variables	
PI	0.425*** (10.05)
P.A.	0.091[NS] (1.86)
Control variables	
Male	0.123[NS] (1.38)
Age: <24	0.079[NS] (1.02)
Age: 25-34	0.104[NS] (1.27)
Education: Master or higher	0.098[NS] (1.11)
Education: Bachelor	0.114[NS] (1.23)
R^2	**0.231**

***p-value<0.001; **p-value<0.01; *p-value<0.05.
[NS]p-value>=0.05; the values of t statistics are shown in brackets.

Table 6
Measurement validity across groups.

	Opaque (N = 262)		Transparent (N = 246)	
	CR	AVE	CR	AVE
PI	0.858	67.1%	0.841	63.9%
PA	0.797	50.2%	0.801	50.3%
WA	0.885	72.2%	0.892	73.5%
	CFI = 0.932; TLI = 0.929; RMSEA = 0.044		CFI = 0.934; TLI = 0.931; RMSEA = 0.042	

We can conclude that the model has configural invariance as it fits the data well (χ_2/df = 1.129, p < 0.001; CFI = 0.988; TLI = 0.987; and RMSEA = 0.025). Therefore, the structure of the model is optimally represented with the pattern of paths and factor loadings.

5.4. Measurement invariance

Second, we perform the measurement invariance test involving the following hierarchical steps: metric, scalar, and strict invariance tests. Metric invariance tests whether respondents in the groups interpret and respond to measurement items similarly (Steenkamp and Baumgartner, 1998; Yoo, 2002). Hence, we constrain all the free factor loadings to be equal across the two groups. This model also shows an excellent fit to the data: χ_2/df = 1.14, p < 0.001; CFI = 0.987; TLI = 0.987; and RMSEA = 0.023. We record a slight variation in the degree of freedom (Δdf = 7) and χ_2 ($\Delta\chi_2$ = 8.72). The likelihood-ratio (LR) test confirms that the model is characterized by metric invariance (p = 0.458). Scalar invariance tests the invariance of intercept terms to determine the consistency between differences in the latent and observed means (Meredith, 1993; Steenkamp and Baumgartner, 1998; Yoo, 2002). Hence, we constrain all invariant factor loadings and observed variable intercepts. Again, this model shows an excellent fit to the data: χ_2/df = 1.16, p < 0.001; CFI = 0.986; TLI = 0.985; and RMSEA = 0.025. Although we have higher variation in the degree of freedom (Δdf = 15) and χ_2 ($\Delta \chi_2$ = 19.48), the LR test confirms that the model is characterized by scalar invariance (p = 0.237). Finally, strict invariance verifies invariance in the residuals. Thus, we constrain the loadings, intercepts, and residuals. In this case, the model shows an excellent fit to the data: χ_2/df = 1.15, p < 0.001; CFI = 0.986; TLI = 0.985; and RMSEA = 0.024. With this variation of the

degree of freedom (Δdf = 17) and χ_2 ($\Delta \chi_2$ = 21.23), the LR test confirms that the model is characterized by strict invariance (p = 0.307).

5.5. Structural coefficient invariance

Finally, we perform structural invariance testing. First, we constrain the structural paths to be equal across groups and retain all equality constraints of factors.

This fully constrained model still fits the data well (χ_2/df = 1.17, p < 0.001; CFI = 0.981; TLI = 0.979; RMSEA = 0.031); however, the variation of the goodness of fit indicators (ΔCFI = 0.07), the degree of freedom (Δdf = 3), and χ_2 ($\Delta\chi_2$ = 6.29) result in a model characterized by non-invariance of the structural path, as confirmed by the LR test (p = 0.043). Hence, as the final step, we test for invariance of the single path (structural) coefficient between the opaque and transparent business models. Our procedure compares the models wherein individual path coefficients can differ (one by one) between the two business models with the metric invariance model (*Model 2*). By relaxing each structural coefficient individually, we test the hypothesis regarding the invariance of particular path coefficients using the Wald, Score, and LR tests. Table 8 summarizes the results.

Looking at the metric invariance model, we can already see that the hypothesis of equality of group coefficients is rejected only in the case of the relationship between *PA* and the *WA*. To verify whether this non-invariance is significant, we compare this model to that in which we constrained the structural paths to be equal across groups, except for the path found to be non-invariant in the metric invariant model. For this case, the Wald test confirms that the structural coefficients between the two groups for path *PA →WA* are not equal, and this constraint should not be added to the model. The Score test confirms that the group coefficients are equal for path *PI →WA*, representing a valid constraint. This constrained model fits the data well and is characterized by a Δdf = 9 and $\Delta\chi_2$ = 11.89. The LR test, with p < 0.05, demonstrates that a non-invariance of the structural paths characterizes this model.

Table 8
Structural coefficient invariance.

	Path	Opaque coefficient	Transparent coefficient	Test
Model 2 - Metric invariance (df = 73; χ_2 = 83.2; CFI = 0.987; TLI = 0.987; RMSEA = 0.023)	PI → WA	0.469*** (8.36)	0.371*** (5.84)	W: 0.327[NS]
	PA → WA	0.083[NS] (1.12)	0.173* (2.52)	W: 0.032*
Model 6 - Privacy attitude → Willingness to adopt invariant (df = 82; χ_2 = 95.09; CFI = 0.984; TLI = 0.983; RMSEA = 0.025)	PI → WA	0.432*** (9.16)	0.409*** (9.14)	S: 0.291[NS]
	PA → WA	0.06[NS] (0.85)	0.167* (2.32)	W: 0.028*
Model 7 - Personal innovativeness → Willingness to adopt invariant (df = 82; χ_2 = 86.47; CFI = 0.983; TLI = 0.983; RMSEA = 0.026)	PI → WA	0.464*** (8.24)	0.371*** (5.82)	W: 0.329[NS]
	PA →WA	0.082[NS] (1.73)	0.085[NS] (1.71)	S: 0.116[NS]

W = Wald test; S = Score test; ***p-value<0.001; **p-value<0.01; *p-value<0.05; [NS]p-value>=0.05; the values of t statistics are shown in brackets.

Table 7
Invariance test results.

	df	Chi	Chi/df	CFI	TLI	RMSEA	$\Delta\chi_2$	Δdf	LR
Model 1 - Configural invariance (unconstrained)	66	74.49	1.13	0.988	0.987	0.025	–	–	–
Model 2 - Metric invariance (loadings invariant)	73	83.21	1.14	0.987	0.987	0.023	8.72	7	p > 0.1
Model 3 - Scalar invariance (loadings and intercepts invariant)	81	93.97	1.16	0.986	0.985	0.025	19.48	15	p > 0.1
Model 4 - Strict invariance (loadings, intercepts, and residuals invariant)	83	95.72	1.15	0.986	0.985	0.024	21.23	17	p > 0.1
Model 5 - Structural invariance (structural parameters invariant)	69	80.78	1.17	0.981	0.979	0.031	6.29	3	p < 0.05

To double-check, we also compare the metric invariance model to that where the relationship of $PI \rightarrow WA$ is set free to vary across groups. The Wald and Score tests are insignificant for both paths in the model, and the LR test confirms invariance for the structural paths ($\Delta df = 9$, $\Delta \chi_2 = 3.27$, p > 0.1). We can conclude that the business model transparency positively moderates the relationship of $PA \rightarrow WA$ (thus accepting H2), given that this relationship is stronger (and significant) in the case of more transparent business models. We do not find any moderating effect for the relationship of $PI \rightarrow WA$. This relationship is positive and invariant across groups; hence, H1 is rejected.

5.6. One-way ANOVA

After phase 2 of the experiments, in which the respondents are exposed to the second business model, we perform two types of ANOVAs.

We first conduct a between-subjects ANOVA to analyze whether differences in *Willingness to adopt* are present between the group of respondents shifting from the opaque to the transparent business model and the group exposed to the opposite scenario (Table 9).

In the overall sample, there is a decrease in *WA*. However, (1) in the case where the respondent transitions from the transparent to the opaque case, there is a decrease in the *WA*. Instead, (2) in the case where the respondent transitions from the opaque to the transparent case, there is a slight increase in the *WA* Overall, this difference between groups is significant (p < 0.01).

To understand the nature of these changes, we perform a within-subject ANOVA with repeated measures, in which the change of the *WA* is analyzed within the two groups. We compare the values during the exposure to the first business model and those recorded after the business model change (Table 10).

The slight increase in the WA is not statistically significant for the group first exposed to the opaque business model. Hence, an increase in the transparency of the business model does not likely lead to a significant increase in the *WA*. Therefore, H3a does not receive empirical support. Conversely, the group first exposed to the transparent business model sees a statistically significant decline in the *WA*. This finding implies that a decline in business model transparency does lead to a decline in the willingness to adopt the service. Hence, H3b is empirically supported.

6. Discussion

The PI explains the willingness to adopt a digital service (Mun et al., 2006), while the *PA* (Chellappa and Sin, 2005) does not directly correlate with the users' *WA*. Considering the rational choice theory (Becker, 1968), the benefit outweighs the costs driving the decision process. Such a result is interesting as both theory and practice agree on the role of privacy in digital businesses. The previous sections discussed the recent scandals, showing a growing awareness regarding data privacy and the practice of technology giants leveraging DDBMs. In this context, many studies emphasize the influence of privacy perception and attitude on users' decision to adopt (Betzing et al., 2020; Gimpel et al., 2018), considering it a personal trait (Hann et al., 2017; Spiekermann et al., 2015).

Table 9
ANOVA – Variation of willingness to adopt between groups.

	N	Mean	Std. Deviation
Opaque → Transparent	*262*	0.05	0.82
Transparent → Opaque	*246*	−0.139	0.73
Total	*508*	−0.04	0.79
Between groups:			
Sum of squares = 4.772			
F = 7.781			
p = 0.004**			

Table 10
Within-subject ANOVA with repeated measures.

		Mean	St. dev.	Mean difference	p-value
Opaque → Transparent (F = 0.949, p = 0.331[NS])	Willingness to adopt before	2.907	1.058	−0.050	p > 0.1
	Willingness to adopt after	2.956	0.915	0.050	p > 0.1
Transparent → Opaque (F = 8.779, p = 0.003**)	Willingness to adopt before	3.068	0.892	0.139	p < 0.01
	Willingness to adopt after	2.928	0.927	−0.139	p < 0.01

Although previous research operationalizes privacy as a driver of self-reported user behaviors (Acquisti et al., 2013), self-reported measures have still proved highly biased when dealing with privacy (Kokolakis, 2017). This study goes beyond self-reported operationalization by asking the respondents to test their perceptions of services before expressing their willingness to use them. Our study also shows that experiments might be more insightful than surveys when investigating users' sensitivity in relation to their behaviors.

6.1. Users' perspective

In addition to the above considerations, business model transparency in DDBMs influences the adoption decision. On the one hand, it does not moderate the relationship between the *PI* and the *WA* (thus rejecting H1). This finding implies that the willingness to adopt the service is independent of the decisions related to business model transparency in DDBMs in the presence of *PI*. On the other hand, it has a relevant impact on the relationship with the *PA*. As shown by Awad and Krishnan (2006), transparency procedures negatively affect users' decisions to adopt a service. By having a deeper understanding of how information is collected and used, customers could be less open to trying the service, though our data show the opposite effect. When interacting with a mock-up digital service, a higher degree of transparency (what data are collected and how they are used) contributed to users' *WA*. In the current scenario, users were long unaware of data collection measures and use objectives. However, the recent scandals surrounding data privacy violations have informed users about the reality of data use. It has resulted in companies' transparent disclosure of data policies and activities. Such disclosures have produced positive results. However, transparency generates trust (Amit and Zott, 2001; Sun and Tse, 2009). These results support the idea that transparency may be a valid strategy for companies running DDBMs.

H3a and H3b analyze the effect of a change in business model transparency based on the second section of our experiment. Even if the first part of the experiment showed the relevance of personal attitudes on the *WA*, the second part defused such findings. By showing a different case to the same respondent, we observed a change in the *WA*.

Our experiments also show that moving from opaque to transparent models does not induce a significant increase in the *WA* while moving from a transparent to an opaque model causes a significant decrease. On the one hand, the less substantial increase in the first case (from opaque to transparent) can be explained by the stickiness of user behavior (Cusumano et al., 2019; Ram, 1989) as well as the probable lack of trust toward digital service providers, which may explain this result (Bansal et al., 2016). Conversely, a movement from transparent to opaque shows a significant decline in the *WA*, which may be considered an essential indication for companies. Once users realize the existence of transparent business models, they will be willing to "not go back" to the previous situation. In other words, they will not accept opacity after becoming aware of transparency.

The Kano model may help us discuss these results (see Fig. 5). Berger (1993) used the Kano model to describe the impact of a product, or a service attribute on the satisfaction of end customers, highlighting three
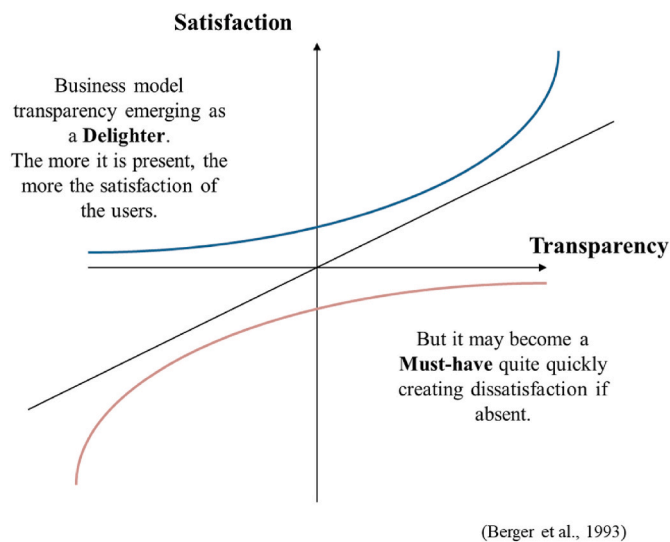
Fig. 5. Application of the Kano model to our case.

main types of attributes: (1) must-have (if the attribute is present, it does not generate satisfaction; if it is absent, it generates dissatisfaction), (2) linear performers (the better the performance of the attribute, the higher the satisfaction), (3) delighters (if the attribute is absent, it does not generate dissatisfaction; if it is present, it generates satisfaction).

A critical characteristic of the Kano model relies on the assumption that attributes are not static over time but could change as the socio-cultural and business environments evolve. A typical example can be taken from the car industry, as an airbag can be viewed as a delighter in the early phase of the industry. Today, having an airbag is a must-have feature. Such an evolution is optional for all the attributes but shows how customer perception can vary over time. Interestingly, our results suggest something similar. Indeed, our data suggest that business model transparency can be seen as either a delight or a must-have attribute, depending on the scenario. After moving from an opaque to a transparent business model, we found that the customers considered transparency a weak benefit (there is an increase, even if it is not significant). Transparency was considered a delight, given that the absence of it did not seem to have a negative impact. After moving from a transparent to an opaque business model, we found that the effects were significantly stronger, and customers were dissatisfied as today, users still need to be fully accustomed to transparency. Few service providers have embraced the transparency paradigm. The majority remain stuck in the belief that increased transparency will eventually lead to a decrease in their user base owing to the effect of the privacy attitude. Our study has already proved this to be wrong.

Moreover, we recorded a second path-dependent effect: users who experiment with transparency do not accept opacity. After moving from a transparent business model to an opaque one, customers seemed to consider transparency a must-have attribute. These results accord with the Kano model, which sees attributes dynamically, moving from delighters to must-haves over time (Berger, 1993).

6.2. Companies' perspective

Even if we adopt the user perspective, our results impact companies' managerial practices as our results can sustain both the decisions regarding business model design and the implementation of two-sided digital platforms.

Dealing with two-sided platforms, our results revive the relevance of non-transactional platforms (Filistrucchi et al., 2014). In this regard, there have been studies on client-as–source strategies; these studies have shown how digital companies may find groups of customers ready to exploit the value of gathered data (Trabucchi et al., 2017). Nevertheless,

this strategy is limited by two challenges. First, the current widespread practice of declaring the actual use of data in the privacy policy but not mentioning it in the service presentation may quickly become problematic and upset end users when fairer practices emerge, setting a new must-have standard. Second, a significant challenge in two-sided platforms is the creation of a double value proposition (McIntyre et al., 2020; Muzellec et al., 2015; Zhao et al., 2020) or the ability to convince both sides to join the platform (Stummer et al., 2018). We acknowledge that finding a second non-transactional side is challenging to sustain two-sided platforms. Our data show that transparency positively influences trust creation. It suggests that, according to the Kano model, transparency is rapidly shifting from a delighter to a must-have attribute for service providers. This study unveils new opportunities for value proposition design in non-transaction platforms, allowing platform providers to match the proposition for the end users and the customers interested in data, embracing the matchmaking process based on "transactional" two-sided platforms (Cusumano et al., 2019). It would partially reduce the differences between transactional and non-transactional platforms, increasing the awareness level of the first side in being a co-creator of the value of the overall platform (Sun and Tse, 2009).

From a business model design perspective, this study highlights the importance of leveraging the service's functional dimensions and stressing the relationship dimension. The role of trust has often been highlighted as critical in creating lock-in effects in digital business (Amit and Zott, 2001). It is even more valid for two-sided transactional platforms (Ert et al., 2016). This study shows how being clear on the overall business model will not negatively impact the willingness to adopt the service but may create the basis for building a positive relationship with users. Moreover, in consideration of the recent available literature around data disclosure, data transparency, even if when not imposed by regulatory bodies on companies to operate in a particular market, has been shown to have positive effects on trust in companies and their business models in the more extensive user base of the service (Willis et al., 2021).

7. Conclusions and further developments

This study demonstrated that business model transparency should be considered a relevant variable for DDBMs. The results reveal how the perception of end users regarding how companies use data is increasing, influencing users' decision-making process. While data transparency does not directly impact the willingness to adopt a service, it helps build trust among users and companies based on DDBM (Willis et al., 2021). In particular, while users do not radically change their willingness to adopt a service when the business model moves from opaque to transparent, users are negatively affected when it moves from transparent to opaque. It proves companies need to consider transparency a must-have feature, even considering the increasing government regulations.

7.1. Theoretical contributions

The main contributions of this research relate to the implication of privacy perceptions on DDBMs. First, it expands the understanding of DDBMs by adding a user perspective (Del Vecchio et al., 2018). Second, it shows how transparency is becoming a key variable in DDBMs (Acquisti et al., 2013; Hann et al., 2007).

Understanding how end users may react to data-driven strategies sheds light on a variable often understudied in such a context (Trabucchi et al., 2017, 2018). Scholars researching two-sided platforms should pay attention to the implication that privacy awareness may have on non-transactional models (Filistrucchi et al., 2014; Trabucchi and Buganza, 2019), remarking on the necessity to consider network externalities. From a business model design perspective, users' awareness may impact value proposition design, especially when multiple groups of customers are on the same platform (Muzellec et al., 2015).

This study builds on rational choice theory and supports the idea that the perception of transparency contributes to adopting a transparent service rationale (McCarthy, 2002). Such findings have relevant implications for scholars researching business models and business model innovation, highlighting the importance of considering the users' perspective (Martins et al., 2015).

One final implication for scholars is related to the research design. This research builds on a web-based experiment to explore the potential impact of changes in the business model, addressing customers' relationships. It may present avenues for future research extending the experimental setting into business models.

7.2. Practical implications

From a managerial perspective, this study helps managers decide more consciously on the transparency of their business models, considering different types of awareness. First, business model transparency is a crucial variable to be pivoted. Second, transparency has implications regarding perceived fairness, which plays a considerable role in users' decision-making processes.

The results of this study are valuable for any companies operating in a (potentially) data-rich environment since transparency seems to be a legitimate DDBMS, opening up avenues to (more freely) design data-gathering oriented services. Having even more data may open up opportunities regarding data usage, following the recommendations regard data-driven innovation (Trabucchi and Buganza, 2019), defined as the chance to design an additional ad-hoc service to gather specific data.

Our findings suggest that the degree of business model transparency is a long-term goal. The decision to adopt a service based on a DDBM is primarily explained by personal attitude, with no significant shift based on the transparency level.

Nevertheless, our findings suggest that the transparency level may have a more significant impact in the medium term, as shown by the Kano model. On the one hand, users appreciate the transparency model, allocating great value to it. On the other hand, such a value could only be temporary, as transparency becomes a must-have feature. This is a relevant finding not only for those companies that operate in fields where competitors are more transparent but also for others that may decide to invest in transparency, aiming to obtain a superior competitive advantage in the future.

The patterns discussed above mirror other attributes of products and services that followed similar trends in the past. For example, a green image of products has been a relevant delight on the market for many years, giving a competitive advantage to firms that invested early on in the sustainability of their products and/or processes. As more organizations have embraced this strategy, there is a need to find new ways to bring this strategic perspective forward. Could (business model) transparency be the new green?

7.3. Limitations and future developments

This study has limitations that suggest further developments. First, the choice of the web-based experiment as an empirical setting provides lower internal validity, which is affected by external influences, but higher external validity. Furthermore, as this is an explorative study, testing a similar approach in a different context may be relevant.

From a research design perspective, the rationale in this study has been built on the rational-choice theory to model end-user behavior through a cost–benefit perspective. The model design does not allow us to test the relative strength of the two variables, which may be interesting. Future research may explore this dimension better to exploit the decision process in such a complex environment. In addition, future research could formalize the different business models through decisional models and evaluate their effectiveness using actual company data.

From a methodological perspective, our sample includes primarily young people and those with a high educational background. Although these variables are not statistically associated with higher or lower WA, this population subset will likely be more open to accepting data-driven business models. Further research should focus on studying these relationships using a more diversified sample. In addition, to increase the robustness of the findings, several variables should be analyzed in different settings. This experiment is based on the health and fitness field, which uses behavioral data on sports activities as a data-driven strategy. The field and the data type were selected because DDBMs have often been studied in these settings. Nevertheless, it may be interesting to see whether and how the results may change by considering other types of personal data in different settings.

Data availability

Data will be made available on request.

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