School of Industrial and Information Engineering
Master of Science in Management Engineering

Design Management, Innovation and Entrepreneurship

Business model transparency:

Do users mind about how digital platforms use their data?

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A.Y. 2017/201

POLITECNICO
MILANO 1863
Ringrazio il Professor Tommaso Buganza per avermi dato la possibilità di approfondire un tema di mio grande interesse, che riguarda ognuno di noi nella vita di tutti i giorni. Ringrazio il Professor Daniel Trabucchi per avermi seguito nel percorso di stesura dell’elaborato e aver contribuito a formare la mia figura personale e professionale.
Table of contents

Abstract ................................................................................................................................................. 9

Abstract in Italiano ................................................................................................................................. 10

Executive Summary .............................................................................................................................. 11

1. Introduction ....................................................................................................................................... 22

2. Literature Review ............................................................................................................................. 26

  2.1 Platforms ...................................................................................................................................... 26

    2. 1. 1 Engineering Design Perspective ......................................................................................... 27

    2. 1. 2 Economics Perspective ........................................................................................................ 32

    2. 1. 3 Data-driven Business Models ............................................................................................. 46

    2. 1. 4 Big data platforms: service-dominant logic perspective ...................................................... 48

2. 2 Information technologies adoption and privacy ............................................................................. 50

    2. 2. 1 Information technologies adoption theories .......................................................................... 50

    2. 2. 2 Privacy in IT adoption ........................................................................................................... 53

3. Research question and research model ............................................................................................. 57

    3.1 Constructs and Hypothesis .......................................................................................................... 59

4. Research Methodology ..................................................................................................................... 65

    4.1 Experiment Design ...................................................................................................................... 65

      4.1.1 The role of experiments in research studies ........................................................................ 66

      4.1.2 Classifying experimental research designs .......................................................................... 66
4.1.3 The taxonomy of field experiments proposed by Carpenter et al. (2004) ..................... 68

4.1.4 Preliminary Analysis ........................................................................................................ 69

4.1.5 Experiment procedure and design .................................................................................. 71

4.2 Operationalisation ............................................................................................................. 73

4.3 Operationalization of Constructs ..................................................................................... 75

4.4 Testing and Data gathering ............................................................................................... 80

4.5. Data preparation .............................................................................................................. 83

5. Data analysis and Results ..................................................................................................... 84

5.1 Multivariate Analysis of Covariance ............................................................................... 84

5.2 Measurement Model Validation ....................................................................................... 85

5.2 Research Model Assessment ............................................................................................ 88

6. Discussion ............................................................................................................................ 93

6.1 Users’ consenting contribution .......................................................................................... 95

6.2 Privacy Attitude ................................................................................................................ 97

6.3 Users as an active source of data ..................................................................................... 99

7. Conclusions ........................................................................................................................ 101

7.1 Theoretical Contributions ................................................................................................. 103

7.2 Managerial Contributions ................................................................................................. 105

7.3 Limitations and Future Research ..................................................................................... 106

Appendixes ............................................................................................................................ 108

Appendix 1 – Survey ............................................................................................................... 108
List of Figures

Figure 1 - Research Model .................................................................................................................. 15

Figure 2 - Experiment procedure ....................................................................................................... 16

Figure 3 - Platform structure ............................................................................................................. 28

Figure 4 - Platform types comparison ............................................................................................... 28

Figure 5 - Conceptual framework ..................................................................................................... 29

Figure 6 - Adapted from "ICT platforms and regulatory concerns in Europe" (P. Ballon & E. V. Heesvelde, 2011) ......................................................................................................................... 30

Figure 7 - Adapted from "Two-sided markets: a progress report" (Rochet, Tirole; 2006) ............. 38

Figure 8 - Adapted from "Two-sided internet platforms: a business model lifecycle perspective" (Muzellec et al; 2015) .......................................................................................................................... 40

Figure 9 - Adapted from "Two-sided internet platforms: a business model lifecycle perspective"
- B2B&C oriented business model...................................................................................................... 41

Figure 10 - Adapted from "Two-sided internet platforms: a business model lifecycle perspective"
- B2C&B oriented business model ...................................................................................................... 41

Figure 11 - Adapted from "Give away your digital services" (Trabucchi, Buganza, Pellizzoni; 2017)
- Enhanced advertising model ........................................................................................................... 44

Figure 12 - Adapted from "Give away your digital services" (Trabucchi, Buganza, Pellizzoni; 2017)
- e-Ethnography model .................................................................................................................... 45

Figure 13 - Adapted from "Give away your digital services" (Trabucchi, Buganza, Pellizzoni; 2017)
- Data trading model ......................................................................................................................... 46

Figure 14 - Adapted from "Capturing value from big data" (Hartmann et al.; 2016) ............... 48
List of Tables

Table 1 – Descriptive statistics of the sample – Part 1................................................................. 81
Table 2 - Descriptive statistics of the sample – Part 2 ................................................................. 83
Table 3 - Coefficients for construct reliability evaluation ............................................................. 87
Table 4 - Fornell-Larcker criterion ............................................................................................... 88
Table 11 - Model 3 - Dependent variable computation................................................................. 89
Table 12 – SPSS Model - Multivariate Tests for the independent variable................................. 90
Table 13 – SPSS Model - Test of Between-Subjects Effects for the independent variable ......... 91
Table 14 - SPSS Model – one-way ANOVA ................................................................................. 92
Table 15 - Descriptive Statistics .................................................................................................. 115
Table 16 - SPSS Model - Tests of Between-Subjects Effects ......................................................... 117
Abstract

In the last decades, thanks to the massive diffusion of Information and Communication Technologies, new digital business models emerged. Among these, many two-sided digital platforms arose, connecting two interdependent groups of users linked by strong network effects. The millions of interactions that users have with the digital platform allow platform providers to gather terabytes of data. User-generated Big Data constitute a new asset that open a broad range of business opportunities for platform providers, including data trading. At the same time, tough, there is a direct consequence in terms of privacy issues as users might be discouraged in joining the two-sided platform.

Literature about two-sided markets started investigating new strategies enabled by User-generated Big Data and IT adoption literature has examined drivers affecting users’ adoption of services also considering privacy issues. However, current studies lack in understanding the relationship between new business models based on User-generated Big Data with the resulting privacy implications and users’ adoption. This research aims at answering this question, considering two-sided digital platforms in the health and fitness applications market that leverage data selling strategies. An experiment was designed, where two services were described, and participants rated their adoption level. Privacy was included by design in the business model as a direct implication of the data selling strategy.

Data gathered through a survey were analysed with a MANCOVA analysis. Results show that there is no statistical evidence of business model transparency affecting users’ adoption.

This thesis has two main contributions: firstly, IT adoption models were expanded to include the business model; secondly, it contributed empirically to two-sided markets literature by demonstrating that users’ adoption of a service is not influenced by business model transparency on data selling strategies.
Abstract in Italiano

Negli ultimi decenni, grazie alla diffusione capillare delle tecnologie dell’informazione e della comunicazione, sono nati nuovi modelli di business digitali, tra cui molte piattaforme digitali che collegano due gruppi interdipendenti di utenti legati da forti esternalità di rete. I milioni di interazioni che gli utenti hanno con la piattaforma digitale permettono al fornitore della piattaforma di raccogliere una grande mole di dati. Gli User-generated Big Data sono una nuova risorsa che apre per i fornitori delle piattaforme un’ampia gamma di opportunità di business, tra cui la possibilità di vendere i dati. Allo stesso tempo, però, ci sono dirette implicazioni in ambito privacy poiché gli utenti potrebbero essere disincentivati ad utilizzare la piattaforma.

La letteratura nell’ambito dei two-sided markets ha esaminato le nuove strategie basate sull’utilizzo degli User-generated Big Data e la letteratura nell’ambito dell’azione delle tecnologie dell’informazione ha esaminato i fattori che influenzano gli utenti nell’adozione dei servizi digitali, considerando anche le problematiche di privacy. Tuttavia, gli studi correnti non hanno analizzato la relazione tra i nuovi modelli di business basati sugli User-generated Big Data con le conseguenti implicazioni di privacy e l’adozione degli utenti. Questa tesi ha l’obiettivo di indagare questa relazione, focalizzandosi sul caso di applicazioni di fitness e salute che utilizzano strategie di vendita di dati.

È stato progettato un esperimento in cui sono descritti due servizi e i partecipanti indicano il loro livello di adozione. La privacy è stata inclusa nel modello di business già in fase di progettazione come implicaizione diretta di una strategia di vendita di dati.

I dati raccolti tramite un sondaggio sono stati analizzati con un’analisi MANCOVA. I risultati mostrano che non c’è evidenza statistica del fatto che la trasparenza sulla vendita dei dati influenzi gli utenti nell’adozione del servizio.

Questa tesi ha due contributi principali: primo, si è espanso l’ambito di indagine per i modelli di adozione di nuove tecnologie, includendo il modello di business; secondo, si è contribuito empiricamente alla letteratura sui two-sided markets dimostrando che l’adozione di un servizio da parte degli utenti non è influenzata dalla trasparenza del modello di business in merito alla vendita dei dati.
Executive Summary

The concept of platform has existed for years in many different industries. According to engineering design perspective, a platform is a set of subsystems and interfaces, embodied in products, services or technologies, that form a common structure from which a stream of products can be developed (Gawer, 2014; Gawer, Cusumano, 2014; McIntyre, Srinivasan, 2017). In the early stages, platforms were observed within firms across a family of products; however most recently technological platforms have been noticed to operate across firms within supply-chains or within larger networks of firms that are not tied by a buyer-seller relationship, which are called “industry platforms”.

Nowadays, platform businesses bring together two groups of users, typically producers and consumers, in high-value exchanges. Industrial organization economics literature started identifying platforms with two-sided markets.

A two-sided market is a market structure in which the firm is an intermediary between two groups of consumers, delivering them two different value propositions (Rysman, 2009). According to Evans (2003), platform businesses compete in multi-sided markets. When the business model is successful, these platforms catalyse a virtuous cycle: more demand from one user group fosters more from the other. The driving force and characterizing feature behind two-sided markets is the presence of network effects (Van Alstyne, Parker, Choudary; 2016), which reflect an underlying interdependency and complementarity between the demands from the two groups of users. The existence of cross-side externalities give raise to the “chicken-and-egg” problem, which regards all types of two-sided markets. The “chicken-and-egg” problem regards how to engage and grow matched markets (Parker, Alstyne; 2005), which practically means which side to engage on-board first. Due to the “chicken-and-egg” problem, pricing in two-sided markets is a crucial decision, as changing the price from one side has indirect effects on the other side as well (Rochet & Tirole, 2003). In fact, if the first group has less motivation to join due to higher prices, less users will join and the value for the second group will reduce, being the first side smaller. This leads to fewer members of the second group to join, which erodes the value for the first group again (Evans and Schmalensee, 2016).

Filistrucchi et al. (2014) distinguish between two fundamental types of two-sided markets: non-transaction markets and transaction markets.

Two-sided transaction markets, such as payment cards, are characterised by the presence and observability of a transaction between the two groups of platform users. Taking a business
model perspective and focusing on internet-based transaction two-sided platforms, they typically connect an end-user side (B2C), who is the consumer of the service, and a business side (B2B), who is the business costumer and normally pays for a service (Muzellec, Ronteau, Lambkin; 2015). Normally, the platform charges a transaction-sensitive fee, that business costumers are willing to pay because they can exploit the size of the consumer audience, its characteristics and the usefulness of the data derived. Concluding, business companies are subsidizers, that pay to reach the audience and benefit from its private data, and consumers are “loss leaders”, that provide personal data in exchange for service usage. The monetization is “B2B oriented”.

Non transaction two-sided markets, such as most media markets, are characterised by the absence of a transaction between the two sides; consequently, it is not possible for the firm to charge for a transaction-sensitive fee. Therefore, often non-transaction two-sided platforms offer the core product or service to one group and then sell access to that group to the other side, which is charged a membership fee to access the network. The diffusion of ICT led to stronger competition, which resulted in the digital service = free equation (Trabucchi et al., 2017). Therefore, non-transaction two-sided markets were forced to find new revenue streams for profitability. At the same time, the diffusion of ICT and the pervasive use of digital services in users’ life enable a wide range of new opportunities based on new assets that are generated in co-creation with users. Indeed, the considerable quantities of data that customers generate while using digital services represent a new type of asset that characterizes the digital revolution.

Over the last few years, the amount of data available has exponentially increased, supporting the conceptualization of Big Data. Big data are characterized by 5 Vs: volume, velocity, variety, veracity and value. A considerable portion of Big Data are generated by users interacting with existing digital products and services: they are called User Generated Big Data (UGBD). UGBD require a passive contribution from users and allow a high level of generalizability, providing a deep understanding of how consumers interact and leverage digital technologies, and consequently their needs (Trabucchi et al.; 2017). The use of UGBD can be a source of competitive advantage (Marshall et al., 2015; Sorescu, 2017) and the three main strategies (Trabucchi et al., 2017) that are implemented to realize this competitive advantage are:

1. Enhanced advertising, where UGBD is used for making advertising more targeted;
2. E-ethnography, where UGBD is used to support and improve products and services and to develop better relationships with customers;
3. Data trading, where UGBD are sold normally to a very distant business, becoming a direct source of revenues.

Due to the diffusion of ICT and the increasing number of users of digital services, consumers can exploit services for free; however, to enjoy them, they are required to provide personal information, information about their preferences or their online activities, which permits individuals to be targeted with far greater precision than ever before. Therefore, for consumers personal information operates as a currency in the exchange of online services. Indeed, users have an active role in the realization of company’s business models and consequently profits. Service-dominant logic starts from the concept that firms cannot deliver value, they can only offer potential value, which is realized through customer usage (Xie et al; 2016).

Because when end-users access the platform and generate UGBD they leave a “digital footprint” that can be followed, analysed and monetized, the privacy capital they provide needs to be examined from a privacy perspective.

Information Systems literature has deeply examined users’ acceptance of new technologies, investigating how and why users adopt new information technologies. In the last decades, many research models started including privacy as an independent variable affecting consumers adoption of information technologies. Indeed, understanding the value that individuals assign to the protection of their personal data is crucial for business, in order to take more conscious decisions in designing platforms (Acquisti et al., 2013). Many research models focused on the relationship between personalization and privacy, as the more personalized is the service, the more personal information users must share. Privacy costs are modelled under several perspectives of analysis; however, the common examined dimensions are:

1. Privacy concern (Zhou; 2012), which reflects users’ concern on personal information disclosure, and it is highly influenced by personal traits (Spiekermann et al., 2015);
2. Perceived risk and trust (Zhou; 2012). Trust reflects a party’s willingness to be vulnerable, as it has positive expectations on another party’s future behaviour. Trust has a positive impact on usage intention and mitigates perceived risk, that has a negative impact on users’ adoption.

Even though many research models investigated drivers affecting IT users’ adoption, users’ privacy perception is still unclear, and it appears to be context-dependent and malleable (Hann et al., 2007; Acquisti et al., 2013) At the same time, “due to Internet users’ apparent comfort with sharing their data, more and more organizations today engage in the trading of consumer data” (Spiekermann et al., 2015, p. 162). Because users’ perception of privacy issue is still
unclear, firms that leverage data trading strategies should worry about privacy implications. However, the relationship between information transparency on business models leveraging UGBD and users’ adoption has not been investigated yet by IT literature.

The aim of this research is to understand whether firms’ transparency about their business model and consequently about UGBD trading strategies affects users’ service adoption, as “end-users are being used but they are not necessarily a negotiating party that is willing to exchange data” (Muzellec, Ronteau, Lambkin; 2015, p. 141).

**Q. Investigate whether business model clearness about UGBG usage affects users’ adoption of digital two-sided services.**

To do so, this research completely changes the perspective: the dimension related to privacy is not anymore considered as one of the drivers affecting users’ adoption, but it is included in the two-sided platform business model. Considering the research model, the independent variable is the Business Model Clearness, which does not come from literature, but it is self-developed integrating past theories about business model (Baird, Raghu, 2015) and about information transparency and privacy concern (Awad, Krishnan, 2006; Kim, Son, 2009). The dependent variable Digital Two-sided Service Adoption is measured through three items adapted from Venkatesh et al. (2012). The other control variables that are included in the research model are:

- Privacy Attitude adapted from Chellappa and Sin (2005) scale which considers the different typologies of information shared. This construct is measured through four items;
- Propensity to Innovative Services, adapted from Yi et al. (2006), which considers individual different propension to adopt innovations. This construct is measured through three items;
- Education, adapted from Awad and Krishnan (2006) scale that consists of five different levels of education;
- Gender and Age, that have been shown to influence the adoption in technology adoption contexts (Morris and Venkatesh 2000; Venkatesh and Morris, 2000).

Each construct taken from the literature was analysed and adapted to fit the empirical setting of the research. Therefore, the following hypotheses on the relationships between each construct and the dependent variable were formulated:

**H1. Business Model Clearness negatively influence Digital Two-sided Service Adoption.**
**H2.** Privacy attitude negatively influences Digital Two-sided Service Adoption: keeping the other variable constant, the higher privacy attitude, the lower the adoption.

**H3.** Propensity to innovative services positively influences Digital Two-sided Service Adoption: keeping the other variable constant, the higher the propensity to innovative services, the higher the adoption.

**H4.** Education positively influences Digital Two-sided Service Adoption: keeping the other variables constant, the higher the education level, the higher the adoption.

**H5.** The influence of Business Model Clearness on Digital Two-sided Service Adoption is moderated by age and gender.

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The final aim is to derive meaningful, empirically proven guidelines for managers on which aspects to consider when implementing strategies based on UGBD.

To investigate this research model, the health and fitness application market is chosen as the empirical setting. Indeed, this industry is already leveraging non-transaction two-sided business model, delivering different value proposition to the different sides and exploiting data trading strategies.

The research model is tested through an artefactual field experiment (Podsakoff P., Podsakoff N., 2018; Carpentel et al., 2004), which has been designed after a deep analysis of the procedures that were implemented in past researches to investigate adoption. Figure 2 shows the five steps that have been implemented: hypothesis definition, research model definition, testing phase, data collection phase and data analysis phase. In the data collection phase, the experiment is based on two similar counterfeit services – FitYou and Weights - that have been shaped based on the current players on the market such as Strava or Runtastic. Because the experiment has a within-subjects design, participants are subjected to two scenarios: in the first
scenario, participants assess one service in the Business Model Opaque case, and in the second scenario they assess the other service in the Business Model Transparent case. The order of the two scenarios has been randomized, as shown in figure 2.

![Figure 2 - Experiment procedure](image)

The experiment is realized with a survey delivered through Qualtrics. Appendix 1 contains the full version of the survey. Each question is evaluated on a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). The survey was first validated by researchers from Politecnico of Milan and then it was tested on a small sample to assess the clarity of the statements and of the service descriptions. Minimal adjustments were needed; then invitations to complete the survey were sent through e-mail, social network messages and LinkedIn posts. Totally, 500 responses were collected; however, after the data cleaning phase only 345 responses were considered valid.

Karwatzki et al. (2017) methodology, which is based on the study elaborated by MacKenzie et al. (2011), was used as a baseline for the data analysis phase. Before any data analysis is conducted, data reliability and consistency must be checked through a Confirmatory Factor analysis to assess whether the items delivered in the survey effectively measure the research constructs. Indeed, the constructs are latent variables, because they are not directly observable: this means that a construct refers to a specific theoretical phenomenon to be studied and the item is “a recorded trace taken as evidence of the construct” (Edwards & Bagozzi, 2000). Reliability was assessed through factor loadings, Cronbach’s alpha coefficient, average variance
extracted, composite reliability and Fornell-Larcker criterion. All items were considered valid, except for one of the items of Propensity to Innovative Services, which was dropped.

Once the data was organised and ready, the research model is implemented in SPSS. A MANCOVA analysis with a significance level equal to 5% is carried out, mapping all the control variables as covariates.

Within-subjects designs that generate repeated measurements are commonly analysed with the analysis of variance (ANOVA) or the multivariate analysis of variance (MANOVA). However, if the experiment contains control variables, they are mapped as covariates and the data are analysed using analysis of covariance (ANCOVA) or multivariate analysis of covariance (MANCOVA), according to the number of dependent variables. Because in this research model the dependent variable is multi-item, a MANCOVA analysis was performed.

The model that is implemented in SPSS measures the dependent variable Two-sided Digital Service Adoption not in terms of the absolute value that participants assessed during the survey, but in terms of the delta between the answers given by each participant to the two service. Because the significance value of the Test of Equality of Covariance Matrixes is equal to 0.059, the Multivariate Tests must be interpreted considering the Wilks’ Lambda coefficient.

MANCOVA analysis results show that the value of the Wilks’ Lambda coefficient of the independent variable Business Model Clearness is greater than 0.05, meaning that there is no statistical evidence that the independent variable affects the dependent variable Digital Two-sided Service Adoption. Therefore, H1 is not supported for the research model. To validate this result, a one-way ANOVA was carried out, which confirms that there is not statistical evidence that Business Model Clearness affects users’ Digital Two-sided Service Adoption. Considering the other control variables, all the Wilks’ Lambda coefficients are greater than 0.05, meaning that the other hypothesis H2, H3, H4 and H5 are not supported.

Therefore, the main findings of this research are the described hereafter.

**Users’ consenting contribution**

Business Model Clearness has no direct impact on users’ Two-sided Digital Service Adoption. This means that even though final users are aware about their personal data being sold by service providers, their willingness to adopt the service does not change. In literature there are opposing theories about the relationship between information transparency and users’ adoption, with some researches supporting a positive relationship (Culnan, Armstrong; 1999)
and others demonstrating the opposite (Awad, Krishnan; 2006). The current overview is quite unclear, and this research study contributes in making it clearer by negatively answering the question proposed by Spiekermann et al. (2015): “will people not want to continue freely to communicate online, chat, talk, post and provide their data?”.

Moreover, the research study is one of the first ones introducing the business model as an independent variable affecting users’ adoption. Contrary to the findings of Baird and Raghu (2015), the results show that the variations in the underlying digital service business models are not likely to have significant impacts on consumers’ adoption. Concluding the results of this research study confute what Muzellec et al. (2015) stated: “end-users are being used but they are not necessarily a negotiating party that is willing to exchange data” (Muzellec, Ronteau, Lambkin, 2015, p. 141). The inner motivation explaining this disagreement among theories relies in the difference in the typologies of information that are collected and how they are perceived by users, as better explained in the next point.

Privacy Attitude

Considering the Privacy Attitude construct, there is a significant, structural difference in how users perceive the treatment of the different information typologies. Results confirm that Privacy Attitude varies among personal traits, but they also suggest that individuals’ personal differences in privacy concern (Zhou, 2012) may differ among the type of information is shared. Indeed, the survey that was delivered during the experiment considered Chellappa and Sin (2005) classification of information typologies. This framework distinguished between anonymous information (IP address, …), personally identifiable information (geographical position, …), and personally unidentifiable information (sex, age range, …).

Results show that users’ perception and privacy concern varies among two groups of information types:

- On one side anonymous information and personally identifiable information;
- On the other side personally unidentifiable information, which are perceived as the general information that are shared with service providers

More specifically, users seem to be more concerned of sharing anonymous and personally identifiable information – as the mean value of the responses is higher - which are perceived to be more sensitive.
Coherently with this finding of privacy concern changing among the information typologies, Steward & Segars (2002) research shows that privacy constructs should not only address “what” and “how” information is collected and used, but it should also consider consumers’ perceptions, which may vary among different aspects of privacy.

By demonstrating that Privacy Attitude should not be considered as a unique dimension characterized by different aspects that are perceived differently from users, this finding enlarges the current state-of-art of IT literature.

**Users as an active source of data**

Within the context of two-sided markets literature (Trabucchi et al., 2017; Hartmann et al., 2016; Sorescu, 2017) and service-dominant logic (Xie et al., 2016; Vargo & Lusch, 2008), the business model that was tested in the experiment unifies both research perspectives in one unique value proposition. Indeed, the business model proposed in the experiment relies on data as a key resource that is directly used as a source of revenues, a value proposition that is realized only through customers interaction. In fact, in the case of a non-transaction two-sided platform that leverages a data trading strategy, the contribution of end-users is fundamental to enable the two-sided platform to realize the value proposition that is then sold to the business side.

If traditional non-transaction two-sided markets considered end-users as a passive target, in this perspective end-users have a consenting active role in the value creation process, enabling to change the perspective about the role of data and consequently creating new business opportunities in two-sided markets.

Traditionally, non-transaction two-sided markets have been considered as a strategic choice to profit from services offered for free or almost for free to end-users, both in the Client-As-a-Target and in the Client-As-a-Source perspectives (Trabucchi, Buganza, 2019). This means that normally, in the definition of the two-sided business model, the decision to add a second non-transaction side was made to monetize what was being offered to the first side, end-users, by exploiting User-generated Big Data as a by-product. On the contrary, if customers who are searching for data are considered the starting point of the business model (Trabucchi, Buganza, 2019), then data become the primary product of the innovation process. This vision cannot be delivered without the necessary condition of users consenting and active contribution to Big Data generation. For example, Duolingo (Trabucchi, Buganza, 2019) is an education app that sells text translations to companies that needed them, while allowing end-users to learn new
languages as they translate texts. In this case, the trigger point that gave birth to the Duolingo app actually was the companies’ need for translations from various languages to English. The second side consists in end-users, which have been involved later with the active role to realize the value proposition – millions of data about translations - that is sold to companies.

In this perspective end-users are the main source of value creation in the two-sided business model, creating and supplying data while enjoying (maybe for free) a service [...] which is not necessary the fundamental reason why the entire system has been created (Trabucchi, Buganza, 2019). This vision twists the established line of reasoning, that used to see UGBD as a by-product asset with a hidden value to extract.

Concluding, the proposed business model creates a bridge between the two theories, reinforcing both and highlighting the business potentialities that rise.

This finding also enlarges the current state-of-art of literature by proposing in the service-dominant logic framework a new role for customers. In the new category customers act as data providers: while normally using the service and exploring the functionalities that the digital service offers within its value proposition toward users-side, they passively leave “digital traces” that can be monetized to the other side, enabling firms to realize also the business-side value proposition.

The findings that arise from this research indicate that managers should start or continue to implement data-driven strategies, moving from data-driven decision strategies, to product improvements or even data trading strategies, which are those that rise most relevant privacy issues. However, before implementing data trading strategies, managers should take some preventative measures, which include:

- Clear communication and information transparency about the final usage of UGBD, highlighting which are the benefits that users may derive from sharing their data and enabling the realization of firms’ two-sided value proposition;
- Implement GDPR compliance processes, which reassure users about the security concerns that the may have about unauthorised access to their data.

If these preventative measures are taken, managers should not be concerned about privacy issues affecting users’ adoption of the digital two-sided service.

Limitations of this research include the restricted area of analysis of the research model limited to the fitness and health applications empirical setting; the exclusion of the security construct,
that has been ensured by design in the research model; the exclusion of other drivers of IT adoption such as Social Norms or Relative Advantage. Consequently, future researches might extend the application area by investigating the research model in different empirical settings; extend the variety of the sample that is mainly focused on Italian population; or extend the research model with other constructs such as Security or Social Norms.
1. Introduction

The daily routine of millions of people relies on smartphones and applications, that support a wide range of activities, moving from food delivery, to gaming or fitness. These digital service providers are platforms that while connecting two interdependent groups of consumers have the opportunity to transform the millions of interactions into a valuable asset that can be leveraged in several ways, completely twisting traditional business models. In the internet era data is often described as the new oil. Just as with oil, the value contained within data is universally recognized.

Platform businesses deeply differ from the conventional “pipeline” businesses that have dominated industry for decades (Libert et al.; 2016). Pipeline businesses create value by controlling a linear series of activities. They are based on the classic value-chain model: inputs at one end of the chain undergo a series of steps that transform them into an output that can be sold (Van Alstyne et al.; 2016). For platforms, the focus shifts to interactions, that are exchanges of value between two different groups of users, such as producers and consumers. Whenever these two sides are interdependent, cross-side network effects arise, which means that the value perceived by one side increases with the number of participants of the other side, and vice-versa. These types of platforms that connect interdependent groups of users are called two-sided markets. Often the unit of exchange can be so small, such as a view of a video, that little or no money can be charged. Nevertheless, the number of interactions and the associated network effects are the ultimate source of competitive advantage. In fact, in the internet economy, firms that attract the highest number of platform participants offer a higher average value per transaction. This happens because the larger the network, the better the matches between supply and demand and the richer the data that can be used to find matches.

The extremely high number of interactions is translated into a constantly growing amount of data, that nowadays can be measured in zettabytes - millions of terabytes (Trabucchi et al.; 2017). Big data usually includes data sets with sizes beyond the ability of commonly used software tools to capture, curate, manage, and process data within a tolerable elapsed time. Big data satisfy five characteristics: volume, velocity, variety, veracity and value (McAfee, Brynjolfsson; 2012). Platform providers extract from big data valuable insights, that enable several strategies and opportunities (Fosso Wamba et al.; 2015).
For example, Uber monitors data on every journey taken by users and exploits this information to determine demand, allocate resources and set fares. The company also analyses public transportation network in the cities it serves, so it can focus its coverage in poorly served areas. Uber works with many types of data: for example, it calculates fares automatically using GPS, traffic data and the firm’s algorithms adjusts them to reach the expected time of the journey, which is the base for their pricing strategy (Marr; 2017).

While the majority of companies uses their data to improve decision-making, data is becoming increasingly important for the everyday operations. In fact, data help optimizing almost every organizational function, either the firm wants to improve the manufacturing process by automatically detecting faults, optimize routes, target the most appropriate customers or detect fraud quickly. So, data can improve the manufacturing process, warehousing and distribution processes, business processes such as accounting or customer service, sales and marketing processes. For example, Netflix used Big Data to create hit movies or TV shows such as House of Cards by analysing and predicting preferences of its viewers instead of relying on a creative director’s ideas. In fact, Netflix leveraged its store data about streaming activities to forecast that remaking the series House of Cards with the actor Kevin Spacey and director Davin Fincher would be a success (Erevelles et al; 2016).

Thanks to Big Data, firms can create incremental and radical innovation. However, improving the effectiveness of marketing activities through incremental innovation is necessary but not sufficient to have a sustainable competitive advantage. Firms should use customer insights obtained through Big Data to continuously redefine marketing activities and implement radical innovation. An example of radical innovation derived from Big Data is provided by Amazon, which filed a patent for anticipatory shipping that enables the firm to predict customers purchases and shipping the product to the warehouse before the order. This means that Amazon uses Big Data to recreate the distribution strategy rather than only improving those activities (Erevelles et al; 2016).

Finally, data can be used as a business asset that can be monetized by selling them back to customers or third interested parties and so creating extra value. Tesco’s Clubcard data is a good example, as the firm is selling customer-based insights to consumer goods companies such as Coca-Cola. However, this does not mean selling data only on individuals or customer groups: sometimes highly specialized or niche data can be really valuable. For example, Deere & Company creates extra revenues by selling farmers the access to data on machinery performance or soil condition (Marr; 2017).
However, what is the role of users in this process? Are they aware about their fundamental contribution to companies’ business models? Are they aware about how companies use their information?

*Personal data is the new oil of the internet and the new currency of the digital world.*

*Meglena Kuneva, European Consumer Commissioner, March 2009*

Nowadays consumers provide detailed information about their preferences through their online activities which permits individuals to be targeted with far greater precision than ever before. For consumers, therefore, personal information operates as a currency, and sometimes the sole currency, in the exchange of online services. This inner feature of current digital services is even stronger in the case of two-sided platforms, that connect interdependent users. The millions of interactions produce zettabytes of User-generated Big Data, that can be analysed to extract valuable insights. This aggregated information is then sold to third parties. This raises an important privacy issues, as everyone has the right to keep its personal life or personal information secret or known only to a small group of people. Each individual has its own privacy attitude, that influences its propensity to two-sided digital services adoption; however, nowadays often users are not aware about their “digital footprint” they leave while using digital service, and they are not aware about the potential value of their data, which are leveraged by digital services providers (Fish; 2009).

*"If you're not paying for it, you become the product"*

Therefore, the objective of this thesis is to introduce the business model as an independent variable that might affect users’ adoption of digital services, particularly investigating whether users’ adoption of two-sided digital services is influenced by companies’ transparency about their use of User-generated Big Data in the business model. Companies disclosing their business model communicate to final users how their data are used and exploited to generate value: this can affect users’ adoption of digital services.

The following chapters are organized as follows: Chapter two analyses the current state-of-art of literature on two-sided markets, highlighting the role of Big Data in the business model, and literature on Information Technologies, focusing on privacy. Chapter three describes the research question and model. Chapter four focuses first on the experiment design, explaining
how the research model is tested, and then on the data gathering process. Chapter five is devoted to the description and interpretation of the results of the MANCOVA analysis. Chapter six outlines the discussion of the results taking the theoretical lenses that were explained in Chapter two. Finally, Chapter seven explains the conclusions, focusing on the theoretical and managerial implications of the results and defining the limitations and possible future researches.
2. Literature Review

This chapter aims at exploring the state-of-art of the literature that supports and creates the basement for the entire study. There are two main topics that are investigated and that act as limits for the area of analysis. The first one revolves around the concept of platform, which is analysed according to two different literature theories: paragraph 2.1.1 considers engineering design perspective, which sees platforms as technological architectures; paragraph 2.1.2 focuses on economics perspective, which sees platforms as two-sided markets. These analyses concentrate on the business models that platforms leverage to succeed in the market and the increasing importance of Big Data in creating competitive advantage. Specifically, the concept of Big Data is introduced, and it is explained how they can foster new revenue streams in two-sided markets. Paragraph 2.1.3 examines more broadly speaking data-driven business models and paragraph 2.1.4 explores big data platforms according to service-dominant logic, which focuses on the role of users in the co-creation of big data assets. Finally, chapter 2.2 is devoted to investigating Information Technologies literature, converging to the increasing importance of privacy in digital services adoption. The research question has its roots in all these areas.

2.1 Platforms

The concept of platform has existed for years in many different industries, from the newspaper business to the videogame one, with an important presence in the high-tech businesses that are driven by Information and Communication Technologies (ICT). Platform businesses bring together two groups of users, typically producers and consumers, in high-value exchanges. The credit card industry, for instance, links merchants to buyers; search engines join users and advertisers. What has lately changed is that ICT have profoundly reduced the need to own physical infrastructure and assets. In fact, the key assets in a platform business are information and interactions, which together are also the source of value and competitive advantage. When the business model is successful, these platforms catalyse a virtuous cycle: more demand from one user group fosters more from the other. For example, the higher the number of videogames that developers create for the Microsoft X-Box platform, the higher the number of players that are interested in the latest X-Box. Also, the more players who use X-Box, the more developers are willing to pay Microsoft a licensing fee to produce new games (Eisenmann, Parker, Van...
Alstyne; 2006). Network effects are the driving force behind every successful platform (Van Alstyne, Parker, Choudary; 2016).

In this field, literature is divided into two main perspectives:

- Engineering design perspective, which sees platforms as technological architectures;
- Economics perspective, which sees platforms as two-sided markets.

Each research stream focuses on different aspects of the same topic; therefore, it is relevant to examine both of them to have a complete overview of the concept.

2. 1. 1 Engineering Design Perspective

In this literature stream, the concept of platform has its roots in new product development theory and in industrial organization theory. A platform is a set of subsystems and interfaces, embodied in products, services or technologies, that form a common structure from which a stream of products can be developed. It is a component and subsystem asset that is shared across a family of products for improvements or new developments. The key concept is the presence of a component sharing, that enables economies of scope in innovation. “Economies of scope in innovation occur when the cost of jointly innovating on product A and B is lower than the cost of innovating on A independently of innovating on B” (Gawer; 2014, p. 1242).

In the early stages, platforms were observed within firms across a family of products; however most recently technological platforms have been noticed to operate across firms within supply-chains or within larger networks of firms that are not tied by a buyer-seller relationship. The latter are defined as “industry platforms”, extending the concept of platform to new contexts. In this case, platforms have an additional role as building blocks that provide an essential function to a broader technological system, solving a business problem for many firms and users. These platforms are a foundation for the whole innovation ecosystem for developing complementary products, services or technologies (Gawer, Cusumano, 2014; McIntyre, Srinivasan, 2017).

According to engineering design perspective, platforms have not only a modular architecture but they are also structured around a core and a periphery. The architecture is a cardinal element, because it is the mean for platforms to provide value, being the specification of interfaces that allows an ecosystem to be portioned into a relatively stable platform and a complementary set of modules. This particular structure helps reducing complexity by breaking down a system into its standardized components that interact through standardized interfaces.
The decomposition supports innovation because it allows specialization by reducing the scope of innovation. The scope breakdown fosters two different innovation directions: autonomous innovation within modules and mix-and-match innovation through recombination of modules. Therefore, in this modular architecture and innovating functioning, interfaces have the fundamental role of dividers, but also the role of connectors and conduits of information. In fact, interfaces contain information that are accessible to external agents and usable to build compatible complementary innovations.

The degree of interface openness affects the broadness of innovation: the wider the openness, the wider the access to external capabilities and knowledge. So, the degree of openness influences industry-level innovation.

Considering these features, platforms can be classified into three main types (A. Gawer, M. Cusumano, 2014), as shown in figure 4: internal platforms, supply chain platforms and industry (or external) platforms.

<table>
<thead>
<tr>
<th>Agents</th>
<th>Internal platform</th>
<th>Supply-chain platform</th>
<th>Industry platform</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Firm and subunits</td>
<td>Assemblers and suppliers</td>
<td>Platform leader and complementors</td>
</tr>
<tr>
<td></td>
<td>Closed</td>
<td>Selectively open</td>
<td>Open</td>
</tr>
<tr>
<td></td>
<td>Firm</td>
<td>Supply-chain</td>
<td>Potentially unlimited pool of external capabilities</td>
</tr>
<tr>
<td>Accessible innovative capabilities</td>
<td>Authority through managerial hierarchy</td>
<td>Contractual relations</td>
<td>Ecosystem governance (in two-sided markets: pricing)</td>
</tr>
<tr>
<td>Coordination mechanism</td>
<td>Modular design, Core and periphery structure</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technological architecture</td>
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</tbody>
</table>
To better understand the concept of industry platforms, the attention is moved to some examples of products and technologies that have served as industry platforms: Microsoft Windows and Linux operating systems (OS); Intel and ARM microprocessors; Apple products’ design along with the iOS operating system; Apple’s iTunes and App Store; Google’s Internet search engine and Android operating system for smartphones; social networks (Facebook, LinkedIn, and Twitter); and videogame consoles. Payment technologies, from credit and debit cards to micropayment schemes, can also be seen as platforms that enable different types of financial transactions (Leblebici, 2012). The most critical distinguishing feature of an industry platform compared to an internal platform is the potential creation of network effects, as the agents that are involved belong to an ecosystem with possible interdependencies and complementarities.

Researchers in Industrial Organization economics started using the term platform to identify markets with two or more sides and potentially with network effects across different sides, also defined as two-sided markets, which will be deeply analysed in the following paragraph. However, the two concepts of platform and two-sided market are not overlapping and therefore it is interesting to make a comparison between them. Indeed, “while the concept of a multisided market can sometimes apply to supply-chain platforms as well as industry platforms, it does not entirely conform to either category. [...] At the same time, not all multi-sided markets are industry platforms [...]. Double-sided markets where the role of the platform is purely to facilitate exchange or trade, without the possibility, for other players to innovate on complementary markets, seem to belong to the supply-chain category. A multi-sided market that stimulates external innovation could be an industry platform. However, while all industry platforms function this way, not all multi-sided markets do” (Gawer, Cusumano; 2014, p. 422). This concept comparison is synthetized by the conceptual framework in figure 5.

![Figure 5 - Conceptual framework](image)
Going back to the key notions of the engineering design perspective, Ballon and Heesvelde (2011) analysed the concept of ICT platforms from a modular architecture perspective, identifying different types of business models. Indeed, ICT systems are increasingly characterized by technical and product modularity, which is necessary to deal with the increasing complexity and systemic nature of ICTs. As aforementioned, a modular architecture implies the presence of interfaces, that control the access to the subsystems. ICT literature introduce the concept of platform gatekeeper, which is the owner of these interfaces, joining it with the concept of information gatekeepers, which is commonly used to describe the entities selecting and processing ideas and information. Merging the two concepts, gatekeepers not only filter and select information, but also qualitatively change the informational contents through active accumulation, processing and packaging. In the context of ICT platforms, gatekeepers are the owner of interfaces and consequently of the information transiting through them. Their role is strategically crucial, because they are responsible for making information and communication resources available, consequently attracting a high number of users to the platform. According to Ballon & Heesvelde (2011), “a platform should therefore not be considered as a given architectural and organisational entity, but as a collection of a number of crucial gatekeepers roles that may be used to attract as well as to lock in various types of customers” (Ballon & Heesvelde; 2011 p. 704).

Considering a business mode perspective, Ballon & Heesvelde model is based on the starting notion that all platforms aim at controlling a set of gatekeepers’ functionalities, but they may differ profoundly in terms of the control they have over the business assets that are needed to create value and in terms of control over the consumers to whom the value proposition is offered. Considering these two axes – control over assets and control over customers – the model distinguishes between four types of platform business models:

<table>
<thead>
<tr>
<th>No control over assets</th>
<th>Control over assets</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>No control over customers</strong></td>
<td><strong>Control over customers</strong></td>
</tr>
<tr>
<td>Neutral Platform (e.g. Google search engine)</td>
<td>Broker Platform (e.g. eBay)</td>
</tr>
<tr>
<td>Enabler Platform (e.g. Intel)</td>
<td>Integrator Platform (e.g. Microsoft OS)</td>
</tr>
</tbody>
</table>

*Figure 6 - Adapted from "ICT platforms and regulatory concerns in Europe" (P. Ballon & E. V. Heesvelde, 2011)*
• Neutral Platform, which refers to the case in which the platform owner does not have control over the assets necessary for the value proposition neither over customers relationship. The platform has no customer ownership because it does not establish a billing relationship with end-users and may be even invisible to them. An example of Neutral Platform is Google search engine platform, which does not interfere with the offering of the content or services it spreads. Also, customers lock-in is minimal and there is no subscription or billing relationship. However, Google internalizes the externalities that arise, which are captured through advertisement revenues.

• Broker Platform, which refers to the case in which the platform does not have control over the value proposition, but it has control over customers. For example, eBay merely provides the place where sellers and buyers meet, which means it has no control over the contents generated in its platform. However, consumers are very aware of the brand and its guarantees, plus eBay dominates the billing process.

• Enabler Platform, which refers to the case in which the platform owner has control over the assets that generate the value proposition, but has no control over consumers. For example, Intel platform manages several of the assets involved in the PC value proposition, which are embedded in the “Intel inside” quality label; however, consumers still recognize the brand of the PC manufacturers, who takes care of the marketing and sales processes;

• Integrator Platform, which refers to the case in which the platform owner has control over both assets and customers. A typical example is Microsoft Windows platform, which controls the operating system standard and the Microsoft Store, for the purchase of applications. Microsoft Windows therefore can filter the content that access its store and decides the OS standards, but it also controls customers relationship in terms of branding and the whole purchasing process.

This classification highlights that platforms that control the same gatekeepers’ functionalities, such as collecting and processing data or enabling transactions, may leverage different types of business models, depending on the degree of control they have over assets and over customers ownership.

Concluding, engineering design perspective sees platforms as modular technological architectures structured around a core and a periphery to foster innovation through economies of scope. This architecture relies on interfaces as information centres to support innovation. Interfaces are owned by gatekeepers, that have a crucial role in attracting users to the platform. Gatekeepers’ functionalities can be achieved through several business models.
2. 1. 2 Economics Perspective

Industrial organization economics literature deeply analysed the concept of platforms, which have been identified as two-sided markets. Indeed, economists view platforms as a particular type of market that facilitates the exchange between different groups of consumers that otherwise could not interact. This chapter aims at examining the concept of two-sided market, the main strategic choices and finally the different typologies of two-sided markets.

3.1.2.1 Introduction to Two-sided Markets

In literature many researches have proposed diverse definitions, but they all revolve around one common logic: a two-sided market is a particular market structure in which the firm is an intermediary between two groups of consumers, delivering them two different value propositions.

Rysman (2009, p.125) states that “a two-sided market is one in which:

1. two sets of agents interact through an intermediary or platform;
2. the decisions of each set of agents affects the outcomes of the other set of agents, typically through an externality.”

According to Evans (2003), platform businesses compete in multi-sided markets. For example, video game console companies such as Sony, Nintendo, and Microsoft compete for game developers and users, while payment card companies such as American Express, MasterCard, and Visa compete for merchants and cardholders. Multi-sided platforms can rise in many different industries, from media to payment systems and software; they rise in bricks and mortar industries as shopping malls and in information-based industries as portals.

There are three necessary conditions for the emergence of a two-sided market:

1. The presence of more distinct groups of customers: these are gamers and developers in the videogames industry; merchants and cardholders in the payments cards case; retailers and customers for malls.
2. The presence of externalities associated with the two groups of users, which arise when the value obtained by one kind of customer increases with measure of the other kind of customer.
3. The presence of an intermediary that internalizes the externalities created by one group for the other: the platform.
The driving force and characterizing feature behind two-sided markets is the presence of network effects. The concept of network effects derives from the conceptualization of network good, which is a good whose benefits increase with the number of its current or future users. Consequently, network effects are the positive effects that an additional user has on the product’s value to other users’ eyes. They arise when consumers’ benefits do not only depend on product characteristics, but also on the network of consumers who adopt or use that product (H. K. Bhargava; 2014).

There are two types of network effects: same-side network effects, which occur between individuals belonging to the same group of users, and cross-side network effects, which occur between individuals belonging to different groups of users. The presence of cross-side externalities (or indirect network effects) is what characterizes and differentiates a two-sided market from a traditional one, where same-side externalities might as well be present.

The presence of cross-side externalities implies that an increase in the number of users on one side makes it less or more valuable to the users on the other side. This type of externality reflects a pre-existing underlying interdependency and complementarity between the demands from consumers. For example, in the payment card market, any additional merchant that enables card payments increases the benefits that cardholders derive by joining the network. This is a bidirectional relationship, which means that also any additional cardholder increases the benefits that merchants derive by joining the network. Indirect network effects are often positive, but can be negative – for example an increase of advertisers in a radio program decreases the value for the listeners.

The existence of cross-side externalities give raise to the “chicken-and-egg” problem, which regards all types of two-sided markets. This metaphor aims at giving the idea that when a business aims at attracting two inter-dependent groups of customers it is hard to tell who comes first, as you need chickens to have eggs, but you also need eggs to have chickens. The crucial point is that the “chicken-and-egg problem” occurs when two separate groups are mutually dependent. In two-sided markets literature it regards how to engage and grow matched markets (Parker, Alstyne; 2005). In fact, in two-sided markets “indirect network externalities give rise to a “chicken-and-egg” problem: in order to attract buyers, an intermediary should have a large base of registered sellers, but these will indeed be willing to register only if they expect many buyers to show up at the intermediary” (Caillaud, Jullien; 2001; p. 5). For example, considering the payment card market, the cardholder side would not join the circuit if there were not enough
merchants accepting that specific card; on the other side, merchants are not willing to join the platform and pay the relative fees if there are no customers using that payment method.

Economics literature deeply investigates how pricing strategies can optimize the price structure to ensure both sides on board, solving the aforementioned “chicken-and-egg problem”. Pricing strategies will be better examined in the next paragraph.

2.1.2.2 Strategies in Two-sided Markets

Because of network effects, successful platforms leverage increasing returns to scale, with higher margins as the user base grows. Fuelled by the expectation of increasing returns, competition in two-sided network industries can be really high, so platform providers - mainly platform leaders - invest their higher margins in R&D or in lowering the prices, to cut competitors out. In this competitive environment, the two most important strategic choices for a two-sided platform are pricing and openness.

Pricing Strategies

In literature pricing is seen as the strategic choice that can be leveraged to solve the “chicken-and-egg problem”. This paragraph is devoted to the analysis of the pricing strategies, focusing on the results and passing by the mathematical modelling.

Economics literature has developed many models for pricing strategies. A key starting point for modelling is that “pricing on one side of the market depends not only on the demand and costs on that side, but also on how their participation affects participation on the other side and the profit that is extracted from that participation” (Rysman; 2009, p. 129). This is a consequence of the cross-side network effects, that determine an interdependency between the demand functions of the two groups of users. In fact, prices on both sides depend on the joint demand elasticities and marginal costs on each side. This is translated in a larger price elasticity effect, because when price falls on side $i$, more consumers on that side are attracted and also more participation on side $j$ is attracted and prices on side $j$ can be raised. Thanks to this larger price elasticity effect, a firm operating in a two-sided market can rationally invest in a product that is

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1 Price elasticity of demand is the percentage change in quantity demanded in response to a one percent change in price. It shows the responsiveness of the quantity demanded of a good to a change in its price, keeping all the other variables constant.
then distributed for free to one side, the “subsidy side”, treating it as a loss leader or financially neutral and treating the other side as the profit centre (Rochet, Tirole; 2003, p. 2). This happens because the increased demand in a complementary premium-goods market more than covers the cost of investment in the free-goods market, by generating cross-market network externality benefits greater than intra-market losses. This result is mathematically supported by the model elaborated by Parker and Alstyne. Another output of the model developed by Parker and Alstyne is that the decision about the “subsidy side” depends on the relative network externality benefits. “At high level of externality benefit, the market that contributes more to demand for its complement is the market to provide with the free good. At lower levels, firms may charge positive prices in both markets, keeping one price artificially low” (Parker, Alstyne; 2005, p. 1503).

With the diffusion of digital technologies, many industries that were preserved by entry barriers were enlarged to the entrance of new competitors. The competition increased and users gained bargaining power, as the concentration of the offer market decreased. As consumers had the possibility to choose among several service providers, the free-to-consumers business models expanded. These types of business models often rely on the fact that the platform attracts the most “eyeballs” possible and then monetizes on the advertising side. “Selling visitors’ eyeballs” (McGrath, 2010) is still one of the most popular value-capture mechanisms in the world of digital services. Because this approach has proliferated across the Internet and app spheres, now customers expect digital services to be free. Therefore, a business model that aims at raising revenues without neglecting customers’ expectation is the freemium model, where users get free basic services, but they have to pay for exclusive premium features. For example, Spotify is treating users as the “subsidy side”, offering them a basic music streaming service, but to have premium functionalities customers have to pay a monthly fee.

Indeed, in literature the “chicken-and-egg problem” has been also investigated as growth-and-profitability dilemma. Two-sided markets have to pursue simultaneously growth and profitability, which are conflicting objectives. As platforms are network goods, network size is a critical metric, and especially in the early stages of the lifecycle. Therefore, it becomes almost essential for the firm to give away the product and sacrifice margin in order to mobilize the network. Several platform firms have chosen to foster network growth by providing heavy subsidies to one side, thereby drawing participation from that side and, in turn, making participation on the other side more attractive. The freemium approach can help firms managing both growth and profitability, offering a free or low-price version to drive mass adoption and a premium higher-price version to generate revenues.
However, the pricing strategy is further complicated by same-side network effects (i.e. PlayStation consoles), which intrincate the decision about which side to subsidize and which side to charge. Eisenmann et al. (2006) suggest some variables that should be considered by platform providers in this strategic choice:

- Ability to capture cross-side network effects (i.e. BlaBlaCar platform had to change its revenue formula in the business model because end-users were able to reach the other side - drivers - even without the platform, so cross-side network effects were not captured);
- User sensitivity to price, because the most price-sensitive side should be subsidized, while the side that increases its demand more strongly should be charged;
- User sensitivity to quality, because the platform should charge the side that must supply quality and not the side that requires it;
- Output costs, which depend on the output provided. Whether it is a digital good and the cost associated is almost zero, risks are low; whether output costs are considerable then it is crucial that the “money side” repays the “subsidy side”, otherwise the platform may incur in big losses;
- Same-side network effects, which could be even negative. In this case platform providers should consider securing exclusive rights to a single user in each transaction category and charging for this possibility;
- Users’ brand value, which is the platform’s value perceived by users. This can be increased by the participation of some “marquee users”, such as big buyers, which can be really important in attracting other users and therefore accelerate the platform growth.

Openness Strategies

The other strategic choice in two-sided markets is related to openness, firstly in terms of number of sides to pursue, secondly in terms of relationship type with competing platforms (compatibility\(^2\) – incompatibility - integration). The number of pursued sides often is a consequence of the maturity of the business: many platforms start as one-sided and they

\(^2\) Compatibility is the ability of a consumer using one platform to reach a seller that uses another one (Rysman; 2009).
enlarge the business model to other sides only when they become more established, overcoming the “chicken-and-egg problem”.

The second openness choice is related to the horizontal relationship with rival platforms. Platform providers often prefer incompatibility, encouraging exclusive membership or usage, as it locks in current customers and locks out competitors. If one side of the market can be made exclusive, normally there is no reason to look for exclusivity on the other side, because the latter is subjected to monopoly prices to access the exclusive side. The incompatibility choice derives from the expectation of increasing returns to scale which open up the possibility of fat margins, leading platform providers to winner-take-all dynamics. Eisenmann et al. (2006) state that a networked market is likely to be served by a single platform when all the three following conditions are satisfied:

1. Multi-homing costs are high at least on one side. Homing costs are all those costs that users face in order to access and use the platform; if they are high, users need a good reason to affiliate to more than one platform (multi-homing condition);
2. Network effects are positive and strong at least for the side with high multi-homing costs, so that users concentrate on one platform;
3. Both sides have standard requirements and do not need special features.

In this openness choice, firms also have to consider the threat of envelopment, as competing platforms often have overlapping user bases. This threat is serious when competitors offer one platform’s functionality as part of a bundle of features; in this case the two value propositions can not be compared and the narrow one will be swallowed by the bundled offering. Therefore, the stand-alone provider can choose to exit the market, change business model and differentiate its value proposition from competitors or establish partnerships within the industry.

Concluding, economics literature sees platforms as two-sided markets, dominated by network effects that fuel platform competition. Economists have mainly concentrated in defining how pricing and openness choices can make the platform thrive, the next chapters will focus on the different typologies of two-sided platforms, focusing on the underlying business model.

2.1.2.2 Two-sided Markets Typologies

Filistrucchi et al. (2014) distinguish between two fundamental types of two-sided markets: non-transaction markets and transaction markets, which are analysed in this paragraph from a
business model perspective. The dichotomy involves the presence or absence of a transaction between the two parties.

**Transaction Two-sided Markets**

Two-sided transaction markets, such as payment cards, are characterised by the presence and observability of a transaction between the two groups of platform users. Therefore, the firm can ask for both a transaction-insensitive fee and transaction-sensitive fee, so it can ask for a two-part tariff. This is translated in the presence of both membership externalities (or indirect network effects) and usage externalities\(^3\). Membership decisions generate membership externalities whenever an end-user on side \(i\) derives a strictly positive net surplus from interacting with an additional end-user \(j \neq i\). Usage decisions generate usage externalities whenever an end-user on side \(i\) derives a strictly positive net surplus from interacting with an additional end-user on side \(j \neq i\) (Rochet, Tirole; 2006, p. 647). As the value of joining the platform depends on the number of users on the other side, the benefit of using the platform similarly depends on the number of customers using it on the other side.

![Figure 7 - Adapted from "Two-sided markets: a progress report" (Rochet, Tirole; 2006)](image)

These externalities are not internalized by the platform users. For example, considering the payment cards market, both sides – merchants and cardholders – when interacting only consider their own convenience. Supposing a merchant would benefit from being paid by card because he would not need to go to deposit cash, the cardholder would not take that into account when deciding to pay whether by card or by cash. This happens because the positive demand network effects are not internalized by the platform users, which perceive them as externalities; but they are internalized by the platform itself.

\(^3\) An externality is a cost or a benefit imposed upon someone by actions (i.e., consumption or production) taken by others.
As Rochet and Tirole (2006) pointed out, in a two-sided market where two different value propositions are sold to different sides it is possible to distinguish between the price level, which is the total price charged by the platform to the two sides, and the price structure, which is the decomposition or allocation of the total price between the buyer and the seller. According to Rochet and Tirole (2006), the market between two sides is one-sided if the total volume of realized transactions depends only on the price level. By contrast, if the total volume of transaction depends on the price structure while keeping the price level constant, then the market is two-sided. This means that a two-sided platform can affect the total volume of transactions by charging more one side and reducing the price paid by the other side by an equal amount. As a result, the price structure must be designed optimally to bring both sides on board.

Pricing strategies have been deeply analysed in the previous paragraph, here the focus is shifted to the business model of transaction two-sided markets. The centre of attention are internet-based platforms, because digital two-sided platforms have grown rapidly with evolving and innovative business model proposals and imposing them as new market standards.

Internet-based two-sided platforms typically connect an end-user side (B2C) who is the consumer of the service and a business side (B2B) who is the business costumer and normally pays for a service (Muzellec, Ronteau, Lambkin; 2015). Platforms need to design two different value propositions, one for each side. This additional complexity derives from the fact that the business customer and the end-users of the service are different group of agents. Typically, in two-sided digital business model consumers exploit the benefits offered by the platform, while the business side takes advantage of the size of the audience, its characteristics and the usefulness of the data derived. So, business companies are subsidizers, that pay to reach the audience and benefit from its private data (“privacy capital”) and consumers are “loss leaders”, that provide personal data in exchange for service usage.

Summarizing, in most of the cases end-users constitute an audience which can be monetized because of its size or because of its demographic, psychographic or behavioural characteristics, so they are the value proposition for B2B segment. The monetization is “B2B oriented”.

Internet-based business models often are open business models, who rely on the co-creation with users and consequently they evolve over time. Muzellec et al. (2015) elaborated a model that explains how business model changes over time, focusing on four stages:
1. Embryonic stage, which is concentrated on the development of the product technology necessary to deliver the value proposition. At this stage the marketing strategy is not clearly defined yet and services are tested in alpha or beta versions to improve the technology;

2. Emerging stage, which is centred on delivering the value proposition to end-users to get them on board, while ignoring business targets. As the goal is to validate the offer and reach critical mass, services at this stage are offered for free through the first operational platform. Activities are B2C-oriented, so they are supported by a “front-office marketing strategy” which relies on search engine optimization and push communications on social media;

3. Growth stage, which shifts the focus to the business side, that is now interested since the platform has reached a valuable audience. The value proposition and the marketing strategy need to be realigned to target the business side and generate revenues;

4. Maturity stage, that focuses on the creation of a balanced value proposition that targets both end-users and business side. Here, two different models could emerge: B2B&C oriented business model or B2C&B oriented business model. In the first case the main value proposition targets the business side, offering them to co-develop dedicated applications that are used to provide additional services to their clients. In this case the end-user website is a promotional showcase for B2B value propositions (back-office marketing strategy);
In the B2C&B oriented business model, the main value proposition is directed to end-users (front-office marketing strategy), which become part of the value proposition for a business audience. Indeed, the platform monetizes consumers segments to business partners, offering them the marketing ability to reach the audience through search engine optimization tools.

However, in both cases the business side forces the platform to design a balanced value proposition which includes services that are interesting for both end-users and business side.
Non-Transaction Two-sided Markets

This type of two-sided markets, such as most media markets, are characterised by the absence of a transaction between the two sides. Because the interaction is not observable, it is not possible for the firm to charge for a transaction-sensitive fee, but only for a transaction-insensitive one. This means that often non-transaction business models offer the core product or service to one group and then sell access to that group to the other side, which is charged a membership fee to access the network. The key point is always which side to charge and which side to subsidy. The model proposed by Parker and Van Alstyne (2000) suggests that intermediary or platform firms in non-transaction two-sided markets can raise profits by giving products away because the increased demand in a complementary market can cover the costs of investment in the free one, as long as the platform can internalize the network effects.

The diffusion of information and communication technologies made available to the mass market an increasing number of services that used to be bounded by physical constraints, consequently strengthening two phenomena: from one side it has emphasised the role of two-sided markets as gatekeepers of information and value flows between different groups of stakeholders (Ballon & Heesvelde, 2011); on the other side the diffusion of ICT led to stronger competition, which resulted in the digital service = free equation (Trabucchi et al., 2017). Therefore, non-transaction two-sided markets were forced to find new revenue streams for profitability. The answering strategies at a business level are:

- Freemium business models;
- In-app purchase models, which provide the basic service for free but offer users opportunities to enrich their experience with it through paid add-ons;
- Cross-selling models, in which companies offer a free service that supports a physical product (i.e. Fitbit’s mobile app that complement the fitness tracker).

These strategies are only a first attempt to innovate the revenue streams that lead two-sided digital services to profitability. Nowadays, the diffusion of information technologies and the pervasive use of digital services in users’ life enable a wide range of new opportunities, leveraging new assets that are generated in co-creation with users. Indeed, the considerable quantities of data that customers generate in using digital services represents a new type of asset that characterizes the digital revolution.

Data itself is not new to companies, as often firms have been using them to support business. In fact, many firms exploit data in their hands to manage employees, track their sales and obtain insights about customer behaviour. But over the last few years, the amount of data available
has exponentially increased as a result of the emergence of new devices, sensors, social media, and other sources, supporting the conceptualization of Big Data.

The technology research firm Gartner defined Big Data as “high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making” (Gartner, 2012). Nowadays, Big Data are characterized by 5 Vs (Lau, Zao; 2016):

- **Volume**, which refers to the magnitude of data. Normally this measure is in terms of terabytes or petabytes, however it should be context specific and not universal;
- **Velocity**, which refers to the production rate of data, that influence the data collection rate and data analysis rate, that should be aligned with the speed at which data are generated;
- **Variety**, which refers to the heterogeneities of the structures, formats and sources of data. We can distinguish between structured data (i.e. ratings or questions with binary answers), semi-structured data (they incorporate various types of software that can bring order to unstructured data) and unstructured data, typically user-generated contents such as images, comments or audios.
- **Veracity**, which refers to the uncertainty linked to the quality and validity of data within an enormous data set. It is necessary to have effective filtering techniques to isolate low-quality data and then apply analysis techniques only to the high-quality dataset;
- **Value**, which refers to the relative value density of big sets of data. For example, a huge number of clickstreams in a website has little business value unless it is possible to identify which customers are involved in the clickstreams and what are their behavioural patterns.

It is interesting to notice that a considerable portion of Big Data are generated by users interacting with existing digital products and services: they are called User Generated Big Data (UGBD). They require low level of awareness from users (passive contribution) and also allow a high level of generalizability. They furnish a deep understanding of how consumers interact and leverage digital technologies, and consequently their needs (Trabucchi et al.; 2017). The use of UGBD can be a source of competitive advantage: in fact, the 2014 IBM innovation survey found that “organizations using big data and analytics within their innovation processes are 36% more likely to beat their competitors in terms of revenue growth and operating efficiency” (Marshall et al., 2015; Sorescu, 2017).
Big Data have been exploited mainly in marketing strategies, to implement more effective solutions to target customers. These include pricing strategies that leverage dynamic pricing, the use of sophisticated location-based recommendations and targeted marketing services. However, these are only a few possible applications: there is much more value in big data. The next paragraph examines how business model strategies can exploit these potentialities to create competitive advantage.

2.1.2.2 User-generated Big Data Enabled Strategies in Two-sided Markets

This paragraph is focused on how digital two-sided platforms can apply different strategies to leverage user-generated big data, capturing value and sustaining a free-to-consumers business model (Trabucchi et al; 2017). In fact, these platforms enable rich interactions among two groups of users, which generate data that have a much finer granularity and are recorded at much higher frequencies than those from traditional offline platforms (Sriram et al; 2015). Also, as products are becoming more and more digitalized, the potentialities of combining two-sided market structures with the huge volume of user-generated data opens up a set of business opportunities in which data represent a complementary market.

Trabucchi et al. (2017) identify three possible strategies to leverage user-generated big data (UGBD):

1. **Enhanced Advertising**, in which users are a target for revenue-generating activities, not a source of revenues. Consumers also act as a data source, which is used for making advertising more targeted. For example, Runtastic uses “information gathered from users via smartphone sensors to offer highly contextualized advertising messages and links to advertisers that make ads look like the answer to users’ needs, for instance, rewards for reaching workout goals that link users to advertisers, such as a special discount with an advertising partner” (Trabucchi, Buganza, Pellizzoni; 2017; p. 47).

![Figure 11 - Adapted from "Give away your digital services" (Trabucchi, Buganza, Pellizzoni; 2017) - Enhanced advertising model](image-url)
2. **e-Ethnography**, in which consumers are a data source that is not a direct source of revenues, but it is used to support and improve products and services and to develop better relationships with customers. UGBD can be exploited for two types of “using data” strategies: the first application aims at enlarging the bundle of activities within the service; the second application aims at moving to the adjacent activity chains. For example, Deliveroo⁴ provides restaurants with insights on customer satisfaction or on the average time per order, shaping a meaningful value proposition also for food providers (Trabucchi et al.; 2017). This strategy is more common in companies that use the two-sided platform to integrate their core business, such as Nike with Nike+ Running. Concluding, e-ethnography can be associated to the category where data are used to drive operational improvements; 

![Diagram of e-Ethnography model](image)

*Figure 12 - Adapted from "Give away your digital services" (Trabucchi, Buganza, Pellizzoni; 2017) - e-Ethnography model*

3. **Data trading**, in which user-generated data are a direct source of revenues. In fact, digital platforms, especially when they are linked to a physical device, produce a huge volume of data, which can be useful for third parties. For example, Strava, a mobile ride-tracking app for bicyclists, sells data to many departments of transportation in London, Glasgow, Orlando and other cities. In this strategy data are normally sold to a very distant business. This strategy can be associated with the category in which data are an asset.

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⁴ Deliveroo is an online food delivery company, whose mission is to bring world’s local restaurants into everyone’s home or office – fast.
2.1.3 Data-driven Business Models

As it emerges from the previous paragraph, user-generated big data nowadays are a valuable asset, that can be leveraged to open new revenue streams. Summarizing, Trabucchi et al. (2017) identified three different strategies that two-sided markets apply to unlock the potentialities of user-generated big data. This paragraph takes a broader view and generally analyses the types of business models that can be built around the key asset of data.

A data-driven business model is defined only after a clear data strategy has been outlined. A good data strategy is not determined by what data is readily or potentially available, but it is about setting a clear objective and identifying how data can support and facilitate the way to this goal. The possible objectives (Spiekermann et al., 2015) can be divided into three categories of application of big data:

- Data as strategic capital to improve decisions making;
- Data as strategic capital to drive operational improvements;
- Data as an asset itself, a product that can be monetized.

Data is becoming an increasingly important input into the decision-making process and this is probably the most common application of Big Data (B. Marr, 2017). Indeed, data provide valuable insights that help in identifying criticalities and finding solutions. Nowadays, the most common strategy is to use data to better understand customers and markets, to make decisions that are rooted not in assumptions, but in data. Companies get a full picture of their customers, receiving data about who they are, where they are, their behaviour and preferences, so they can better interact with customers. Data are also useful to identify in customers or in the whole industry some trends, which can be used to make predictions.
However, so far, few academic papers have described or analysed business models relying on data. Hartmann et al. (2016) provide a conceptualization of data-driven business models (DDBMs), focusing on companies that use data as a key resource in their business model. In their formulation, a DDBM is not limited to companies conducting analytics, but includes companies that are “merely” aggregating or collecting data. Also, a company may sell not just data or information but also any other product or service that relies on data as a key resource.

Hartmann et al. (2016) developed a framework that identifies six common dimensions constituting a data-driven business model: key resources, key activities, offering / value proposition, customer segment, revenue model and cost structure.

By definition a DDBM has data as a key resource, even though it is not the only one. Data sources needs to be distinguished into internal and external sources. Internal sources include: data that is currently created through existing IT systems (i.e. ERP, CRM data), but which is not used; data generated for the specific purpose, through web-tracking, sensors or crowdsourcing; and data that is created by an ecosystem of contributors through collaborations. External data sources comprehend: acquired data purchased from data providers or social media companies; data that is provided by customers or business firms and not available to the general public; and freely available data, which is publicly available with no direct costs. The latter class can be further subdivided into three categories: open data, which is free, downloadable, machine readable, and structured without prior processing (Lakomaa, Kallberg; 2013); social media data; and web-crawled data, which is publicly available but not in a database format (i.e. full text documents).

The key activities that extract value from data follow the “virtual value chain”: data generation and data acquisition (gathering process), data processing and data aggregation (organising and selecting process), data analytics (synthesising process) and data distribution.

The offering can be divided into: raw data; information or knowledge, which is data with interpretation (i.e. the output of analytics); and non-data product/service.

The dimensions of customer segments and revenue model for a DDBM are common to any business model. The cost structure is differential only in the case of a firm that has a specific cost advantage regarding data use. This occurs if the data used in its product or service are created independently of the specific offering (i.e. Twitter can use its own data without additional costs to provide an analytical service).
2.1.4 Big data platforms: service-dominant logic perspective

As aforementioned, due to the increasing number of users of digital services, companies foster the perception that platforms are provided for free; indeed, individuals are required to provide personal information to enjoy them, but they are not required to pay. Consumers provide detailed information about their preferences through their online activities which permits individuals to be targeted with far greater precision than ever before. For consumers, therefore, personal information operates as a currency, and sometimes the sole currency, in the exchange of online services. Therefore, users have an active role in the realization of company’s business models and consequently profits. This paragraph aims at analysing data-driven business model focusing on the co-creation of value and on the key role of users in this process, which is investigated by service-dominant logic literature.

Service-dominant logic starts from the concept that firms cannot deliver value, they can only offer potential value, which is realized through customer usage (Xie et al; 2016).

According to S-D logic literature (Vargo & Lusch, 2008; Xie et al., 2016), all agents are resource integrators, but firms and customers integrate resources differently. The integration process to which both actors participate creates value, that is materialized in cooperative assets. The
centre of our attention are cooperative assets created through big data. This is due to the fact that IT technologies have empowered firms to be more customers-centric and to collect and manage customer data, in order to respond to market changes and be competitive. Therefore, big data platforms represent an interesting channel for firms to co-create value with customers.

Big data platforms are digital service platforms enabled by big data technologies. There are many types of big data platforms: online transaction platforms that support exchanges; virtual social networking platforms that support communication within communities; open-design platforms that enable customer self-design; and mobile interaction platforms that enable customer-firm communication.

Xie et al. (2016) conducted an interesting study that identified four different customer roles, that generate four types of big data resources that are linked to four types of big data platforms provided by firms:

1. When customers are buyers, they generate transaction big data, which mainly are information related to purchasing behaviour, including price, product category, colour, numbers, location, demographics, etc. This resource can be found in a transaction platform, which is a digital service platform that supports customer purchasing and enables the collection and transmission of transaction big data (i.e. shopping platform connected to ERPs and CRMs). This information can be used internally to guide transaction operations and improves sales performance.

2. When customers are ideators, they generate communicational big data, normally by purchasing through interactive websites, instant messages, telephone lines. (i.e. customer feedbacks and complaints, virtual social platforms, emotional feeling, favourite topics). This resource is generated through communication platforms, which are digital service platforms that support customer group communication and enable the collection and transmission of communication big data (i.e. forums, fan clubs). This information constitutes the basis for data analytics on customer needs.

3. When customers are designers, they generate participative big data, which are linked to the reconfiguration of product and services, thanks to an active user’s participation in product development. This is possible through participative platforms, which are digital service platforms that support firms’ attraction of customers to involve them in the product development process (i.e. room open-design platform). This information can be really valuable in the innovation process, both for processes improvement and for reconfiguration of products and services.
4. When customers are intermediaries, they generate transboundary big data by sharing different service ecosystems and facilitate import and export of knowledge across them (i.e. customer standard on delivery time). This is possible through a transboundary platform, which is a digital service platform that supports firms in acquiring new knowledge shared by customers who build connections across diverse ecosystems (i.e. multi-brand and multi-industrial virtual communities). This information help firms and customers acquiring heterogeneous knowledge and being aligned with the market.

Concluding, this classification of big data resources and platforms shows that all the above-mentioned classes provide information that can be used internally by the firm to improve its business model, opening a wide range of opportunities.

2. 2 Information technologies adoption and privacy

With the diffusion of information technologies, two-sided business models proliferated on the market, as interaction became much easier and faster. Digital interactions imply the fact that users leave “traces” about how they interact with other users and with the digital services itself: these “traces” are user-generated big data, that can be strategically leveraged by companies to create value. The increasing importance of User-generated Big Data in digital platforms is directly linked to a privacy topic. As aforementioned, when end-users access the platform, they leave a “digital footprint” that can be followed, analysed and monetized. The privacy capital they provide needs to be examined from a privacy perspective. Therefore, this paragraph will firstly focus on generally understanding the drivers of IT services acceptance and usage; secondly the role of privacy in IT services usage will be examined, to investigate whether in the state-of-art of literature privacy affects users’ willingness to adopt digital services.

2. 2. 1 Information technologies adoption theories

User acceptance of new technologies is one of the most mature research areas in the information systems literature, investigating how and why users adopt new information technologies. Research in this area has resulted in several theoretical models, with roots in information systems, psychology and sociology. Unified Theory of Acceptance and Use of
Technology (UTAUT) (Venkatesh et al.; 2003) gives a general overview of the current state of art of literature, comparing and then unifying eight different theories:

- **Theory of reasoned action (TRA)** (Fishbein and Ajzen, 1975). It states that consumers adoption depends on both attitude towards behaviour, which is an individual’s positive or negative feelings about performing the target behaviour, and subjective norm, which is the person’s perception that most people who are important to him think he should or should not perform the behaviour in question.

- **Technology acceptance model (TAM)** (Davis, 1989). This model was developed by Davis and his colleagues and it is one of the most applied frameworks. It states that users’ adoption depends on perceived usefulness, which is the degree to which a person believes that using a particular system would enhance his or her job performance; perceived ease of use, which is the degree to which a person believes that using a particular system would be free of effort; and subjective norm.

- **Motivational model (MM)** (Davis et al, 1992). It states that consumers adoption depends on both extrinsic motivation and intrinsic motivation;

- **Theory of planned behaviour (TPB)** (Ajzen, 1985). This theory is grounded in social psychology, but it is a general framework that was applied in many diverse use cases. It states that consumers adoption depends on attitude toward behaviour, subjective norm and perceived behavioural control, which is the perception of internal and external constraints on behaviour;

- **Model combining TAM and TPB** (Taylor &Todd, 1995);

- **Model of PC utilization (MPCU)** (Thompson et al. 1991). It states that consumers adoption depends on job-fit; complexity of use; long-term consequences; affect towards use, which are the positive or negative feelings associated to the usage; social factors and facilitating conditions, which are the objective factors in the environment that observers perceive as enablers for some actions;

- **Innovation diffusion theory (IDT)** (Rogers, 1995). It states that the rate of adoption of an innovation is partially determined by its perceived attributes. In this model the diffusion of an innovation depends on relative advantage; ease of use; image, which is the degree to which an innovation brings image or status advantages; visibility; compatibility with existing values and needs or potential adopters; results demonstrability, in terms of observability and communicability; and voluntariness of use.

- **Social cognitive theory (SCT)**. It is not mentioned as it uses adoption as a dependent variable.
According to UTAUT research model (Venkatesh et al., 2003), users’ adoption of an information technology is affected by four determinants of intention and usage, that can be found also in the abovementioned theories:

1. Performance expectancy, that includes perceived usefulness and relative advantage;
2. Effort expectancy, which is similar to the perceived ease of use and complexity;
3. Social influence, which is similar to subjective norms;
4. Facilitating conditions, which are the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system.

The model also considers some moderating factors that influence the relationship between the independent variables and the dependent variable:

1. Gender;
2. Age;
3. Experience;
4. Voluntariness of use.

For many years UTAUT has been used as a baseline model in several studies. As UTAUT research model was originally developed to explain employee technology acceptance and use, UTAUT 2 was developed to extend the model to other contexts, such as consumer technologies. In this analysis new relationships between moderating factors and constructs were proposed and three

\[Figure 15 - Adapted from "User acceptance of information technology: Toward a unified view" (Venkatesh et al., 2003)\]
additional constructs were included in the scheme: hedonic motivation, which is the fun or pleasure derived from using a technology; price value, which is consumers’ cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them; and habit, which is the extent to which people tend to perform behaviours automatically because of learning.

![Diagram](image)

**Figure 16 - Adapted from “Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology” (Venkatesh et al., 2012)**

In the current state-of-art of literature there are three main types of UTAUT extensions (Venkatesh et al., 2012):

1. Examination of UTAUT in new contexts, such as new technologies, new user populations and new cultural settings;
2. The addition of new constructs in order to expand the scope of the endogenous theoretical mechanisms outlined in UTAUT;
3. The inclusion of exogenous predictors of the UTAUT variables.

### 2.2 Privacy in IT adoption

Within the abovementioned studies, some research models started including privacy as an independent variable affecting consumers adoption of information technologies. In fact, Acquisti et al. (2013) state that understanding the value that individuals assign to the protection
of their personal data is crucial for business, in order to take more conscious decisions in designing platforms. It is necessary to identify privacy-enhancing initiatives that create competitive advantage and potentially intrusive initiatives that trigger adverse reactions in end-users. A first distinction that needs to be specified is between privacy and security. Privacy involves users’ willingness to share information online, the ability to control and eventually choose to divulge personal information. Control of personal data and privacy are not necessarily synonymous. For example, a user may not have control over how a credit card number is used in an e-commerce transaction once it is submitted online, but the individual does have an expectation of privacy in this scenario (i.e. the credit card number will be kept private and not shared). Security is related to the protection against threats from unauthorised access to personal information.

In privacy literature, many studies have investigated the relationship between personalization and privacy. In fact, online services offer an important trade-off: the more the service is personalized, the more personal information users have to share. This leads to the personalization-and-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 Unger; 2012, p. 625). In fact, when using a platform service, users typically accept some conditions to what extent personal data is collected and processed. In some cases, the provision of personal data is necessary to use a platform service (i.e. social networks) while in other cases services do not require the collection of user data per se (e.g. search engines or video platforms). In both cases the provision of data from a user perspective can be interpreted as a price the user is willing to accept in exchange for the use of the platform.

There are many forms of online personalized product offerings and services such as personalized YouTube features, Spotify customized music playlists or Google personalized results based on individuals’ search queries. Research has found that it is more effective to use personalization techniques in an online than in an offline environment, because of the possibility to leverage user-generated big data that lead to real time recommendations (Li, Unger; 2012). However, online personalization services belong to a class of economic goods with a “no free disposal” (NFD) property, which means that consumers do not always prefer more services to less because of the privacy concerns (Chellappa, Shivendu; 2010, p. 1766). Even though personalization has some clear benefits in terms of customer needs fulfilment and loyalty increase; it is intrinsically related to some hidden privacy costs that hinder user’s adoption. First of all, customers have privacy concerns that may prevent them from using online personalized services, therefore the
value of personalization needs to outweigh these concerns to improve consumers’ adoption. Secondly, there may be a trust problem as it may happen that consumers do not trust the web environment to the point that it can deter the service adoption. However, companies can mitigate this problem by improving website quality and reputation in order to build trust and overcome customers’ doubts. These costs are modelled in research models under several perspectives of analysis, however the common examined dimensions are:

- Privacy concern (Zhou; 2012), which reflects users’ concern on personal information disclosure. This dimension is highly influenced by personal traits (Spiekermann et al., 2015), as users may be afraid that their habits and interests can be predicted, or they may fear unauthorized access to accounts. Privacy concern not only negatively affects users’ adoption, but also lowers users trust in service providers.

- Perceived risk and trust (Zhou; 2012). Trust reflects a party’s willingness to be vulnerable, as it has positive expectations on another party’s future behaviour. It often includes ability, integrity and benevolence. Ability means that service providers have the knowledge and skills to fulfil their tasks; integrity means that service providers keep their promise; benevolence means that service providers care about users’ interests and not just about their own benefits. Trust has a positive impact on usage intention and mitigates perceived risk, that has a negative impact on users’ adoption.

These dimensions highly depend on personal traits and preferences. In fact, Hann et al. (2007) developed a classification that distinguish between three different classes of users: privacy guardians, information sellers and convenience seekers. This classification considers that online personalized services offer both an advantage in terms of convenience, as they facilitate and customize a service, and sometimes also in monetary terms, offering rewards to users. Privacy guardians are those users who attach a relatively high value to information privacy, being small users of personalized service and assigning great monetary value to their personal data. Information sellers are those users who attach a relatively high value to monetary reward, as they have past experiences in “selling” personal information with little regard for convenience or Website privacy policies. Finally, convenience seekers are those users who value the most convenience, deriving great value from the service and ignoring both monetary reward or website privacy policies. Given these differences between users, firms should target first convenience seekers, who are looking for the advantages that could derive from the service subscription (i.e. simplification of website navigation or personalization of contents). Then, if firms want to target also information sellers, they should use monetary rewards to attract them to provide personal information. By elimination, the individuals who do not respond to either
monetary reward or convenience are privacy guardians. This is an example of strategy that considers personal privacy concerns to take more effective decisions.

As it also emerges from the classification provided by Hann et al. (2007), another key aspect that has been deeply investigated in the privacy literature is privacy valuations, which focused on trying to understand the exact individuals’ monetary valuation of privacy. Most of these efforts have concentrated on individuals’ propensity to accept payment in exchange for disclosing private information (Acquisti et al.; 2013). From the economics perspective, a first set of studies focuses on individuals’ WTA, which is the lowest price a person would accept to sell the protection of her personal data, that she initially owned. A second set of studies focuses on individuals’ WTP, which is the maximum price a person would pay to acquire the protection of her data. In the privacy literature, these two standpoints are treated as equivalent. However economic experiments have discovered a discrepancy between WTP and WTA and various experiments tried to explain this gap. The dichotomy between WTP and WTA is still unclear and it appears to be context-dependent and malleable. This suggests that ordinary studies investigating privacy valuations may not tell us much about whether consumers will actually pay to protect their data (Acquisti et al.; 2013).
3. Research question and research model

“Digital footprints are the digital ‘cookie crumbs’ that we all leave when we use some form of digital service [...] this happens regardless of whether we are actually cognisant of this. We intuitively accept, when forced to think about it, that these traces exist and we somehow expect that, over time, the waves will wash over the digital footprints to erase them like the ones on the beach – but they are not. Like everything on the web, digital data cannot be washed away, it remains forever, but we could actually benefit from taking control of our own digital footprint” (My Digital Footprint, T. Fish, 2009)

So far, we have examined the concepts of two-sided markets, investigating both engineering design and economics perspectives, also focusing on a business model perspective. Indeed, with the digital revolution the business models that two-sided markets leverage can rely on new assets. Specifically, we analysed the role of user-generated big data and the enabled opportunities to unlock their value. It clearly emerged that nowadays data is an asset (Spiekermann et al., 2015) that can be monetized. We then investigated the drivers of information technologies adoption and how they changed over time, until the inclusion of privacy and security in the research models.

Given that nowadays two-sided platforms enable rich and dynamic interactions among participants on both sides and among the platform and its participants, these relationships support the creation of a huge amount of data that open up a wide range of opportunities. Two-sided platforms have developed many strategies to leverage user-generated big data, implementing in the end also “data selling” strategies. In fact, “due to Internet users’ apparent comfort with sharing their data, more and more organizations today engage in the trading of consumer data” (Spiekermann et al., 2015, p. 162). Leveraging data to open new revenue streams includes worrying about privacy implications. It is not interesting anymore to investigate digital business models discriminating on privacy dimensions, because nowadays all the digital services have a quite common privacy and security policy, that involves data trading with third parties. On the other hand, information technologies literature has already deeply investigated the drivers of user adoption, however mainly focusing on privacy valuation or on the relationship

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\(^5\) A digital footprint is the persistence of data trails online by a user’s activity in a digital environment (T. Fish; 2009)
between personalization and privacy. In fact, considering as a baseline the UTAUT 2 model, which has been adapted to consumer technologies cases, and its extensions, it emerges that privacy is only one of the many independent variables modelled in the research frameworks.

This research completely changes the perspective: the dimension related to privacy is not anymore considered as one of the drivers affecting users’ adoption, but it is included in the two-sided platform business model, as it happens in real business cases. Indeed, as aforementioned, nowadays digital services relying on two-sided business models insert user-generated big data in their value proposition towards one of the two sides, deriving a direct source of revenues from them. Therefore, this research is focused on investigating how companies’ transparency about their business model and consequently about the platform’s usage of UGBD affects users’ service adoption. In fact, from Trabucchi et al. (2017) study, it emerges that in many two-sided platforms, including Twitter, Spotify, Strava and Deliveroo, the level of users’ awareness about their contribution to the service provider business model is low. This means that the current state-of-art of literature has not deeply examined this correlation. In fact, Spiekermann et al. (2015) clearly question whether “will people not want to continue freely to communicate online, chat, talk, post and provide their data”.

Concluding, this study aims to clarify the relationship between business model clearness and users’ service adoption, as “end-users are being used but they are not necessarily a negotiating party that is willing to exchange data” (Muzellec, Ronteau, Lambkin; 2015, p. 141).

Q. Investigate whether business model clearness about UGBG usage affects users’ adoption of digital two-sided services.

The following figure synthetizes all the constructs that constitute the research model.
To build this research model, a deep analysis on the literature was conducted. The aim was to understand, also considering other use cases, how to design an experiment that tests the research model. This procedure will be better explained in chapter 4.1.

3.1 Constructs and Hypothesis

In the research model, there is a distinction between the independent variable and the control variables, that moderate the relationship between the independent and the dependent variable. This choice is due to the fact that experiments need to focus on one causal relationship between an independent and a dependent variable, as it will be better explained in chapter 4.1.

**Business Model Clearrness**

The independent variable is the Business Model Clearrness: this dimension is constituted by two values, Transparent Business Model and Opaque Business Model, that represent two possible and mutually exclusives values. This dimension does not come from literature, but it is self-developed “ad hoc” on the needs of the research question. In fact, as aforementioned, the existing models in digital services adoption literature focus on other independent variables, that in this case are not relevant to fill the research gap.

A relevant analysis was conducted by Baird and Raghu (2015), who carried on a study based on personal health records (PHR) services, aiming at demonstrating that consumer value for digital service business models may be quite different even when consumers have similar preferences for standard technology characteristics. This means that variations in the underlying digital
service business model are likely to have significant impacts on consumer valuations of the digital service. The introduction of the business model as an independent variable affecting users’ adoption of digital service is new compared to the common perspective, as Information Technologies literature has focused on several drivers affecting users’ adoption, however all coming from the same dimensions of performance expectancy, effort expectancy, social factors, and facilitating conditions (Venketesh et al., 2003; Dwivedi et al., 2017). Therefore, this research aims at better understanding the role of business model in users’ adoption of digital two-sided services.

As service-dominant logic states (Xie et al., 2016), the role of users in companies’ business model is fundamental; in fact, firms cannot deliver value, they can only offer potential value, which is realized through customer usage. Customers can cover several roles — buyers, ideators, designers or intermediaries — but in each case their contribution is critical for the realization of firms’ value proposition. While interacting with the service and realizing its value proposition, users leave behind digital marks of their interaction (Trabucchi et al., 2017). This happens because “the mechanism that leads the user to provide those data is a typical quid pro quo one. [...] Customers have no problem leaving this digital information behind as it is necessary to enjoy the service. Moreover, this information has little value per se unless you join together large amounts of it. [...] The level of awareness of users in contributing is low, while the context has an influence on the user’s contribution” (Trabucchi et al., 2017, p. 8 - 9). This means that normally users are not aware of the value hidden in their privacy capital. Considering Information technologies literature, particularly focusing on privacy topics, scholars introduce the concept of information transparency as a measure of customer awareness of how companies deal with the data they collect from customers (Malhotra et al, 2004). It is well-agreed that awareness is a very important dimension to take into consideration when customers are confronted with a request to reveal more private information. In fact, “consumers may be largely unaware of the privacy implications of disclosing their information, and so may not see the privacy downside. For example, many people disclose their Facebook profiles to play quizzes, not realizing that the quiz app retains their complete profile information, which can be used by marketers” (Li, Unger, 2010, p. 622).

Many previous researches have provided insights that information transparency and privacy concerns have a negative influence on customers’ willingness to adopt the service (Awad, Krishnan, 2006; Kim, Son, 2009); therefore:

**H1. Business Model Clearness negatively influence Digital Two-sided Service Adoption.**
Privacy Attitude

Privacy attitude is a construct that is adapted from Chellappa and Sin (2005) scale and it includes four measurement items. This scale measures people’s concern towards the collection and use of different types of personal information:

- Anonymous information, which refers to the standard information sent with any Internet request. Such information includes machine’s IP address, domain type, browser version and type, operating system, browser language, and local time;
- Personally unidentifiable information, which refers to information that, taken alone, cannot be used to identify or locate an individual. They comprehend age, date of birth, gender, occupation, education, income, interest and hobbies. Personally unidentifiable information also often involves the use of sophisticated tracking technologies (e.g. cookies) which enable the information-collecting entity to design an effective customer profile;
- Personally identifiable information, which refers to information that can be used to identify or locate an individual. They comprehend email addresses, name, address, geographical position, phone number, credit card number, etc. Personally identifiable information is almost always collected explicitly from the customer.

Research in Information Communication Technologies and Marketing has argued that information privacy and consumer concern can be considered in the most important issues of today’s technology-based environment (Miyazaki & Fernandez, 2000; Stewart & Segars, 2002). A report from the FTC states that even though often digital online services gather anonymous information, it often happens that the profiles derived from tracking consumers’ activities on the Web are linked or merged with personally identifiable information. This consumer data can also be combined with data on the consumer’s offline purchases, or information collected directly from consumers through surveys and registration forms. Therefore, in the online context consumers are not only concerned about the privacy of their personally identifiable information but also other information that can be linked together later.

Many recent studies have shown that consumers may not be willing to share information about themselves due to concern for privacy and that consumers may still choose to not use digital

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services if their privacy concerns that arise from the associated information sharing overcome the benefits deriving from service usage (Chellappa, Sin, 2005). Therefore:

**H2.** Privacy attitude negatively influences Digital Two-sided Service Adoption: keeping the other variable constant, the higher privacy attitude, the lower the adoption.

**Propensity to Innovative Services**

Propensity to Innovative Services is a construct adapted from Yi et al. (2006), which considers the fact that individuals have different personal traits and some of them are more willing to take risks and try innovations, while others are more hesitant. According to Innovation Diffusion Theory, people act differently due to their dissimilarities in innovativeness, a predisposed tendency toward adopting an innovation. Rogers (1962) divides users into five groups: innovators, early adopters, early majority, late majority and laggards.

![Figure 18 - Rogers Innovation Diffusion Theory Model](image)

The green line shows the adoption from all the groups over time, while the yellow line indicates the market share that in the end reaches saturation.

The construct that is used in this research is based on four items and it is adapted to the case of an innovative digital two-sided service. It is hypothesised that the more innovative the person, the more willing he or she will be to adopt an innovative digital service as well. In fact, many researches have introduced individual characteristics in their research model explaining users’ adoption, as explained in chapter 2.2.2.
As Information Communication Technology literature highlights that several individual characteristics including attitude, computer self-efficacy, and personal innovativeness influence users’ adoption (Dwivedi et al., 2017), we assume that:

**H3.** Propensity to innovative services positively influences Digital Two-sided Service Adoption: keeping the other variable constant, the higher the propensity to innovative services, the higher the adoption.

**Other Control Variables**

The other control variables mainly come from literature, but they have been adapted to fit the specific context.

These control variables are mostly demographics, such as age, gender and education, which is measured according to Awad and Krishnan (2006) scale: less than high school, high school, bachelor’s degree, master degree, PhD. According to Awad and Krishnan (2006, p. 20), “having a more educated population that is familiar with the Internet may imply that the overall sample is actually less worried about information misuse on the Internet than a national sample” (Klobas, Clyde, 2000). This implies that the higher the level of education, the higher the probability that users adopt the digital service. Therefore:

**H4.** Education positively influences Digital Two-sided Service Adoption: keeping the other variables constant, the higher the education level, the higher the adoption.

As aforementioned in chapter 2. 2. 2., Information Communication Technology adoption considers UTAUT model (Venkatesh, 2003) as a baseline, therefore this research model takes into consideration the moderating factors that were implemented in UTAUT model to evaluate which ones might be interesting in this research study.

The UTAUT model analyses and unifies all the theories developed under one unique model, stating that gender and age differences have been shown to influence the adoption in technology adoption contexts (Morris and Venkatesh 2000; Venkatesh and Morris 2000). In looking at gender and age effects, it is interesting to note that Levy (1988) suggests that studies of gender differences can be misleading without reference to age. Therefore:

**H5.** The influence of Business Model Clearness on Digital Two-sided Service Adoption is moderated by age and gender.
The proposed research model is ready to be verified with empirical data gathered through an experiment.
4. Research Methodology

This chapter is devoted to the description and analysis of the methodology implemented in the entire study, that led to the answer to the research question. Firstly, it is explained why the experiment was chosen as a tool to test the research question and how the experiment was designed (chapter 4.1). Then, it is presented the empirical setting that was chosen to investigate the research question (chapter 4.2) and how the constructs of the research model were translated into items (chapter 4.3). Finally, it is described how the data was actually gathered (chapter 4.4).

Considering the literature analysis, articles were gathered through Scopus (www.scopus.com), Scholar (www.scholar.google.it) and Cible+ databases, which allowed to accomplish the collection phase. This starting point is crucial because it allows to understand the main research areas on the selected topics and to understand the theories developed.

4.1 Experiment Design

Q. Investigate whether business model cleanness about UGBG usage affects users’ adoption of digital two-sided services.

To carry out the study, the research question is tested through an experiment. In fact, this tool is very effective in case of new business models that generate new revenue streams, which is the case of digital two-sided markets that exploit UGBD as a monetizable asset. Therefore, a fitting empirical setting was needed.

The experiment includes service mock-ups and a survey and it was distributed through the software Qualtrics. To assess the constructs of the research model, the survey considers items deriving from literature, that have been adapted to fit the context. Items were assessed on a 5-points Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Chapter 4. 1. 1. focuses on highlighting the current role of experiments in business literature; chapter 4. 1. 2 describes a first experiment classification elaborated by Podsakoff P. and Podsakoff N. (2018); chapter 4. 1. 3 explains the taxonomy of field experiments proposed by Carpenter et al. (2004). Then, chapter 4. 1. 4 illustrates the procedure that led to the experiment
design and finally chapter 4. 1. 4 concentrates on explaining the methodology selected to conduct the experiment.

4.1.1 The role of experiments in research studies

As Ganguly & Euchner (2018) state, new business models are characterized by high uncertainty, because they may need new channels, new partnerships or new customer segments, they may rely on different marketing strategies, revenue models or technologies. These risks can become proper barriers, preventing companies from entering new business opportunities. In this context, well-designed business experiments are a valuable tool for reducing these risks. They enable companies to deeply understand the underlying assumptions of new business opportunities and therefore reduce related uncertainties. This means that experiments can be used to understand, quantify, and reduce risks of a new business model. “Experiments have been used to quantify value creation, test customers’ willingness to pay, understand an unfamiliar technology in use, design ways of shaping user behaviour, measure channel effectiveness, quantify costs of providing a service, and test the effectiveness of new partnerships” (Ganguly, Euchner, 2018).

Experiments belong to Experimental Research literature. According to Posdakoff P. and Posdakoff N. (2018), this tool is really appreciated for its power to establish cause-and-effect relationships, consequently becoming critical for knowledge development in organizational and behavioural sciences. This perspective is supported by other scholars, who have referred to experiments as the “gold standard” of scientific research. Particularly, Jones in his book (1985, p.282) stated that experiments are “the most powerful technique available for demonstrating causal relationships between variables”.

However, to be effective an experiment needs to be well-designed. In fact, experiments help in answering research questions like “What is the impact of X on Y?”, which means that they should be focused on one research question and a few well-chosen factors. Mixing multiple assumptions in one big experiment can allow interactions that produce inconclusive results.

4.1.2 Classifying experimental research designs

There are many types of possible experiment designs, but the most widely used ones in management and leadership research are laboratory experiments, field experiments, and quasi-experiments. To understand to which category an experiment belongs to, Podsakoff P. and
Podsakoff N. (2018) designed a framework, that divides experiments according to three questions.

1. The first question is whether the independent variable is explicitly manipulated or not. In a study designed to determine if changes in an independent variable impact on a dependent variable, there should be at least two different treatment conditions. For example, a research study investigating the simple question of what effect the manipulation of an independent variable has on a dependent variable, could exploit the comparison between a treatment group and a control group that does not receive the treatment. Experiments that compare the effects of the presence or absence of an independent variable using an experimental and a control group can be particularly useful in the early stages of a research program.

2. The second question used to determine the type of experiment design is if participants are randomly assigned to conditions. Random assignment is used in experimental studies to create multiple groups that are equivalent in terms of various attributes (e.g., age, gender, nationality, personal characteristics, etc.). In a study designed to examine the effects of an independent variable on dependent variables at the individual level, this is accomplished by randomly assigning participants to treatments.

3. A) Assuming that participants have been assigned to treatment conditions randomly, the third question is if researchers have control over the experimental setting. Indeed, experimental settings involve many variables, such as the setting’s physical characteristics (physical layout, ambient noise, equipment, ...), psychological characteristics (cognitive requirements of the task, job stress, work-related distractions, ...) and social characteristics (presence of other people, number and type of interactions with others, ...). It is fundamental to consider these factors in the classification framework, as they may affect the dependent variable directly or through interactions with the independent variable. If researchers have control over experimental settings, it is a laboratory experiment; if not, it is a field experiment.

B) In case participants have not been randomly assigned, the third question is if the experiment design includes a control group, or multiple observations of a single group of participants. If this requirement is satisfied, then the study is as a quasi-experiment. If not, then the study is non-experimental, even if the independent variable has been manipulated. The following figure synthetizes the framework developed by Podsakoff P. and Podsakoff N. (2018).
In this research study, the experiment that is conducted is a field experiment. In fact, as it will be better explained in paragraph 4.1.5., the independent variable Business Model Clearness is manipulated; participants are randomly assigned to different scenarios; and the researcher has no control over the experimental setting.

4.1.3 The taxonomy of field experiments proposed by Carpenter et al. (2004)

In the broad world of experiments, Carpenter et al. (2004) developed a taxonomy for field experiments. In fact, depending on the research question, different types of experiments are possible, however all field experiments have in common the random allocation of participants to different conditions (treatments). To divide field experiments in subgroups, the researchers consider the following five variables:

- the nature of the subject pool. It can be a standard pool, when it includes students, simply because they are the convenience sample for academics, or a non-standard pool, whenever the researcher looks for field subjects;
- the nature of the information and experience that the subjects bring to the task;
- the nature of the commodity. The distinction here is between physical goods or actual services and abstractly defined goods;
- the nature of the task or institutional rules applied, which considers the fact that subjects may have prior experience regarding the context;
- the nature of the environment that the subject operates in, which is important to consider because the environment can suggest strategies and hypothesis that a lab setting might not.

The taxonomy that is proposed by Carpenter et al. (2004) divides field experiments in four different categories:

1. a conventional lab experiment, which employs a standard subject pool of students, an abstract framing, and an imposed set of rules;
2. an artefactual field experiment, which is a conventional lab experiment but with a non-standard subject pool;
3. a framed field experiment, which is an artefactual field experiment but with field context in either the commodity, task, or information set that the subjects can use;
4. a natural field experiment, which is a framed field experiment, but with the environment where subjects naturally undertake these tasks and where subjects do not know about the experiment.

According to this framework, the experiment conducted in this research is an artefactual field experiment, because the subject pool is non-standard but users do not have an active role in the field context.

### 4.1.4 Preliminary Analysis

To design the experiment, a deep analysis was conducted. Many papers whose research question was based on an experiment about adoption have been selected and investigated, in order to understand the procedure to follow.

The following picture shows the first sample of papers selected, that were used as a first basis to understand the variables to define in the experiment design phase.
All these studies focus on experiment about adoption and this first selection was useful to identify some common dimensions that were considered in experiment design, such as: experiment type, response rate, number of scenarios, sample size, within-subjects experiment, between-subjects experiment.

The possible experiment types have been deeply analysed in paragraph 4.1.2 and 4.1.3. The response rate is the number of participants that start the experiment over the total number of addressed participants. The number of scenarios is the number of different levels of the independent variable, which corresponds to the number of different conditions that participants might be subjected to. The sample size is the number of participants that complete the experiment; it can be referred to the entire experiment or it can be referred to the single scenario. Considering the experimental design, an experiment might have:

- A within-subject design, if all participants are exposed to every condition;
- A between-subjects design, if different participants are exposed to each condition, therefore one participant only sees one scenario.

This information allowed to understand how to shape the experiment and how to distribute it.

Then, some of the papers belonging to the first selection were substituted in favour of adoption experiment that consider privacy as a dimension of the research model. The following table

<table>
<thead>
<tr>
<th>Title</th>
<th>Authors</th>
<th>Journal</th>
<th>Year</th>
</tr>
</thead>
</table>

Figure 20 - First Paper Sample for the Experiment Design
shows the final paper sample, that acted as a foundation for the experiment design of this research in terms of procedure, dimensions in the research model and statement for the survey design.

<table>
<thead>
<tr>
<th>Title</th>
<th>Authors</th>
<th>Journal</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>User Acceptance of Information Technology Towards a Unified View</td>
<td>V. Venkatesh, M. G. Morris, G. B. Davis &amp; F. D. Davis</td>
<td>MIS Quarterly</td>
<td>2003</td>
</tr>
<tr>
<td>The personalization privacy paradox: An empirical evaluation of information transparency</td>
<td>N. F. Awad &amp; M. S. Krishnan</td>
<td>MIS Quarterly</td>
<td>2006</td>
</tr>
<tr>
<td>Understanding information technology acceptance by individual professionals: Toward an integrative view</td>
<td>M. Y. Y, J. D. Jackson, J. S. Park &amp; J. C. Probst</td>
<td>Information &amp; Management</td>
<td>2006</td>
</tr>
<tr>
<td>Associating consumer perceived value with business models for digital services</td>
<td>A. Baird &amp; T. S. Raghu</td>
<td>European Journal of Information Systems</td>
<td>2015</td>
</tr>
</tbody>
</table>

Figure 21 – Final Paper Sample for Experiment Design

4.1.5 Experiment procedure and design

Thanks to the aforementioned deep analysis, the experiment has been designed. Zhou (2012) and Baird and Raghu (2015) research studies were fundamental in the shaping of the experiment procedure.

The experiment methodology is structured on five steps:

1. Hypothesis definition, arising from the literature review. They have been deeply investigated in chapter 3.4;

2. Research model definition, which was shaped according to the research gap and the research area. It has been described in chapter 3.4. From an operational perspective, it was chosen to build the two constructs of Transparent Business Model and Opaque Business Model on two different services belonging to the same industry and offering the same value proposition. The services are as similar as possible to remove any bias and concentrate on the research question. Therefore, there are four possible scenarios, as shown in the following matrix.
3. Testing phase, in which the research hypothesis is tested on a first sample, to understand if the constructs and the statements were clear and consistent;

4. Data collection phase, in which the experiment was carried out through personal interviews with a survey. To deliver the experiment, a within-subjects design was chosen, in which the participants are exposed to multiple treatments over time. This choice is due to the fact that the research question aims at investigating whether the business model clearness influence users’ adoption of digital two-sided services. Therefore, each participant should be subjected to all the treatments. Within-subject designs have the advantage of reducing the error variance associated with individual differences among the participants and so increasing statistical power.

In this phase users were given the survey through Qualtrics and they first had to fill in a section devoted to personally unidentifiable information. Then the experiment randomly allocates them to one of the four scenarios, where users state whether they would adopt the service or not. Finally, users are led to the other service in the opposite scenario, where again they state whether they would adopt the service or not. Therefore, for example, a user could be led first to scenario 1 and then to scenario 4; another possibility could be first scenario 3 and then scenario 2. Concluding, as a consequence of the choice of a within-subject design, the actual number of scenarios was reduced to two. The experiment procedure is designed to prove that the disclosing order of the two possible values of the independent variable – Transparent Business Model and Opaque Business Model – does not influence the adoption of the service.
Indeed, as the two services are perfectly identical, users should not be influenced by the order in which the two business models are presented;

5. Data analysis phase, in which the data gathered were firstly validated through a reliability analysis and then analysed through a MANCOVA analysis with SPSS program.

The following picture summarizes the methodology for the experiment.

As aforementioned, considering Posdakoff P. & Posdakoff N. (2018) framework, the experiment is a field experiment, because the independent variable, which is business model clearness, is manipulated; participants are randomly assigned to the different treatments; and the researcher has no direct control over the experimental setting.

Considering Carpenter et al. (2004) classification, the experiment is an artefactual field experiment, because the subject pool is non-standard but users do not have an active role in the field context.

4.2 Operationalisation

To conduct the experiment, a fitting empirical setting had to be selected. Considering the wide opportunities arising in the digital service business, it was crucial for the experiment effectiveness to select an industry that already was delivering two-sided business model, delivering different value proposition towards different customer groups. Also, one of the two
value propositions had to be structured around data trading. Therefore, the industry that satisfies all of the stated above requirements to conduct an optimal research investigation was identified in health & fitness applications. In fact, there are already many players in market that offer this kind of service, bringing together users, that exploit a fitness service to monitor and support their training, and companies or government entities, that leverage the insights system that is elaborated on users’ data.

Considering the industry, it is important to provide a general overview of the mobile application market, as the health & fitness application business is part of this wider market. The global mobile application market is segmented on the basis of marketplace, app category, and geography. By app categories, it is divided into gaming, music & entertainment, health & fitness, travel & hospitality, e-Commerce & retail, education & learning, and others (news and media, magazines, whether forecast, food and beverages, and utilities).

Generally speaking, the global mobile application market is rapidly growing. Many players are developing mobile applications to satisfy customers’ needs. This fast evolution concerns also the app & health application business. Indeed, in the past the access to fitness programs was limited to fitness centres and clubs, but thanks to the increasing adoption of smartphones and download of mobile applications, many players are entering the fitness market with advanced fitness apps. Among all the different technologies that have recently emerged, mobile applications have become the most popular technological tool that users leverage to get fit. The main benefit of fitness apps is that they are easy-to-reach, free and easy-to-use. Customers can download them with no charges and then use them anytime or anywhere, which means that there are little to zero adoption barriers. Moreover, good fitness apps show users progress through visualizing tools like graphs, allowing users to have a deeper understanding of how long it takes to reach goals, which week’s they did well ... Also, fitness apps have been beneficial to keep people motivated by offering personalized routines or supported trainings, creating competition among family and friends, and offering rewards.

While using the health & fitness application, users generate a huge amount of information such as the starting and ending time of the activity, the geographical location to track routes, the contents accessed in the application, ... This UGBD can be aggregated to generate insights that are sold to third parties. Concluding, the value proposition that the service provider addresses to brands or government entities is constituted by UGBD.

The experiment is based on two similar services, that do not exist but have been shaped on the basis of the current players on the market. The first service has been called FitYou, while the
second service Weights. In both cases, the application access users’ location in order to monitor their activities, which may vary among three categories: walking, running or cycling. Also, the application accesses the health information that are recorded by the smartphone, in order to gain information about the steps during the whole day, and other additional information that depend on the health devices that have been synchronized by users: diet and calories, sleeping activities, heart rate or other information typically recorded by wristbands or smartwatches. By aggregating this information with those ones provided by the accelerometer, FitYou and Weights can build personalized boards that show to the single user all the information about his activities over time. Both applications offer many other functionalities, such as training videos or challenges, to create a gaming experience that spurs users to get fit.

UGBD are aggregated and then sold to departments of transportation and municipalities, that are in charge for delivering transportation services to citizens. In fact, both applications have a “FitYou for Cities” or “Weights for Cities” section, that sells to government entities information about the areas of the city that are mostly used for fitness activities to allow them to improve infrastructures for bicyclists and pedestrians. In fact, if city planners know where cyclists are on the road, the paths that runners actually use, and how people use public transportation, they can use that data for future city improvements.

4.3 Operationalization of Constructs

In this chapter it is analysed how the dependent, the independent and the control variables are translated into measurable items. All the items were measured on a 5-point Likert scale from strongly disagree (1) through neutral (3) to strongly agree (5). In Appendix X the entire survey is reported. The survey was delivered in English.

**Business Model Clearness - Independent Variable**

The independent variable is the Business Model Clearness. As aforementioned in paragraph 3.1., the research study conducted by Baird & Raghu is an interesting case of a model considering Business Model variation as an independent variable. However, in the case analysed by Baird & Raghu the business model dimension was described through four constructs: switching costs; effort; privacy; data control. Remind that privacy and data control are intrinsically different, as data control belongs to the security dimensions, as explained in chapter 2. 2. 2.
This research study aims at investigating and measuring the relationship between business model clearness and user’s adoption, therefore all the dimensions and the technological constructs describing the business model and the service performances are kept constant, while changing users’ visibility on it, which is the main objective of this research study. Therefore, the independent variable Business Model Clearness can assume two possible values that have been operationalized in two different constructs – Opaque Business Model and Transparent Business Model – and that are not measured through statements. In fact, the discriminating feature that brings users from the Opaque Business Model scenario to the Transparent Business Model scenario is the clear communication to users of the UGBD use.

In the Transparent Business Model case, users receive precise and clear information about the company’s monetizing use of user-generated big-data: before accessing to its use, the digital service states that UGBD will be sold to third parties. In the Opaque Business Model case, users do not receive precise and clear information about the monetizing use of UGBD: it will be said that data help improving and personalizing the service, but no direct source of revenues coming from them will be mentioned.

To simulate the two different scenarios, two hypothetical service have been developed, as mentioned in chapter 4.2. Hereafter, the mock-ups of scenarios 1 and 4 will be reported. The first sequence refers to FitYou service in the Opaque Business Model case.

The second sequence refers to Weights service in the Transparent Business Model case.

Figure 24 - Scenario 1 - FitYou in the Opaque Business Model case
As it emerges from the two sequences, the customer journey in both cases starts from the same point: the user is welcome to the service, which then asks the access to geographical location and to the health information collected by the health application embedded in the smartphone. Once access is granted, in the Opaque Business Model case the user is led to his profile, where he can find the section devoted to his privacy settings. Here, he can control who to share his information with, choosing among “Everyone”, “Friends”, “Only Me”. This means the application is aligned with the GDPR principles, which state that users must have the right to change their data, transfer them or even delete them.

In the Transparent Business Model case, the customer journey is enlarged. In fact, once access is granted, the user is informed about the purposes for which his data is recorded. Then the “WeightsForCities” (or respectively the “FitYouForCities”) section is explained: UGBD are aggregated and then sold to departments of transportation and municipalities to improve infrastructure in the city. More details about the computed metrics are given to the user. Then, the service specifies all the clauses compliant to GDPR: the shared information is anonymized;
users can control their information sharing level; users can remove their data. Then the customer journey converges to the previous one: the user is led to his profile and then the privacy settings section is shown. This customer journey derives from the analysis of the customer journey of the current health & fitness applications such as Strava, Nike+ or Runtastic, in order to reproduce a fitting empirical setting. The following figure shows the different customer journey in the Transparent and Opaque Business Model cases, applied on Weights.

![Figure 26 - Example of Customer Journey](image)

To track users’ effective interest in the privacy policy and conditions of the service, in both cases the user is asked if he is interested in viewing the privacy conditions. If the answer is positive, a more detailed text is shown, explaining all the data type that are collected and all the purposes that they are used for. Then the user is asked if he would agree. Appendix 3 reports the entire text.

**Digital Two-sided Service Adoption - Dependent Variable** (adapted from Venkatesh et al., 2012)

<table>
<thead>
<tr>
<th>Survey Item</th>
<th>Name in the Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>I would use this service in the future</td>
<td>Willigness1</td>
</tr>
<tr>
<td>I would use this service in my daily life</td>
<td>Willigness2</td>
</tr>
<tr>
<td>I would plan to use this service frequently</td>
<td>Willigness3</td>
</tr>
</tbody>
</table>
The dependent variable is the adoption of the digital two-sided service. This construct is measured through various items, that have been adapted by Venkatesh et al. (2012). In fact, Venkatesh et al. consider the UTAUT model as a baseline and extend it in order to tailor it to a consumer use context, which is the case of this research study, identifying three key items from prior research on both general adoption and use of technologies, and consumer adoption and use of technologies.

Control Variables

Propensity to Innovative Services (adapted from Yi et al., 2006)

<table>
<thead>
<tr>
<th>Survey Item</th>
<th>Name in the Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>If I heard about an innovative digital service, I would look for ways to</td>
<td>PropInn1</td>
</tr>
<tr>
<td>experiment with it</td>
<td></td>
</tr>
<tr>
<td>Among my friends and colleagues, I am usually one of the first to try out</td>
<td>PropInn2</td>
</tr>
<tr>
<td>innovative digital services</td>
<td></td>
</tr>
<tr>
<td>I like to experiment innovative digital services</td>
<td>PropInn3</td>
</tr>
</tbody>
</table>

The original items were slightly changed to fit the context of fitness & health applications. The third item was dropped to keep the survey not redundant and simple and because it adds no value to the first item. Moreover, it is the only item with a negative formulation, therefore the 5-points scale should have been adapted to be coherent.

Privacy attitude (adapted from Chellappa & Sin, 2005)

<table>
<thead>
<tr>
<th>Original Item</th>
<th>Name in the Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>I am sensitive about sharing information regarding my preferences while using</td>
<td>PrAtt1</td>
</tr>
<tr>
<td>mobile apps</td>
<td></td>
</tr>
<tr>
<td>I am concerned about sharing my anonymous information with mobile apps</td>
<td>PrAtt2</td>
</tr>
<tr>
<td>services</td>
<td></td>
</tr>
</tbody>
</table>
I am concerned about how my personally unidentifiable information (es. age range, sex, ...) will be used by mobile app providers

I am concerned about how my personally identifiable information (es. name, surname, e-mail, geographical location...) will be used by mobile app provider

This construct aims at measuring users’ personal attitude towards data sharing. Data are divided according to the information classification developed by Chellappa & Sin explained in chapter 3.4.1. The first statement is more general and is focused on investigating whether users are concerned about information sharing. The following statements refer to the fact that, as aforementioned, during their customer journey, users are asked to agree to different information type sharing that belong to different categories: geographical location that belong to the personally identifiable class, personal data and health data that belong to the personally unidentifiable class.

4.4 Testing and Data gathering

The survey was firstly validated by Politecnico of Milan researchers and then distributed to a small group of 5 respondents, to assess the comprehensibility of the questions by respondents. Each participant was asked to give a feedback on the structure of the questionnaire, the perceived effort level to answer and the clarity of the scenario designs. Minimal adjustments were made in the texts within the services mock-ups and the initial explanation about the service was enriched with details to give more information to respondents. Overall, the feedback was positive and after these changes, pre-tester participants felt the survey was clear and easy to complete.

After the testing phase the survey was delivered. Respondents were invited through personal e-mail, social network messages and LinkedIn posts. The data were collected between January and February 2019. Totally, 500 responses were collected. In the data cleaning phase, all the uncomplete responses were deleted, as well as those observations that did give the consent for personal data processing. The number of valid responses was equal to 345. The following table shows the descriptive statistics of the sample, considering the following variables: gender, age and the scenario – scenario 1 refers to those participants who firstly evaluated Weights in the Business Model Transparent case and then FitYou in the Business Model Opaque case; scenario
2 refers to the treatment in which participants first assessed Weights in the Business Model Opaque case and then FitYou in the Business Model Transparent case.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Values</th>
<th>Responses</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Female</td>
<td>162</td>
<td>47%</td>
</tr>
<tr>
<td></td>
<td>Male</td>
<td>183</td>
<td>53%</td>
</tr>
<tr>
<td>Age</td>
<td>18-24</td>
<td>150</td>
<td>43,5%</td>
</tr>
<tr>
<td></td>
<td>25-34</td>
<td>152</td>
<td>44,1%</td>
</tr>
<tr>
<td></td>
<td>35-44</td>
<td>11</td>
<td>3,2%</td>
</tr>
<tr>
<td></td>
<td>45-54</td>
<td>21</td>
<td>6,1%</td>
</tr>
<tr>
<td></td>
<td>55-64</td>
<td>10</td>
<td>2,9%</td>
</tr>
<tr>
<td></td>
<td>64-74</td>
<td>1</td>
<td>0,3%</td>
</tr>
<tr>
<td>Education level</td>
<td>Less than High School</td>
<td>4</td>
<td>1,2%</td>
</tr>
<tr>
<td></td>
<td>High school</td>
<td>38</td>
<td>11%</td>
</tr>
<tr>
<td></td>
<td>Bachelor Degree</td>
<td>108</td>
<td>31,3%</td>
</tr>
<tr>
<td></td>
<td>Master Degree</td>
<td>186</td>
<td>53,9%</td>
</tr>
<tr>
<td></td>
<td>PhD Degree</td>
<td>9</td>
<td>2,6%</td>
</tr>
<tr>
<td>Scenario</td>
<td>Scenario 1</td>
<td>180</td>
<td>52,2%</td>
</tr>
<tr>
<td></td>
<td>Scenario 2</td>
<td>165</td>
<td>47,8%</td>
</tr>
</tbody>
</table>

*Table 1 – Descriptive statistics of the sample – Part 1*

The table shows that the distribution of participants on gender and scenarios shows is homogenous, with the observations equally distributed on the possible values. Considering the
age variable, the majority of the responses is concentrated on the first two classes, as university students and young adults are more likely to use innovative digital services. As a consequence, also considering the education level variable, almost 88% of participants has concluded a university degree.

The survey was distributed worldwide and the following graph shows the distribution of responses on the nationality variable. Data have been aggregate in the following categories: Italy, that includes the majority of the answers (300); North America (7), which includes USA and Canada; Other European countries (24), which includes France, England, Spain, Belgium and others; Asia and Oceania (7), which includes Thailand, India, Australia and China; South America (6), which includes Argentina, Mexico and Colombia; Middle East (1), which includes Egypt.

![Distribution of responses on the nationality variable](image)

Considering the constructs that measure users’ propensity to innovative services and privacy attitude the following table shows the descriptive statistics.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Item</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Propensity to innovative</td>
<td>propInn1</td>
<td>3.113043</td>
<td>1.2941</td>
</tr>
<tr>
<td>services</td>
<td>propInn2</td>
<td>2.811594</td>
<td>1.167329</td>
</tr>
<tr>
<td></td>
<td>propInn3</td>
<td>2.849275</td>
<td>1.347006</td>
</tr>
</tbody>
</table>
Table 2 - Descriptive statistics of the sample – Part 2

<table>
<thead>
<tr>
<th>Privacy Attitude</th>
<th>prAtt1</th>
<th>3.110145</th>
<th>1.198127</th>
</tr>
</thead>
<tbody>
<tr>
<td>prAtt2</td>
<td>2.944928</td>
<td>1.309573</td>
<td></td>
</tr>
<tr>
<td>prAtt3</td>
<td>3.455072</td>
<td>1.185613</td>
<td></td>
</tr>
<tr>
<td>prAtt4</td>
<td>3.313043</td>
<td>1.294208</td>
<td></td>
</tr>
</tbody>
</table>

4.5. Data preparation

Before any analysis could be done, the variables needed for mapping the model in SPSS had to be created. This means that the answers of the survey had to be codified into numeric variables to be inserted into the model. Specifically:

- Gender variable was mapped as a Boolean variable equal to 0 in the Male case and equal to 1 in the Female case;
- Age variable was mapped as a Likert variable with values from 1 to 6 with the increasing age categories abovementioned;
- Education level variable was mapped as a Likert variable with values from 1 to 5 with the increasing education qualifications;
- Business Model Clearness was mapped as a Boolean variable equal to 0 in the Business Model Opaque case and equal to 1 in the Business Model Transparent case;
- Privacy Consensus was mapped as a Boolean variable equal to 0 if the participant decided to not read the complete Privacy Terms and Conditions before reading the service; it is equal to 1 if the participant decided to read them.

Once the variables were created, the data were imported in SPSS Program to run the necessary analyses to test the hypothesized model.
5. Data analysis and Results

This chapter is devoted to the description of the analysis carried out in this research study. After the constructs have been conceptually defined and measures have been developed, the next step is to test whether the measures behave as expected if they were valid (MacKenzie et al., 2011). The research model is tested and validated through a Multivariate Analysis of Covariance implemented in SPSS Program. Paragraph 5.1. explains why MANCOVA analysis was chosen for the data analysis phase; paragraph 5.2. focuses on the measurement model validation, describing all the validity analysis that have been carried out to check if the constructs were effectively measured by the items of the survey and describing the assessment of the results of the Research Model.

5.1 Multivariate Analysis of Covariance

In this experiment design, as aforementioned in paragraph 4. 1. 5., participants were subjected to successive measurements. Repeated measurement designs (Keselman et al., 1998) often provide the blueprint for experimental manipulations and data collection. Repeated measurement designs have two main advantages:

- They require fewer participants than completely randomized designs when the effects of certain variables can be measured across the same set of participants;
- They have a substantial power to detect treatment effects. By manipulating a variable as a within-subjects variable, which means exposing participants to all the levels of that variable, variability due to individual differences across the levels of the variable is eliminated from the estimate of error variance, making it easier to detect treatment effects when they are present.

Repeated measurement designs are commonly analysed with the analysis of variance (ANOVA) or the multivariate analysis of variance (MANOVA). MANOVA analysis measures the differences for two or more metric variables based on set of qualitative independent variables. It is useful as a multivariate procedure to access group differences across multiple metric dependent variables simultaneously (Liu et al., 2005). However, if the experiment contains control variables, those variables are mapped as covariates and the data are analysed using analysis of covariance (ANCOVA) or multivariate analysis of covariance (MANCOVA) techniques, according to the
number of dependent variables. The analysis of covariance is a model-based method of that reduces bias and controls variation in experiments, quasi-experiments, and observational studies (Leppink, 2018; Huitema, 2005).

Therefore, the data set that was collected through the survey is analysed with a MANCOVA analysis, to consider both the covariates and all the dependent variables. More specifically, MANCOVA was needed to include in the model the following variables:

- One boolean dependent variable (Business Model Clearness);
- Three dependent variables (three items measuring Two-sided Digital Service Adoption);
- Ten covariates (Propensity to Innovative Services, measured by three items; Privacy Attitude, measured by four items; Age; Gender; Education level).

5.2 Measurement Model Validation

This paragraph is devoted to the assessment of data reliability and to the inspection of the measurement model. In fact, before any data analysis is executed in SPSS, reliability and consistency must be checked, to create solid basis for the validity of the research study. More specifically, it is fundamental to assess whether the items delivered in the survey effectively measure the research constructs.

The constructs of the research model are latent variables, because they are not directly observable, but they result from the measurements of their items, which contain the scores from the actual questions delivered through the survey and measured on a five-points Likert scale (from “strongly disagree” to “strongly agree”). Basically, a construct refers to a specific theoretical phenomenon to be studied and the item is “a recorded trace taken as evidence of the construct” (Edwards & Bagozzi, 2000).

Constructs can be reflective or formative according to the nature of the relationships with their measures. In reflective constructs, the measures are caused by the construct itself: they are indeed reflections, manifestations of the construct (Edwards & Bagozzi, 2000). Reflective items should be positively and highly correlated as they measure the same dimension in different questions. In fact, the items in the survey are formulated as almost synonyms.

On the other hand, formative constructs are formed by their items and they usually are the result of the composition of specific variables that are not correlated (Edwards & Bagozzi, 2000).
Therefore, eliminating one of the measures means eliminating one of the aspects that compose
the construct, drastically changing it (Petter et al., 2007).

In this research model, all the constructs are reflective constructs. To assess the convergent
validity of the measured latent variables, some coefficients were checked. The procedure that
has been followed for the data analysis is shaped on the methodology of the research conducted
by Karwatzki et al. (2017), which is based on the study elaborated by MacKenzie et al. (2011).
To assess reliability, the coefficients that have been examined are factor loadings, Cronbach’s
alpha coefficient (Davis, 1989), average variance extracted (AVE) and composite reliability (CR)
(Hair et al., 2002). Factor loadings indicate the contribution of a single item to the overall
construct. Cronbach’s alpha is an estimate of the internal consistency and reliability associated
with a score that can be derived from a scale or a composite score. Average variance extracted
(AVE) is a measure of the amount of variance that is captured by a construct in relation to the
amount of variance due to measurement error. Composite reliability (CR) estimates the extent
to which a set of latent construct indicators share in their measurement of a construct.

These coefficients allow to measure if the constructs are well structured in the sense that their
measures fit well together.

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Factor Loadings</th>
<th>Mean</th>
<th>Std Dev.</th>
<th>Chronbach’s alpha</th>
<th>AVE</th>
<th>CR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Propensity to innovative services</td>
<td>PropInn1</td>
<td>0.857</td>
<td>3.22</td>
<td>1.292</td>
<td>0.425</td>
<td>0.497</td>
<td>0.497</td>
</tr>
<tr>
<td></td>
<td>PropInn2</td>
<td>0.130</td>
<td>2.82</td>
<td>1.167</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PropInn3</td>
<td>0.860</td>
<td>2.85</td>
<td>1.347</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Privacy</td>
<td>PrAtt1</td>
<td>0.926</td>
<td>3.11</td>
<td>1.198</td>
<td>0.834</td>
<td>0.857</td>
<td>0.8575</td>
</tr>
<tr>
<td>Attitude_1</td>
<td>PrAtt3</td>
<td>0.926</td>
<td>3.46</td>
<td>1.186</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Privacy</td>
<td>PrAtt2</td>
<td>0.862</td>
<td>2.94</td>
<td>1.310</td>
<td>0.653</td>
<td>0.743</td>
<td>0.743044</td>
</tr>
<tr>
<td>Attitude_2</td>
<td>PrAtt4</td>
<td>0.862</td>
<td>3.31</td>
<td>1.294</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Williness1</td>
<td>0.899</td>
<td>3.24</td>
<td>1.056</td>
<td>0.907</td>
<td>0.849</td>
<td>0.877969</td>
</tr>
</tbody>
</table>
The factor loadings have been computed through a confirmatory factor analysis with a varimax rotation (Karwatzki et al., 2017). All the factor loadings are over 0.8, highlighting a strong relationship between the items and the component. The only loading factor that has a low value is related to PropInn2 item. This result is not surprising, because items PropInn1 and PropInn3 measure the propensity of an individual to adopt innovative services, while PropInn2 benchmarks the individual propensity with the social context around the participant. This result is coherent with the current state-of-art of the literature, as there is a lack of empirical evidence that addressed the link between personal innovativeness and social influence (Yi et al., 2006), which means that there is no clear evidence about a relationship between the social context and personal innovativeness. Consequently, the Cronbach’s alpha coefficient of the Propensity to Innovative Services is quite low, not overcoming the acceptance threshold of 0.65 which indicate data reliability (Baird & Raghu, 2015; Karwatzki et al., 2017; Hair et al., 2011). The Cronbach’s alpha coefficient explains the percentage of variability on the composite score obtained by combining the items of the independent variables that can be considered internally consistent reliable variance.

Items of Privacy Attitude have been split in two different groups, as the confirmatory factor analysis clearly highlighted two different components: one mainly influenced by items PrAtt1 and PrAtt3 and the other by PrAtt2 and PrAtt4. This is confirmed by the correlation matrix reported in Appendix 2, which shows that some of the correlation values are negative or really low, indicating little correlation between the items. On the contrary, some other items are extremely correlated, with values around and above 0.5 (e.g. propInn1 & propInn3; prAtt2 & prAtt4). Therefore, Privacy Attitude construct has been split into different components. This choice is supported by Privacy researchers within IT adoption literature: Stewart & Segars (2002) find the concern for information privacy construct to be multidimensional.

Considering the dependent variable, Digital Two-sided Service Adoption, all the coefficients are high, indicating a strong reliability and validity of the construct, coherently with the literature (Venkatesh et al., 2012). Validity analysis needs to be performed also on the dependent variable,
to make sure that the items are actually measuring the assessed dimension; however, Fornell-Larcker criterion is not checked, as Digital Two-sided Service Adoption is not a control variable. This is aligned with the procedure performed by Karwatzki and others (2017).

Coherently with the results shown by the Cronbach’s alpha coefficient, when the Fornell–Larcker criterion (Fornell et al., 1981; Karwatzki et al., 2017) is tested the same result is achieved: the criterion states that the square root of the AVE for each variable should be greater than its correlation with any other construct in the model (which are reported off-diagonal in Table 4). As it can be seen, this criterion was satisfied for the Privacy Attitude constructs, but not for the Propensity to Innovative Services one.

<table>
<thead>
<tr>
<th>Propensity to Innovative Services</th>
<th>Privacy Attitude_1</th>
<th>Privacy Attitude_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Propensity to Innovative Services</td>
<td>0.247</td>
<td></td>
</tr>
<tr>
<td>Privacy Attitude_1</td>
<td>0.22833</td>
<td>0.7345</td>
</tr>
<tr>
<td>Privacy Attitude_2</td>
<td>0.362</td>
<td>-0.001</td>
</tr>
</tbody>
</table>

*Table 4 - Fornell-Larcker criterion*

5.2 Research Model Assessment

Once the data was organised and ready, the research model was implemented in SPSS. A MANCOVA analysis with a significance level equal to 5% was carried out, mapping all the control variables as covariates.

The main purpose of the MANCOVA analysis is to establish whether the values of the independent variable, in this case Transparent Business Model and Opaque Business Model, are statistically significantly different on the dependent variables, which is Two-sided Digital Service Adoption, after controlling for covariates. If the results of the MANCOVA analysis are statistically significant, this suggests that there is a statistically significant adjusted mean difference between the values of the independent variable in terms of the combined dependent variable (after adjusting for the continuous covariate).
To assess it, we need to look at the results of the Multivariate Tests. Pillai's Trace, Wilks' Lambda, Hotelling's Trace and Roy's Largest Root are different multivariate statistics that can be used to test the statistical significance of the differences between groups. If the test of equality of covariance matrixes shows that there is no statistical significance, the coefficient that should be used to evaluate the significance is Wilks' Lambda; in the opposite case, the coefficient that should be used is Pillai’s Trace.

The model that was implemented in SPSS measures the dependent variable Two-sided Digital Service Adoption not in terms of the absolute value that participants assessed during the survey, but in terms of the delta between the answers given by each participant to the two services. This means that for each participant, the dependent variable is measured by the following items:

<table>
<thead>
<tr>
<th>Item</th>
<th>Computation</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>deltaWill1</td>
<td>$\text{Service}_1(\text{Willigness}_1) - \text{Service}_2(\text{Willigness}_1)$</td>
<td>[-4;+4]</td>
</tr>
<tr>
<td>deltaWill2</td>
<td>$\text{Service}_1(\text{Willigness}_2) - \text{Service}_2(\text{Willigness}_2)$</td>
<td>[-4;+4]</td>
</tr>
<tr>
<td>deltaWill3</td>
<td>$\text{Service}_1(\text{Willigness}_3) - \text{Service}_2(\text{Willigness}_3)$</td>
<td>[-4;+4]</td>
</tr>
</tbody>
</table>

*Table 5 - Model 3 - Dependent variable computation*

Because the MANCOVA analysis cannot deal with negative numbers, before importing data into SPSS, the values have been transposed into a scale from 1 to 9.

Moreover, because of the results derived by the validity and reliability analysis, the item proInn2 was dropped, as its Chronbach’ alpha coefficient was too low, making the item unreliable. Concluding, the research model that has been implemented into SPSS is the one showed below.
Indeed, in this case the MANCOVA analysis is computed on 345 answers. Because the significance value of the Test of Equality of Covariance Matrixes is equal to 0.059, which is greater than 0.05, the Multivariate Tests must be interpreted considering the Wilks’ Lambda coefficient.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Value</th>
<th>F</th>
<th>Gl hypothesis</th>
<th>Gl error</th>
<th>Sign.</th>
<th>Partial eta squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>bmTransparent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pilla’s Trace</td>
<td>0.008</td>
<td>0.932</td>
<td>3</td>
<td>332</td>
<td>0.425</td>
<td>0.008</td>
</tr>
<tr>
<td>Wilks’ Lambda</td>
<td>0.992</td>
<td>0.932</td>
<td>3</td>
<td>332</td>
<td>0.425</td>
<td>0.008</td>
</tr>
<tr>
<td>Hotellings’s Trace</td>
<td>0.008</td>
<td>0.932</td>
<td>3</td>
<td>332</td>
<td>0.425</td>
<td>0.008</td>
</tr>
<tr>
<td>Roy’s Largest Root</td>
<td>0.008</td>
<td>0.932</td>
<td>3</td>
<td>332</td>
<td>0.425</td>
<td>0.008</td>
</tr>
</tbody>
</table>

*Table 6 – SPSS Model - Multivariate Tests for the independent variable*

The value of the Wilks’ Lambda coefficient (highlighted in bold) is greater than 0.05, meaning that there is not a statistically significant result. Coherently, also the Tests of Between-Subjects Effects indicate a not statistically significant result, because the significance coefficients (highlighted in bold) between the independent and the dependent variables are all greater than 0.05, as shown in the following Table.
<table>
<thead>
<tr>
<th>Effect</th>
<th>Type III Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
<th>Partial eta squared</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>deltaWill1</td>
<td>0.497</td>
<td>1</td>
<td>0.497</td>
<td>0.379</td>
<td>0.538</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>deltaWill2</td>
<td>0.025</td>
<td>1</td>
<td>0.025</td>
<td>0.024</td>
<td>0.878</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>deltaWill3</td>
<td>0.485</td>
<td>1</td>
<td>0.485</td>
<td>0.401</td>
<td>0.527</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.001</td>
</tr>
</tbody>
</table>

Table 7 – SPSS Model - Test of Between-Subjects Effects for the independent variable

These results indicate that the values of the independent variable Business Model Clearrness are not statistically significantly different on the dependent variable Two-sided Digital Service Adoption, which means that H1 is not supported for the Research Model implemented in SPSS.

Considering the other hypothesis, from the MANCOVA analysis of the Research Model, it clearly emerges that neither H2 or H3 are supported, as the both the Wilks’ Lambda coefficient and the significance level of these covariates are much over 0.05, overcoming the significance threshold. This means that both Propensity to Innovative Services and Privacy Attitude do not influence the relationship between Business Model Clearrness and Two-sided Digital Service Adoption. H5 is not supported for both gender and age, as the Wilks’ lambda coefficient and the significance level in the Tests of Between-subjects Effects are over 0.05. This means that neither gender or age moderate the relationship between Business Model Clearrness and Two-sided Digital Service Adoption. Finally, H4 is not supported, which means that Education does not moderate the relationship between the independent and the dependent variable, being the Wilks’ Lambda coefficient and the significance level of the Tests of Between-subjects Effects greater than 0.05. The complete table of Tests of Between-Subjects Effects is reported in Appendix 2.

To validate these results, a one-way ANOVA analysis was performed. One-way ANOVA analysis was chosen because the MANCOVA analysis showed that there is no statistical evidence that the considered covariates that effects how the independent variables act upon the dependent variables. Therefore, the one-way ANOVA analysis was computed, considering the dependent variable Two-sided Digital Service Adoption measured by the three items deltaWill1, deltaWill2 and deltaWill3 and the Independent variable Business Model Clearrness. The results are coherent with what is arising from the MANCOVA analysis.
<table>
<thead>
<tr>
<th></th>
<th>Squared Sum</th>
<th>gl</th>
<th>Squared Mean</th>
<th>F</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>deltaWill1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Between-groups</td>
<td>0.437</td>
<td>1</td>
<td>0.437</td>
<td>0.331</td>
<td>0.565</td>
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<tr>
<td>Within-groups</td>
<td>451.726</td>
<td>343</td>
<td>1.317</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>deltaWill2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-groups</td>
<td>0.049</td>
<td>1</td>
<td>0.049</td>
<td>0.047</td>
<td>0.828</td>
</tr>
<tr>
<td>Within-groups</td>
<td>353.322</td>
<td>343</td>
<td>1.030</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>deltaWill3</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-groups</td>
<td>0.620</td>
<td>1</td>
<td>0.620</td>
<td>0.513</td>
<td>0.474</td>
</tr>
<tr>
<td>Within-groups</td>
<td>414.412</td>
<td>343</td>
<td>1.208</td>
<td></td>
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</tr>
</tbody>
</table>

*Table 8 - SPSS Model – one-way ANOVA*

Indeed, for every item there is no statistically significant difference between the means of the Two-sided Digital Service Adoption among the two values of Business Model Clearness. Moreover, almost the totality of the variance is explained by the within-groups variance, with an almost zero contribution of the variance explained by the between-groups variance (highlighted in bold).
6. Discussion

In this chapter the main findings presented in chapter 5 are going to be discussed according to the theoretical lenses presented in chapter 3.

The goal of this analysis is to obtain meaningful understandings that can help to develop practical and powerful managerial implications. First, the three main findings are schematically presented; then for each point is developed in its own paragraph. Two-sided markets literature and the focus on the emerging business models and the increasing importance of User-generated Big Data as a new asset was used a foundation for the experiment design; however the interpretation of the results emerging from the data collection and the data analysis phases have a major contribution in the IT adoption literature. In fact, as explained in paragraph 2. 2. 2., the role of privacy in current state-of-art of IT adoption literature is quite unclear, with opposing theories (Acquisti et al., 2013).

The aim of this chapter is to contribute to the current state-of-art of IT adoption literature by interpreting the results obtained in the data analysis phase, whose objective was to investigate whether Business Model Clearness was affecting users’ adoption of two-sided digital services.

The main findings that can be drawn starting from the research model results are here described.

Users’ consenting contribution

Data analysis proved that Business Model Clearness has no direct impact on users’ Two-sided Digital Service Adoption. This means that even though final users are aware about their personal data being sold by service providers, their willingness to adopt the service does not change. Literature has contrasting theories about the relationship between information transparency and users’ adoption, with some researches supporting a positive relationship (Culnan, Armstrong; 1999) and others demonstrating the opposite (Awad, Krishnan; 2006). The current overview is quite unclear, and this research study contributes in making it clearer.
Privacy Attitude

Within the classification proposed by Chellappa & Sin (2005) about the Privacy Attitude construct, the results also showed that there is a significant, structural difference in how users perceive the treatment of their anonymous, personally unidentifiable or personally identifiable information. This finding confirm that Privacy Attitude varies among personal traits, but it also suggests that individuals’ personal differences in privacy concern (Zhou, 2012) may differ among the type of information is shared.

Users as an active source of data

Within the context of two-sided markets literature and service-dominant logic, the business model that was tested in the experiment was successful, unifying the contribution of both research areas in one unique value proposition. Indeed, the business model proposed in the experiment relies on data a key resource that is directly used as a source of revenues, a value proposition that is realized only through customers interaction. The proposed business model creates a bridge between the two theories, reinforcing both and highlighting the opportunities that rise from this perspective.
6.1 Users’ consenting contribution

This is the main contribution of this research study. As aforementioned in chapter 3, the current state-of-art of Information Systems and IT literature considers privacy as one of the many independent variables modelled in the research frameworks, investigating whether privacy is one of drivers affecting users’ adoption. However, the role of privacy in the current state-of-art of IT adoption literature is quite unclear, with opposing theories. Acquisti et al. (2013) state that understanding the value that individuals assign to the protection of their personal data is crucial for business, in order to take more conscious decisions in designing platforms.

This research model includes privacy dimension in the underlying business model. Therefore, privacy issue become a side effect of the realization of the business model, moving the focus on how users perceive personal information collection, aggregation and sale. Indeed, the crucial point is to investigate whether this type of business model affects users’ adoption. Data clearly show that there is no statistical evidence that firms’ disclosing the final usage of users’ personal data affects users’ adoption of the service, negatively answering the question proposed by Spiekermann et al. (2015): “will people not want to continue freely to communicate online, chat, talk, post and provide their data?”. This result can be discussed focusing both on the role of information transparency as a driver of users’ adoption or focusing on the business model as a driver of users’ adoption.

Taking the first proposed perspective, the current state-of-art of literature has opposing theories on the relationship between information transparency and users’ adoption. When considering information transparency, researchers in IT adoption literature mean the set or procedure that is implemented by firms to acknowledge users about which type of information is gathered and how it is used. Awad & Krishnan (2006) demonstrate that information transparency procedures have a negative effect of the final adoption by users, who had a deeper understanding of how much information was collected and how it was used, consequently increasing their fears. On the contrary, Culnan & Armstrong (1999) state that when customers are explicitly told that fair information practices are employed, privacy concerns do not distinguish consumers who are willing to be profiled from those who are unwilling to have their personal information used in this way.

This research study is not just coherent with what has been demonstrated by Culnan & Armstrong (1999), but it also enlarges it. Indeed, in their research model Culnan & Armstrong (1999) include within Privacy Concern also Security, underlying the importance of procedures
that can avoid unauthorised access to users’ data. Because this research model does not include Security, the finding that Business Model Clearness does not influence users’ adoption enriches Culnan & Armstrong (1999) findings by giving statistical evidence that if companies clearly state the final use of the personal data, privacy concerns do not distinguish consumers who are willing to be profiled from those who are unwilling to have their personal information.

Taking the second perspective and focusing on the research model, as aforementioned Baird & Raghu (2015) conducted one of the few studies that examines business model as an independent variable affecting users’ adoption. Considering the personal health records business, Baird & Raghu aimed at demonstrating that consumer value for digital service business models could have been quite different, considering consumers with similar preferences for standard technology characteristics. The findings of their study suggest that variations in the underlying digital service business models are likely to have significant impacts on consumer valuations of digital services. This result is opposite to the one achieved in this research study and the answer lies in the empirical setting that was chosen for the two experiments. Baird & Raghu research considers various business model in the health industry, while this research study considers the health & fitness application industry. The inner motivation explaining this disagreement relies in the difference in the typologies of information that are collected and how they are perceived by users. Finding two better explains this concept.

Concluding, the research study shows that even though users are aware about how its personal data is used, the are still willing to use the service. This means that the advantages that they derive from the service usage are higher than their privacy concern, confuting Spiekermann et al. (2015) statement that “if they learned about today’s volume and business done with their data among third parties, they may be surprised and betrayed” and that “third-parties use of data is seen rather negatively”. Coherently with this result, in the survey after rating the adoption of each service, participants had the possibility to add comments. This possibility gave some interesting insights, as some users stated that “there are already several apps doing this (Strava, Runtastic)” and that “it would be an interesting service”, meaning that they are aware about firms selling their data to third-parties but still find the service interesting.

In conclusion, the results of this research study confute what Muzellec et al. (2015) stated: “end-users are being used but they are not necessarily a negotiating party that is willing to exchange data” (Muzellec, Ronteau, Lambkin, 2015, p. 141).
6.2 Privacy Attitude

This result enriches the current state-of-art of literature on the role of privacy in IT adoption. Researchers in Information Systems and many other research fields started investigating why and under which circumstances people disclose their personal data (Dinev & Hart, 2006; Berendt et al., 2005). Privacy Attitude has been included into many research models as an independent or control variable.

Researchers commonly agree that Privacy Attitude is highly influenced by personal traits (Zhou, 2012). This means that there are users that are naturally more concerned about sharing their personal information, while others are more propense to do so. Indeed, information disclosure implies possible negative outcomes, such as information abuse and sales without their knowledge or unauthorised access to personal information.

The results of the data analysis phase are certainly coherent with what has been demonstrated in previous researches: Privacy Attitude strongly depends on personal traits and on the context (Stewart, Segars, 2002; Zhou, 2012). Acquisti et al. (2013) conducted a study whose results call into question the common conclusion that consumers do not care for privacy: whether they appear to care a lot or a little depends critically on context.

The additional comments that participants had the possibility to leave in the survey confirm that Privacy Attitude varies among personal traits, as there were people with high privacy concern that “did not like sharing their information not even with friends” and other participants that were “already using these kinds of services”. Moreover, in the survey users had the possibility to have more details about the Privacy Conditions of the two services: 33% of the total participants decided to read them; among those users, the 84% of them stated that they would have agreed with the Privacy Conditions, while the 16% of them state the opposite.

However, Privacy Attitude does not only vary among personal traits. Indeed, interpreting the results of this research study according to Chellappa & Sin (2005) classification of information types, it emerges that Privacy Attitude varies among the categories of information type: privacy is perceived differently by users depending on the type of information that is disclosed. This result is coherent with Culnan (1993) research, which identified the type of information as one of the characteristics of secondary information use – such as data trading with third parties - affecting users’ attitude.

Considering Chellappa & Sin (2005) classification, which has been implemented in the survey, it emerges that:
• Users perception of sharing information at a high level with service providers is associated mainly to personally unidentifiable information, such as age range or sex;
• Users perception of sharing personally identifiable information (name, surname, ...) is associated with the perception of sharing anonymous information (IP address, ...). This means that an individual with high concern of sharing personally identifiable information will have a high concern also for sharing anonymous information and vice versa.

As reported by the FTC, in the online context consumers are not only concerned about the privacy of their personally identifiable information but also other information that can be linked together later. This emerges also from this research study. In fact, considering the two groups of information types - on one side anonymous information and personally identifiable information and on the other side personally unidentifiable information, which are perceived as the general information that are shared with service providers - users are more concerned of sharing anonymous and personally identifiable information – as the mean value of the responses is higher - which are perceived to be more sensitive.

Concluding, from the research study, it emerges that users have different Privacy Attitude according to the type of information that is shares, as it is perceived differently. This result is coherent with Steward & Segars (2002) research, which shows that privacy constructs should not only address “what” and “how” information is collected and used, but it should also consider consumers’ perceptions, which may vary among different aspects of privacy.
6.3 Users as an active source of data

The proposed research model that has been tested in a fitting empirical setting that creates a bridge between two-sided markets literature (Trabucchi et al., 2017; Hartmann et al., 2016; Sorescu, 2017) and service-dominant logic (Xie et al., 2016; Vargo & Lusch, 2008). Indeed, the experiment design implement a data trading business model (Trabucchi et al., 2017), connecting two groups of users that belong to distant businesses – runners and departments of transportation and municipalities. This is a non-transaction two-sided platform that, according to the classification proposed by Muzellec et al. (2015) belongs to the maturity stage, therefore requiring a specific value proposition for each side, in order to ensure both sides on-board. It is a typical example of B2C&B strategy, where the main value proposition is directed to end-users, which become part of the value proposition for the business audience – in this case transportation departments. The subsidy side is the end-users one, while the business side is paying to access the User-generated data. Data is considered as an asset that can be monetized, coherently with what is stated by Spiekermann et al. (2015, p. 161): “personal data is seen as a new asset because of its potential for creating added value for companies and consumers and for its ability to enable services hardly imaginable without it. [...] Personal data can be a product itself, when it is entangled with user-generated content”.

The bridge with the service-dominant logic emerges while focusing on the value proposition to the end-users’ side. In fact, in the case of a non-transaction two-sided platform that leverages a data trading strategy, the contribution of end-users is fundamental to enable the two-sided platform to realize its value proposition. In fact, service-dominant logic (Vargo & Lusch, 2008) states that firms cannot deliver value, they can only offer potential value, which is realized through customer usage. This implies that the role of users in a digital two-sided platform is even more crucial: firstly, users represent one of the two side that is necessary to have on-board to raise powerful network effects; secondly, users are necessary to properly realize the value proposition that is sold to the other side. If users do not interact with the digital platform, User-generated Big Data are not created and no valuable insights can be sold to the other side, in this case departments of transportation and municipalities.

If traditional non-transaction two-sided markets considered end-users as a passive target, in this perspective end-users have a consenting active role in the value creation process, enabling to change the perspective about the role of data and consequently creating new business opportunities in two-sided markets.
Traditionally, non-transaction two-sided markets have been considered as a strategic choice to profit from services offered for free or almost for free to end-users, both in the Client-As-a-Target and in the Client-As-a-Source perspectives (Trabucchi, Buganza, 2019). This means that normally, in the definition of the two-sided business model, the decision to add a second non-transaction side was made to monetize what was being offered to the first side, end-users, by exploiting User-generated Big Data as a by-product. While previous researches tend to show how data are a by-product to be exploited, Trabucchi and Buganza (2019) highlight that if customers who are searching for data are considered the starting point of the business model, then data become the primary product of the innovation process. This vision cannot be delivered without the necessary condition of users consenting and active contribution to Big Data generation. A good example might be Duolingo (Trabucchi, Buganza, 2019), an education app that sells text translations to companies that needed them, while allowing end-users to learn new languages as they translate texts. In this case, the trigger point that gave birth to the Duolingo app actually was the companies’ need for translations from various languages to English. The second side consists in end-users, which have been involved later with the active role to realize the value proposition – millions of data about translations - that is sold to companies.

In this perspective end-users are the main source of value creation in the two-sided business model, creating and supplying data while enjoying (maybe for free) a service [...] which is not necessary the fundamental reason why the entire system has been created (Trabucchi, Buganza, 2019). This vision twists the established line of reasoning, that used to see UGBD as a by-product asset with a hidden value to extract.

Concluding, the core contribution described in this finding is that the research study has tested in a realistic empirical setting a business model that merges together two theories that appear to be complementary, moving the perspective from end-users as a passive source of data to end-users as an active source of data. This focus shift opens new business opportunities, that consider first customers’ need for data and then shape a coherent value proposition for the end-user side, which actively provides the data. Taking these lenses, finding one about users consenting contribution is fundamental because it ensures through quantitative evaluations that this kind of value proposition is a business model that is not obstructed by privacy concerns. Therefore, model validation and finding one are necessary results to achieve this contribution that bridges two-sided markets literature with service-dominant logic, revealing interesting research opportunities.
7. Conclusions

Two-sided markets bring together two interdependent groups of users, offering a specific value proposition to each side. The fuel of two-sided markets are network effects: the more users join one side, the more users on the other side will be willing to join the platform. Whenever two-sided markets rely on a digital platform, these millions of users joining both sides imply millions of interactions, which are translated into terabytes of data and information that are produced every day by users. User-generated Big Data is the hidden value of two-sided digital platforms, which nowadays can be exploited with many different strategies, opening a new and broad range of opportunities. Indeed, in 2015 70% of the 115 Unicorns all over the world were platform businesses (Evans & Gawer, 2016). User-Generated Big Data can be leveraged in several ways, as it has been deeply analysed in chapter 3; however, the focus of this research study is to investigate non-transaction two-sided digital platforms, which provide to end-users a value proposition that enables platform providers to collect and aggregate valuable information that can be sold to third parties. This data trading strategy often connects apparently unrelated businesses.

In the end of 2018\(^7\), Netflix, a digital two-sided platform that connects viewers with directors and movie-makers, released Bandersnatch, a feature film whose ending depended on end-users’ choices. This means that Netflix was collecting data about 130 million of viewers’ choices, regarding various themes, from breakfast cereals to death choices. But, how is this information used? Is it a new way to violate users’ privacy? Indeed, selling User-generated Big Data has relevant privacy implications. The focal theme of this thesis is to understand whether firms’ transparency about their data selling strategies affects users’ adoption. The research question has its roots in all these topics, therefore:

Q. Investigate whether business model clearness about UGBG usage affects users’ adoption of digital two-sided services.

In order to investigate it, a research model was developed and tested through an experiment, gathering data through an online survey. Data were then analysed with a MANCOVA analysis. Results, which have been deeply discussed in chapter 5, showed that Business Model Clearness,
which is achieved when firms are clearly stating their final purpose of data selling, does not affect end-users’ adoption of the service.

As aforementioned, Netflix interactive content streaming is just one of the million opportunities that companies have to leverage ICT and UGBD. Indeed, whenever companies ensure information transparency procedure towards users, who are aware of how their information are used, valuable data are derived, and many business opportunities arise. For example, Spotify’s product Spotify.Me analyses through AI algorithms the huge amount of data that listeners produce to identify users’ characteristics and habits, even the offline. However, the company clearly asks users the permission to access to their information, explaining which information will be accessed and how they will be used. This information is then sold to Brands to enable targeted marketing campaigns.

Business model clearness and information transparency procedures enable companies to leverage UGBD with innovative strategies that open new business opportunities. Companies need to safeguard themselves from privacy implications that might have negative adoption consequences. Taking Cambridge Analytics example, Facebook sold millions of data about his users without clearly stating it and without explaining the final purpose. Cambridge Analytica used this information for several goals, including targeted political campaigns. Therefore, when the scandal emerged, Facebook adoption was seriously threatened. This case highlights the importance of information transparency towards users.

In the next chapters, Theoretical Contributions of the research are highlighted (chapter 7.1), then, Managerial Implications are derived, discussing the operative choices that managers could exploit to leverage the findings (chapter 7.2). Finally, limitations and the opportunities for future research are reported (chapter 7.3).
7.1 Theoretical Contributions

The main findings, deeply described in chapter 6, showed that in the context of digital two-sided markets there is no evidence of firms’ Business Model Clearness about the usage of UGBD affecting users’ adoption. Moreover, from the results it emerges that users have a different Privacy Attitude towards specific typologies of personal data, as they are perceived differently.

The research is, therefore, contributing to two main literatures:

- The IT adoption literature, that has investigated for years the drivers affecting users’ adoption of ICT technologies and the relative services (Venkatesh et al., 2003; Venkatesh et al., 2012; Acquisti et al., 2013; Li, Unger; 2012), whose important contribution come from the personalization and privacy theories (Chellappa, Shivendu, 2010; Zhou, 2012; Hann et al., 2007);

- The two-sided markets literature, especially the most recent studies about the data-driven business models in two-sided platforms and the role of Big Data in these business models (Muzellec et al., 2015; Trabucchi et al., 2017; Ballon, Heesvelde, 2011; Marshall et al., 2015; Sorescu, 2017; Spiekermann et al., 2015 Hartmann et al., 2016).

Considering IT adoption literature, this research study contributes to two different areas of research. Firstly, Privacy Attitude has been included in many research models to investigate the relationship with users’ adoption. This research study contributes to IT literature by demonstrating that Privacy Attitude should not be considered as a unique dimension characterized by different aspects that are perceived differently from users, but it should divide them into different constructs. This finding is coherent with Steward & Segars (2002) studies that find the concern for information privacy construct to be multidimensional. By separating Privacy Attitude into different constructs according to the different information typologies that are analysed, researches might be able to better understand how and why users perceive differently some types of information.

Secondly, this research study enlarges the current state-of-art of IT literature by introducing a new case of research model that considers business model as an independent variable and investigates its relationship with users’ adoption. By comparing this research study with Baird & Raghu (2015), it emerges that the industry and the typologies of information shared with third parties are perceived differently by users, leading to different adoption behaviours. Indeed,
researchers have evidence that some industries are particularly privacy-sensitive, such as the financial services or the health ones (Li & Unger, 2012; Culnan, 1993).

Considering two-sided markets literature, the findings of this research study have an important contribution. First, this research study examines and analyses two-sided digital platforms applying data trading business model and informing users’ about the final use of their personal data, therefore it investigates a context that has not been explored so far. In fact, Trabucchi et al. (2017) state that it often happens that, even though users contribute through their “privacy capital” (Spiekermann et al., 2015) to service providers’ value proposition, the level of users’ awareness about their contribution is low, as it happens for many service providers as Twitter or Spotify. Secondly, this research study establishes a bridge between two-sided platform literature and service-dominant logic literature. As aforementioned in chapter 6, considering a digital two-sided platform who sells information and insights of one side to the other side, the role of users is fundamental for the proper realization of the value proposition. According to service-dominant logic (Vargo & Lusch, 2008), firms can only propose value, which is realized through the interaction with users.

Focusing on Xie et al. (2015) analysis of the possible roles of customers while interacting with a big data platform, none of the proposed classes fits the current business model. Indeed, considering the implemented services FitYou and Weights, customers are not buyers, as there is not a transaction; customers are not ideators, as the platform does not provide any communication tool; customers are not designers, as they do not participate in the product development process; finally they might be intermediaries sharing knowledge across different platforms, however this is not their main contribution to the realization of the value proposition.

This opens a new area of research, resulting from the application to service-dominant logic to two-sided platforms that leverage a business model based on User-generated Big Data. The proposal is to insert into the classification a new category, where customers behave as data providers: while normally using the service and exploring the functionalities that the digital service offer within its value proposition toward users-side, they passively leave “digital traces” that can be monetized to the other side, enabling firms to realize also the business-side value proposition.
### 7.2 Managerial Contributions

Considering the contributions brought by this research study, some implications for managers dealing with digital two-sided services that generate terabytes of User-generated Big Data may be derived.

In today’s information-intensive environment, organizations that base strategic initiatives on the collection and use of personal information must effectively address individual privacy concerns or risk substantial consumer negative responses (Steward, Segars, 2002). Indeed, managers that lead digital businesses know that privacy concerns about are not new, as businesses have collected customer information for thousands of years. However, privacy concerns often arise when new IT with enhanced capabilities for collection, storage, use, and communication of personal information come into play (Liu et al., 2005). With the massive diffusion of ICT, the main issues that managers of digital two-sided value proposition are related to end-users’ privacy concerns affecting their adoption of the service. Some researcher state that “a general mistrust would be the result in which data-intensive industries will have difficulties to innovate and would need to heavily invest into regaining trust” (Spiekermann et al., 2015). Indeed, two-sided platforms need both sides on board to generate network effects, which are the fuel of this type of market structure. Intense network effects imply intense interactions and consequently massive Big Data production by users.

This research study contributes to managers strategy definition because it brings quantitative evidence that users’ adoption of digital two-sided services selling UGBD is not affected by the clear disclosure of the final business purpose of personal data gathering activities. The results indicate that managers should start or continue to implement data-driven strategies, moving from data-driven decision strategies, to product improvements or even data selling strategies, which are those that rise most relevant privacy issues.

If disclosure about data selling strategies is not a problem for managers, users in the survey showed to particularly appreciate the information transparency about the final purpose of the personal collection phase, leaving comments such as “I appreciated the way in which they provided me information about the usage of my data and how they can be used to improve the city where I live”. This result is aligned with previous researches, which highlight that the implementation of transparency-enhancing mechanisms is one way to overcome privacy concerns (Karwatzki et al., 2017).
Concluding, before implementing data selling strategies, managers should take some preventative measures, which include:

- Clear communication and information transparency about the final usage of UGBD, highlighting which are the benefits that users may derive from sharing their data and enabling the realization of firms’ two-sided value proposition;
- Implement GDPR compliance processes, with reassure users about the security concerns that they may have about unauthorised access to their data. Indeed, this aspect was not included in this research analysis, being both services Weights and FitYou GDPR compliant by design.

If these preventative measures are taken, managers should not be concerned about privacy issues affecting users’ adoption of the digital two-sided service.

7.3 Limitations and Future Research

Although this research study has relevant results that lead to interesting theoretical and managerial implications, it also has some limitations.

Firstly, being one of the first research studies that investigates the business model as a variable affecting users’ adoption and that includes privacy in the value proposition of the digital two-sided platform, it is focused on a restricted case of analysis. Indeed, the research model has been tested only on one of the possible data-driven strategies, which is the data selling strategy (Trabucchi et al., 2017). This strategy has been selected as it is the riskiest one from a privacy perspective. Moreover, the survey is focused on only one empirical setting, which is the fitness and health applications market and around the 90% of the results come from Italian participants belonging to the 18-34 age group.

Secondly, security matters have not been included in this analysis, as security was ensured by design, because both services described in the empirical fitting were satisfying all the GDPR requirements, guaranteeing end-users’ some security levels and procedure against data breaches.

Thirdly, many other dimensions that are normally included in the research models of IT adoption literature have not been included in this research, such as Social Norms or Relative Advantage (Venkatesh et al., 2003; Yi et al., 2006; Venkatesh et al., 2012). This choice is due to the fact that this research study was focused on investigating the relationship between business model and
users’ adoption. Therefore, these constructs have been excluded to not introduce bias into the analyses.

As a consequence of these limitations, future research might proceed in the following directions:

- Extending the application area, by testing the research model in different empirical settings. This aims at investigating if the industry is a variable affecting users’ adoption of digital two-sided services underlying on a data selling strategy. Indeed, researchers have evidence that some industries are particularly privacy-sensitive, such as the financial services or the health ones (Li & Unger, 2012; Culnan, 1993). In fact, Culnan (1993) suggests that information privacy should be examined within varying contexts to fully understand attitudes of consumers towards business practice;

- Extending the variety of the sample, by testing the same research model in different geographical areas and bringing a contribution in terms of the number of participants belonging to different age groups or countries;

- Extending the research model with other dimensions, such as Social Norms, Relative Advantage or Security, to understand how users’ adoption varies when these constructs are included.
Appendixes

Appendix 1 – Survey

Gender

- Male
- Female

Age


Nationality


Education

- Less than High school
- High school
- Bachelor degree
- Master degree
- PhD degree
Please read the following service, pretending to be searching for a training app with those functionalities.

Weights is a training tracker app, that records your activity and measures some indicators such as the distance, the pace, etc. The kind of information collected depends on the devices that are synchronized with the application (e.g., electronic scale, smartwatch). Your activities are recorded to provide you with statistical analyses of your training: we want to support you in your training experience, to give you the information you need to improve! You can run, cycle or walk: you can choose the training that you prefer! Please read the following images for a better understanding of the service.
Would you like to read the privacy policy?

- Yes
- No

Please rate your agreement level with the following statements thinking about Weights and considering that you are pretending to be searching for a new training app with those functionalities.

I would use this service in the future

I would use this service in my daily life

I would plan to use this service frequently

Any comment on your answers?
Please read the following service, pretending to be searching for a training app with those functionalities.

*FitYou* is a training tracker app, designed to support you in your training. We believe it is essential to perfectly know the starting point to improve your training. This is why we record your activity and provide you with some indicators such as the distance, the pace, etc. The number of information collected depends on the devices that are synchronized with the application (e.g., smart scale, smartwatch). With FitYou you can decide what you want to do: run, cycle or walk, in any case, we will show you statistical analysis of your activity!

Please read the following images for a better understanding of the service.

Would you like to read the privacy policy?

☐ Yes

☐ No
Please rate your agreement level with the following statements thinking about Weights and considering that you are pretending to be searching for a new training app with those functionalities.

<table>
<thead>
<tr>
<th>Strongly disagree</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Strongly agree</th>
</tr>
</thead>
</table>

I would use this service in the future

1

I would use this service in my daily life

I would plan to use this service frequently

Any comment on your answers?

—
One last thing: now focus on your daily behaviors - without thinking about the apps you have just seen - and please rate your agreement level for the following statements:

<table>
<thead>
<tr>
<th>Strongly disagree</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Strongly agree</th>
</tr>
</thead>
</table>

I am concerned about how data like my age or sex (personal unidentifiable information) will be used by mobile app providers

I like to experiment innovative digital services

I am sensitive about sharing information regarding my preferences or choices while using mobile apps

I am concerned about how data like name, email or geographical location (personal identifiable information) will be used by mobile app provider

If I hear about an innovative digital service, I will look for ways to experiment with it

Among my friends and colleagues, I am usually one of the first to try out innovative digital services

I am concerned about sharing anonymous information in mobile apps
Appendix 2 – Additional SPSS Results

The following Table shows the Correlation Matrix results obtained by the Correlation analysis of the Privacy Attitude and Propensity to Innovative Services constructs.

<table>
<thead>
<tr>
<th></th>
<th>Pratt1</th>
<th>Pratt2</th>
<th>Pratt3</th>
<th>Pratt4</th>
<th>Propinn1</th>
<th>Propinn2</th>
<th>Propinn3</th>
</tr>
</thead>
<tbody>
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</tr>
<tr>
<td>Propinn2</td>
<td>0.620</td>
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<td>Propinn3</td>
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<td>0.533</td>
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<td>0.491</td>
<td>0.484</td>
<td>0.048</td>
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</table>

The following table shows the descriptive statistics of the Research Model implemented in SPSS. It emerges that there is no relevant difference between the means of the dependent variables on the different values of the independent variable Business Model Clearness measured by the variable bmTransparent. This result is highlighted in bold.

<table>
<thead>
<tr>
<th>deltaWill1</th>
<th>bmTransparent</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>N</th>
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</thead>
<tbody>
<tr>
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<td>5.25</td>
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</table>
The following Table shows the Tests of Between-subjects Effects for the Research Model implemented in SPSS.

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<th>Type III Sum of Squares</th>
<th>df</th>
<th>Quadratic Mean</th>
<th>F</th>
<th>Sign</th>
<th>Partial eta squared</th>
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</tr>
</tbody>
</table>
Appendix 3 – Privacy Conditions

This appendix is devoted to the description of the Privacy Policy Conditions implemented in the survey. The text has been derived after a deep analysis of the Privacy Conditions of similar two-sided digital services belonging to the same empirical setting, such as Strava or Nike Plus, but also of digital services belonging to other industries, such as Stocard or Spotify. The general structure that was detected is the following:

- Explanation of all the types of data that are collected;
- Explanation of the purposes the data are used for.

Therefore, the Privacy Conditions of both services FitYou and Weights have been shaped according to this structure. The following text is the complete text reported in the survey.

In this section you can find all the information about the types of data that are collected, how they are used and shared, coherently with GDPR norms.

FitYou/Weights collects all the information related to a profile, both identifiable and not identifiable, from the moment the user agrees to share them with FitYou/Weights. Users upload data in different moments: before, during and after the training. FitYou/Weights receives them and also collect information on how users utilize the application.

Users can share personal data, data about his friends or about their activities in different manners, for example:

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
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<td>deltaWill2</td>
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<td>0.025</td>
<td>0.024</td>
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<td><strong>0.527</strong> 0.001</td>
</tr>
</tbody>
</table>

Table 10 - SPSS Model - Tests of Between-Subjects Effects
• We collect basic information on the account, as the name, e-mail address, birth date, gender, user name and password, in order to allow and protect the access to the service;

• We collect profile information and the activities, such as when an image is uploaded, all the information about the training (date, time, geolocation, speed and rhythm) or the participation to challenges.

• Users can choose to synchronize their contacts’ information in the mobile. If users agree, the service has access and can store that information.

• We collect information from other apps or devices connected to us, such smartwatches etc.

• We can collect or derive health information, for example from the heart rate, the changes in the rhythm and speed, the weight, height or other indicators. Users agree to share this information with our service and they can fully control or remove them.

• We collect information about users’ position to elaborate statistical analysis on trainings and to active some functionalities, such as challenges on predefined routes.

• If users access our service from third parties account, we automatically receive all the information connected to the third parties’ services, according to those privacy conditions.

The information are used for several purposes, such as:

• First of all, they are used for the proper functioning of our service. For example, we cannot provide some functionalities without the access to users’ position.

• The information about the user, his followers and activities are used to personalize and improve his experience in service.

• To protect users’ vital interest, for example in case of emergency.
• The information collected are also used to promote sponsored products or services. For example, if we know that the user likes running, we can inform him about new running challenges or activities or show him sponsored contents about running.

• We can aggregate the information that users share with us and share it with third parties. In this procedure, we delete the identifiable data and we combine that information with other users’ ones. Some examples could be information about demographics, activities, routes, performances. An example of third parties that we partner with are companies providing public transportation or city planning services, so that they can optimize those services where they are most needed.

• If users accept to use sponsored contents such as a sponsored challenge, third parties can receive information and contents about the user. That information is subjected to third parties conditions and FitYou/Weights is not responsible for third parties privacy conditions.

If users do not want us to use that information, they can control the sharing degree from their profile, in order to disactivate some specific areas. From the private privacy area, it is also possible to delete stored data. Remember that some data are needed for the proper functioning of the service, so if the user disactivates them, he will not be able anymore to use it.

Any additional information or comment related to this Privacy Conditions can be asked by e-mail at this page https://support.FitYou/Weights.com
References


