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BAR – Brazilian Administration Review
Vol. 19, No. 3, Art. 3, e210101, 2022
https://doi.org/10.1590/1807-7692bar2022210101

Research Article

Diffusion of Innovation in Technological Platforms: The Uber Case

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Received October 13, 2021. This paper was with the authors for one revision. Accepted June 04, 2022.
First published online July 07, 2022.
Editor-in-Chief: Ivan Lapuente Garrido (Universidade do Vale do Rio dos Sinos, Brazil).
Associate Editor: Victor Rafael R. Celestino (Universidade de Brasília, Brazil).
Reviewers: Vitor Koki da Costa Nogami (Universidade Estadual de Maringá, Brazil), Verônica Angélica Freitas de Paula (Universidade Federal de Uberlândia, Brazil) and two anonymous reviewers.
Editorial assistants: Kler Godoy and Simone Rafael (ANPAD, Maringá, Brazil).

ABSTRACT

Objective: diffusion theory suggests that customers adopt innovation. However, no research has examined the differences between peers and the balance required of a peer-to-peer platform in the diffusion process. This article investigates whether there was a peer-to-peer balance in the diffusion process of a technological platform, represented here by the Uber case. **Methods:** a total of 843 Uber users, comprising 397 drivers and 446 customers, took part in a probabilistic sample survey in Belo Horizonte, Brazil. The study tests the hypothesis of P2P platform diffusion balance along Rogers' curve with Levene's and t-test. **Results:** the findings are counterintuitive and unexpected. Although the authors expected passengers and drivers to show a similar predisposition for Uber's adoption, empirical data did not confirm this. In contrast to the literature, which predicts that adoption occurs mainly in the initial phases, drivers' predisposition showed a constant diffusion curve. **Conclusions:** considering the peer-to-peer platform context, this article shows that the balance between peers can still be present considering the multiple actors involved, which shows a proposition for this research. Besides, this article develops the 'technological readiness indicator,' thus enabling a better understanding of different empirical contexts.

Keywords: technological platforms; peer-to-peer; Uber; Brazil.

JEL Code: O33, Q55.

INTRODUCTION

Diffusion, defined as the transmitting process of a given innovation or novelty to a given group or social system, is an essential part of any successful innovation (Ali, Raza, Puah, & Amin, 2019; Bhardwaj, 2020; Hadengue, Marcellis-Warin, & Warin, 2017; Zvolska, Palgan, & Mont, 2019). "Diffusion is a process where innovation is communicated to the social system" (Ali et al., 2019, p. 624). This process takes place over time through various channels. It usually occurs from person to person through the influencing and convincing capacity that early adopters have on people close to them. This ability to convince people leads others to adopt these novelties, replacing previous practices and procedures (Rogers, 1962; 2003). In other words, when an innovation appears and spreads, the number of adopters increases, the user experiences accumulate, and the risks of adoption tend to decrease, which results in an increase in diffusion (Bhardwaj, 2020; Dedehayir, Ortt, Riverola, & Miralles, 2017). Several technological platforms are spreading rapidly as a result of diffusion, including Uber.

The platform appeared in 2009 in San Francisco, California, and has since changed the transport market's functioning, affected urban mobility, and even how people report and use the available resources (Azevedo, Pongeluppe, Morgulis, & Ito, 2015; Barbour & Luiz, 2019). For example, "the Uber network is now available in 475 cities in 75 countries" (Barbour & Luiz, 2019, p. 38). For Uber and other consumer platforms based on 'peer-to-peer' systems, i.e., platforms that directly connect people who transact with each other, the diffusion process seeks a balance between tradeoffs and implies the winning over of two types of adopters or users: the end consumers (passengers); and the service providers (drivers). This characteristic makes the diffusion of this kind of innovation more complex (Matzler, Veider, & Kathan, 2015). The greatest challenge for peer-to-peer technological platforms is the necessity of designing intermediation systems capable of integrating organic and economically independent entities (Pu & Pathranarakul, 2019). For Chen, Yang, and Liu (2004), if suppliers' and clients' needs are not balanced, the system will become unbalanced and eventually collapse.

There is already comprehensive literature on the diffusion of innovation focusing on adopting novel technologies (Currie & Spyridonidis, 2019; Lai 2017; Marques, Lontra, Wanke, & Antunes, 2021). However, such literature has been limited to the adoption of novel technologies only by consumers and focuses on describing the variables involved in user adoption (Cheng, 2016; Chu & Chen, 2016; Marangunić & Granić, 2015; Rahman, Lesch, Horrey, & Strawderman, 2017; Rondan-Cataluña, Arenas-Gaitán, & Ramírez-Correa, 2015; Scherer, Siddiq, & Tondeur, 2019; Williams, Rana, & Dwivedi, 2015). Although still incipient, there is also some literature on the specific field of diffusion in novel technologies and technological platforms, including Uber (Borowiak & Ji, 2019; Geissinger, Laurell, & Sandström, 2020; Guda & Subramanian, 2019; Hall & Krueger, 2018; Laurell & Sandström, 2016; Min, So, & Jeong, 2019; Peticca-Harris, Gama, & Ravishankar, 2020; Shokoohyar, Sobhani, & Nargesi, 2020). However, these studies have disregarded the diffusion curve focusing on the peer-to-peer technological platforms process, its different user technological readiness in each phase of the process, and how the P2P balance, necessary for platform diffusion (Bresnahan & Greenstein, 2014; Matzler et al., 2015), occurs along the diffusion process, which are topics that will be discussed in the present paper. Recently, some scholars have emphasized the need for practical studies that address this aspect of diffusion (Barbour & Luiz, 2019; Currie & Spyridonidis, 2019; Guda & Subramanian, 2019; Lai, 2017), especially regarding the balance between peer-to-peer relationships (Bresnahan & Greenstein, 2014; Matzler et al., 2015). Indeed, Atkin, Hunt, and Lin (2015) highlighted the relevance of research that addresses adopters' characteristics in the process stage, and Piscicelli, Ludden, and Cooper (2018) emphasize that broader adoption and diffusion is necessary to tackle pressing societal problems. How they are implemented and what determines their success (or lack thereof) in the market is not yet well understood. However, there remains a lack of understanding regarding the potential differences or similarities between the various types of adopters and users.

This gap becomes more evident when, from a theoretical point of view, we consider the marked lack of research seeking to understand the balance of the peer-to-peer diffusion process considering Rogers' diffusion of innovation theory, one of the first (and now considered seminal) authors on the theme. Dedehayir, Ortt, Riverola, and Miralles (2017) are among the few researchers who have recently sought to reflect on Rogers' diffusion of innovation theory, albeit using a systematic literature review. Rogers' theory explains how novel technologies and ideas spread through the environment, i.e., how a given group's or social system's members come to know about the innovation over time. According to Rogers (1962; 2003), five groups of users make up an adoption curve. The author used risk predisposition and the ability to use innovation in advance to classify users into innovators, early adopters, the early majority, the late majority, and laggards.

No recent study has used Rogers' reflections to understand the balance of the peer-to-peer platform on each phase of the diffusion process. In other words, research is still lacking regarding investigating the platform diffusion curve's evolution considering the different user profiles (peer-to-peer process) and their technological readiness among innovators, early adopters, early majority, late majority, and laggards. A recent study by Min, So, and Jeong (2019) focused on consumer adoption of the Uber mobile application, using insights from diffusion of innovation theory and technology acceptance model, but they only addressed the factors that influenced the use of the platform. Further, few studies have addressed whether innovation occurs in a convergent way among them (Rogers, 1962; 2003). A search carried out by the authors of the present paper using international databases did not reveal any research seeking to understand the evolution of the innovation diffusion curve, considering all the profiles investigated here.

Despite the existence of several studies that aim to explain the adoption models, e.g., technology acceptance model — TAM, theory of reasoned action — TRA, and theory of planned behavior — TPB (Venkatesh, Morris, Davis, & Davis, 2003), there is a lack of studies that measure the balance of peer-to-peer platforms and the level of users' technological readiness in the diffusion process.

Platforms are flexible structures of business networks created around central coordination and can include thousands of independent offers and consumers (Gawer, 2014), facilitating transactions between them (Parker, Van Alstyne, & Choudary, 2016). However, such platforms need to balance peer-to-peer relationships (Bresnahan & Greenstein, 2014; Matzler et al., 2015). This balance is necessary to ensure the proper fit between offers (drivers) and consumers (passengers) and ensure peer-to-peer platform diffusion (Chen, Yang, & Liu, 2004; Pu &

Pathranarakul, 2019). Otherwise, the system will unbalance and eventually collapse (Parker et al., 2016; Rochet & Tirole, 2003; Sundararajan, 2016). Therefore, based on Rogers' (1962; 2003) categories, the following research question is proposed:

RQ1: Does the innovation diffusion process occur with balanced peer-to-peer relationships among Uber drivers and passengers?

The diffusion process includes offers and consumers (Chen et al., 2004). Based on Parasuraman and Colby's (2007) and Bernstein and Singh's (2008) studies, we expect distinct degrees of technological readiness in the continuum of the Rogers' curve (2003), greater degrees into innovators and early adopters, followed by decreasing degrees for the initial majority, late majority, and latecomers. In considering this backdrop, the following research question is proposed:

RQ2: Is there a difference between drivers' and users' technological readiness levels?

The research was probabilistic and stratified and took place in Belo Horizonte city, Brazil. The country is a large developing economy (Raziq, Rodrigues, Borini, Malik, & Saeed, 2020). The municipality was the third to have access to Uber in Brazil, which is currently the second-largest platform market globally, after the US. Representing the entire adult population (18 to 65 years) in Belo Horizonte (1.6 million people — about the population of West Virginia), the sample comprised 843 Uber users, including 397 drivers and 446 customers, that used the platform from 2014 to 2019. They were identified and researched in 32 randomly selected census regions.

THEORETICAL BACKGROUND

Innovation and diffusion

Innovation is a kind of capital (Migdadi, 2021). It refers to a new object, a new method, or a new idea or perception, different from the previously existing standard (Ammirato, Sofo, Felicetti, & Raso, 2019; Migdadi, 2021). According to Rogers (1962; 2003, p.12), innovation is an idea or practice "perceived as new by an individual or other unit of adoption." According to Lazaretti, Giotto, Sehnem, and Bencke (2019, p. 2168), "innovation is the practical implementation of knowledge, ideas, or discoveries, resulting in the introduction of new products, production methods, organizational process changes and the opening of new markets or resources." In turn, diffusion is the "process by which an innovation is communicated by certain channels during a certain time, among the members of a social system" (Rogers, 2003, p. 5). Several other authors have also utilized and further refined the term (Steiber, Alänge, Ghosh, & Goncalves, 2020). For instance, Schumpeter (1982), one of the first to discuss the concept (see Manohar, Mittal, & Marwah, 2019), highlighted the market's diffusion of new products and processes. For Freeman (1995), diffusion is the process of conception, development, and management by which a technology spreads through organizations. Finally, according to Hall (2009), diffusion is the process by which individuals and firms in a society/economy adopt innovative technology or replace an older technology with a newer technology.

Diffusion process vs. adoption process

For Rogers (1962; 2003), the extent, intensity, and speed of the diffusion process can increase the innovation's impact in the market. Regardless of the innovation, whether incremental or radical (Ammirato et al., 2019; Bouncken, Fredrich, Ritala, & Kraus, 2018; Coccia, 2017; Hervas-Oliver, Sempere-Ripoll, Estelles-Miguel, & Rojas-Alvarado, 2019), it can be abandoned and forgotten after a brief period of use or be restricted to small groups. In other words, the innovation's impact depends, to a considerable extent, on its diffusion process. In this context, diffusion is the process by which a given innovation is adopted and gains legitimacy among the members of a particular group or community (Ammirato et al., 2019). Rogers (1962; 2003) distinguished between the diffusion process and the adoption process. While the diffusion process occurs within society due to a group process, the adoption process occurs individually (individual or organization). Rogers (1962; 2003) also described five decisive innovation characteristics for adoption: the comparative advantages of innovation concerning existing products; compatibility with values, standards, and particular needs; the degree of complexity of the innovation to be understood and used; the possibility of being tested by potential adopters; and the capacity for innovation evaluation after being used.

Rogers' adoption curve

Rogers' adoption curve allows the assessment of the pace and form of the diffusion process. According to Rogers (1962; 2003), innovation is adopted gradually, within a temporal sequence. Social system members do not all simultaneously adopt a novelty (innovation), but rather do so gradually within a temporal sequence. Thus, Rogers (1962; 2003) highlights how it is possible to classify adopters according to their respective adoption periods, subsequently representing this on a normal distribution curve. In other words, the normal distribution curve results from the non-cumulative distribution of the adopters, in which categories represent the average of the adoption time and their standard deviation. Rogers' (1962; 2003) adoption curve comprises various segments of the adopters' population considering innovators, early adopters, early majority, late majority, and laggards. The classification of adopters considers the degree of speed or slowness during the adoption process.

Innovators represent 2.5% of the total system units and are unique individuals eager to experiment and test novel ideas or technologies. Early adopters represent 13.5% of the total and are more conventional, but they can still influence other individuals' opinions and habits within a community. The early majority encompasses a large group of individuals, and although they have a relevant role in the diffusion process, they do not act as opinion-makers. They represent 34% of the total and adopt innovation later, as they need information prior to making a decision. The late majority also represents 34% of the total; they adopt innovation due to social pressure. Finally, the laggards group comprises mainly skeptics, who adopt the latest ideas only after much social pressure and always after most members of their social system have already adopted them (Rogers, 1962; 2003). Rogers (1962; 2003) considered that the curve follows a pattern that slowly increases at the beginning when only innovators are adopting it. Subsequently, the curve accelerates, reaching the early adopters and the early majority. At this stage, the curve already represents half of the potential adopters in the system. After this phase, the number of adopters grows more slowly as it expands to encompass the late majority and the laggards (Rogers, 1962; 2003).

Over time, the innovation diffusion process assumes a curve model with an S shape. Initially, the innovation goes through a period of slow and gradual growth. Subsequently, the innovation experiences a dramatic and rapid growth period. After this period, the innovation adoption rate will gradually stabilize and eventually decline (Rogers, 1962; 2003). According to Rogers (1962; 2003), the S curve concept has universal application, linked to the type of innovation studied rather than to potential adopters' behavior. Convergently, Bass (2004) asserted that diffusion occurs through two categories of agents: innovators, who adopt innovations regardless of other agents' decisions; and imitators, who have their decision influenced.

Several studies on the diffusion and adoption of innovations emerged both after Rogers' (1962; 2003) and Bass's (2004) reflections. For instance, Hall, Wallace, and Dossett (1973) developed the concerns-based adoption model (CBAM), which measures change during skill development. The model conceives adoption as a stage result derived from the intensity of motivations, thoughts, and emotions. Davis (1989) elaborated the technology acceptance model (TAM), identifying specific factors involved in accepting a technology. Moore and Benbasat (1991) incorporated other characteristics that can affect diffusion rates. Compeau and Higgins (1995) provided a framework for researchers to predict a technology's behavior and performance. Rogers and Scott (1997) considered that, when innovation reaches the point of critical mass, it is no longer an innovation and the diffusion of the innovation is complete. Parasuraman and Colby (2007) conceptualized technological readiness as people's propensity to adopt and use innovative technologies. These authors classified people into five fundamental segments: explorers; pioneers; skeptics; paranoids; and laggards. Song, Choi, Baker, and Bhattacherjee (2013) studied the adoption of mobile applications and found that the platform's characteristics, network externalities, individual characteristics, and social interaction are key throughout the process.

The theory of reasoned action (TRA) argues that an individual's behavior is determined by his/her intention to behave, which is influenced by the individual's attitude and the subjective norms that influence him/her (Fishbein & Ajzen, 1975). The theory of planned behavior (TPB) is a deployment of the theory of rational action, whose objective was to add to the TRA constructs a new factor to explain the behavioral intention of individuals: i.e., perceived behavioral control. This variable concerns the perceived ease or difficulty of performing the behavior (Ajzen, 2011). Considering the explanatory capacity of this theory, although it includes one more variable to increase its responsiveness, it cannot exceed the level of assertiveness demonstrated by the TAM regarding the explanation of what leads a person to adopt a technology or not (Chu & Chen, 2016; Rahman et al., 2017).

The technology acceptance model (TAM) was developed as an adaptation of the theory of rational action, which is based on the influence that two external variables exert on the behavioral intention, in the present case, the use of an information technology and its effective performance

(Marangunić & Granić, 2015). The variables defended by the model are: perceived usefulness, which concerns the level of performance improvement that the individual believes that the use of a technology can generate, and perceived ease of use, which, in turn, refers to the effort that the individual believes he/she needs to expend to use the technology in question (Davis, 1989).

In addition to the efforts, the TAM model underwent two increment processes over the years, which culminated in the so-called TAM 2 (Venkatesh & Davis, 2000) and TAM 3 (Venkatesh & Bala, 2008) to explain the factors that determine the use of technologies. However, the TAM in its original form is the most successful model to explain the intent to adopt (Rondan-Cataluña et al., 2015), despite some limitations stemming from other factors not considered in the model. Furthermore, the inclusion of new variables in the TAM makes the model more complicated and does not lead to an increased predictive power (Chen, Yang, & Liu, 2004). Among the efforts undertaken to develop the TAM, Venkatesh, Morris, Davis, and Davis (2003) created a new technology acceptance model, the UTAUT. This new structure is comparable to TAM, as its determinants are similar in terms of conceptualization, despite being more difficult to validate due to the greater number of variables used (Nistor & Heymann, 2010; Scherer et al., 2019).

The UTAUT is the result of a review and consolidation of the constructs of eight models that seek to explain the behavior embedded in the use of information systems, thus clarifying the users' intention to utilize an information technology and their subsequent use. The unified theory of acceptance and use of technology (UTAUT) is a unified model with four central determinants of intent to use and four key moderators of relationships, which together provide a useful tool for evaluating the probability of success of new technologies (Venkatesh et al., 2003). Despite the efforts for UTAUT to become the 'ideal model,' such model can only answer about 70% of the questions addressed. Although this index is considered high, there are few studies dedicated to validating and exploring the performance of this model (Williams et al., 2015); there is also evidence that TAM and TPB have higher response levels than those achieved by UTAUT (Rahman et al., 2017).

Therefore, most models focus on the intention to use a technology (Davis, 1989; Venkatesh et al., 2003), but so far, they have not been able to finalize a model whose assertiveness level is higher than that of UTAUT (Venkatesh et al., 2003). There are many models that seek to explain this phenomenon (Lai, 2017; Scherer et al., 2019); however, by observing the state of the art, it is possible to say that the existing models cannot accurately identify all the variables that influence the decision process regarding the use of an information technology or not (Venkatesh et al., 2003). Synthetic models, such as the technology acceptance model — TAM, theory of reasoned action — TRA, or theory of planned behavior — TPB, can only explain approximately 50% of the factors that interfere in the decision to use a technology (Venkatesh et al., 2003). Although recent models are appropriate for explaining the variables that influence the use of technology, Rogers' theory has greater applicability with regard to the analysis of the phases of the diffusion process, especially when identifying whether the adoption levels occur in a balanced way (Bresnahan & Greenstein, 2014; Matzler et al., 2015) in each of the phases of the diffusion process, particularly considering peer-to-peer technology platforms; if the adoption is not balanced, the system will become unbalanced and eventually collapse (Chen et al., 2004).

Diffusion of innovation in the technological platforms context

Technological platforms have several characteristics that make the diffusion process even more complex. Among such characteristics, the following stand out: (a) the payment structure is distinct from salaried workers; (b) usage metrics are focused on the interaction between users, with a high degree of dependence on ratings and reputation data to reduce risk and increase trust; and (c) management of multiple interactions, which impacts the entire value chain (Altman & Tushman, 2017). The various types of platforms make it difficult to design a single definition applicable to them all. Further, Cheng (2016) stressed how research in this field is fragmented. Technological platforms have three main characteristics (Gawer, 2014): (a) they aggregate and coordinate constituent agents that can innovate and compete; (b) they create value by generating and making use of economies of scope in supply and demand; and (c) they have a modular technological architecture. This modular technological architecture comprises a nucleus (leader or key company) and a periphery. In turn, this periphery involves individual actors mutually connected to the center by an interactive network capable of combining innovation with the competition.

Technological platforms have such characteristics. Barnes and Mattsson (2016) stressed how sharing activities have been growing significantly, moving from the field of information to making diverse types of resources available, such as physical goods and credit, among others. Platforms based on peer-to-peer networks, such as Uber, have been radically altering production and consumption systems as well as transaction processes (Matzler et al., 2015).

Claussen and Halbinger (2021) argue that innovators can increase diffusion success by engaging in pre-innovation activities, similar to the experience of novelty. This factor indicates that a similar platform can influence the adoption of a novelty. Thus, a necessary step in the diffusion process is first adoption, which refers to the act of other people starting to utilize a user innovation (Jong, Gillert, & Stock, 2018).

Peer-to-peer diffusion requires adopters to have the capability to test and use novelties as people sensitive to novelties, since there is no producer mediating the process of production and consumption. One illustrative example of peer-to-peer platform diffusion is the Patient Innovation platform, where patients and caregivers around the world connect to share solutions (Monaco, Oliveira, Torrance, Von Hippel, & Von Hippel, 2019).

Despite digitalization, public 'makerspaces' and 3D printing making it increasingly simpler for peers to adopt user innovations without producer intermediation (Svensson & Hartmann, 2018), limited efforts are put into making user innovations accessible to others (Gambardella, Raasch, & Von Hippel, 2016; Hossain, 2016). Understanding the mechanisms might inhibit or support the adoption; the diffusion of socially valuable user innovations is, therefore, important to innovation policymaking (Trischler, Johnson, & Kristensson, 2020).

The service ecosystem does not distinguish between producers and consumers; instead, it has an actor-to-actor orientation. "The study of innovation, in general, has been developed from a view of value creation that separates firms as producers (e.g., innovators) and customers as consumers (e.g., adopters) of market offerings" (Vargo, Wieland, & Akaka, 2015, p. 63). The peer-to-peer orientation thus removes presumed labels and opens new possibilities for defining who innovates and diffuses based on what purpose. The study of peer-to-peer platforms can provide insights concerning the set of actor roles required for an ecosystem diffusion, and a guidance on how users can become an integrated part of an innovation ecosystem (Trischler et al., 2020).

Unlike service delivery modes that depend on large infrastructure and capital resources, market penetration of peer-to-peer platforms was achieved with various tangible resources and often physical presence (Mahmuda, Sigler, Knight, & Corcoran, 2020). In turn, value is created through a digital connectivity that depends on the interaction between individuals and service producers/providers, that is, P2P platforms with proprietary software in which brand value is linked to something more than traditional factors of production (Horowitz, 2018).

The P2P technology platforms refer to a range of activities aided by technology to dramatically reduce the transaction costs and allow the various users to access goods and services (Davidson & Infranca, 2016; Sundararajan, 2016). These platforms create networks that match suppliers and consumers of a variety of products and services and facilitate exchange (Schwab, 2016). As a result, this model impacts the city as a geographic space. At the local scale, P2P platforms are radically transforming transportation and accommodation services, people, and even other urban-related sectors (Davidson & Infranca, 2016). This new business model reshapes the city in terms of space use (Davidson & Infranca, 2016) and leads to new uses of space and urban design (Lam, 2017; Lennert & Schonduwe, 2017).

Large P2P platforms like Uber and Airbnb are rapidly expanding in all corners of the world (Davidson, 2015). So far in academia, P2P platforms are mostly researched in fields that include, but are not limited to, law, governance, and regulation — tax issues, labor rights and labor issues, zoning and land use regulations (Davidson & Infranca, 2016; Lennert & Schonduwe, 2017); in disciplines such as business studies (consumerism, business models, etc.) (Benoit, Baker, Bolton, Gruber, & Kandampully, 2017; Watanabe, Naveed, Neittaanmäki, & Fox, 2017); urban studies (Almagro & Domınguez-Iino, 2019; Barron, Kung, & Proserpio, 2020; Calder-Wang, 2020; Coles, Egesdal, Ellen, Li, & Sundararajan, 2018; Gorback, 2020); organizational research (Castelló, Etter, & Nielsen, 2016; Morgan & Kuch, 2015); competition (Farronato & Fradkin, 2018); tourism (Alizadeh, Farid, & Sarkar, 2018; Almagro & Domınguez-Iino, 2019; Almirall et al., 2016); political economy (Arcidiacono, Gandini, & Pais, 2018; Frenken, 2017); trust (Proserpio, Xu, & Zervas, 2018; Zervas, Proserpio, & Byers, 2021); and inequality and discrimination (Edelman, Luca, & Svirski, 2017; Ge, Knittel, MacKenzie, & Zoepf, 2020; Schor & Cansoy, 2019). In addition, there is much debate about their constitution as technological platforms (Bardhi & Eckhardt, 2012; Frenken & Schor, 2017; Nadeem et al., 2015). However, little attention has been paid to the necessary requirements for the P2P diffusion and the user's profile. To fully understand the diffusion of this kind of organization, it is necessary to explore how these phenomena are described and are evolving considering the diffusion of the user's technological readiness. The ride-sharing apps, like Uber, can be considered a P2P platform, as the consumer/passenger decides to take a ride due to the availability of a driver, constituting pairs that connect directly (peer-to-peer) (Frenken & Schor, 2017).

The Uber platform, for example, was founded in San Francisco in 2009 and rapidly expanded its services, ultimately reaching about 70 countries (Schneider, 2017a; 2017b). The platform revolutionized urban mobile systems worldwide, causing significant controversies and disputes, making it the subject of numerous studies (Laurell & Sandström, 2016; Schneider, 2017a; 2017b). Several recent authors have considered the impact of various types of innovation, including Uber (Azevedo et al., 2015; Moazed & Johnson, 2016). Schneider (2017a; 2017b) and Urbinati, Chiaroni, Chiesa, Franzò, and Frattini (2018) considered the platform as an example of disruptive innovation, i.e., "the process through which an innovation changes the rules of competition in a given industry" (Urbinati, Chiaroni, Chiesa, Franzò, & Frattini, 2018, p. 1). The introductory phase of this type of innovation diffusion targets price-sensitive customers, bringing new attributes, such as simplicity and convenience of use (Govindarajan & Kopalle, 2006). Despite the multiple innovation perspectives, Rogers' theoretical framework remains the most widely used as it leads to a deeper understanding of the innovation diffusion process. The characteristics and classifications described by Rogers' framework are the main factors that influence individual change and the adoption of an innovation in a social system, making its application suitable in the emerging context of technological platforms, such as Uber.

RESEARCH METHODOLOGY

Demographic profile of respondents

The research universe involves users of the Uber platform in the city of Belo Horizonte. Due to the application's confidentiality policy, it was impossible to accurately estimate the number of Uber users at the time of the survey, leading to considering Belo Horizonte's entire population as a research universe. According to the Demographic Census data of the Institute of Geography and Statistics carried out in 2010, Belo Horizonte's total population was 2,375,151. According to most up-to-date estimates, in 2019, the population was 2,512,070 inhabitants, with an adult population (18 to 65 years old) of 1,628,469 inhabitants.

Sampling design

Based on probabilistic and stratified sampling, two samples of users (drivers and passengers) of the Uber application in Belo Horizonte, Brazil, comprised the field research. In addition to being a large urban center, Belo Horizonte was one of the first Brazilian cities to allow the app's operation in September 2014. To calculate the sample size (*n*), we considered a 95% confidence interval with a 5% margin of error, resulting in a total of 384 customers and 384 drivers (Cochran, 1991). Considering the possibility of missing data and outliers, the authors decided to increase the sample to 843 users, comprising 446 consumers and 397 drivers. Subsequently, the authors stratified the sampling by gender (consumers) and city census tracts, which were randomly drawn (Malhotra, 2011). After excluding two interviews, following the European Social Survey criterion, the sample totaled 841 users (444 customers and 397 drivers) (Sambiase, Teixeira, Bilsky, Araujo, & Domenico, 2014).

Questionnaire design

The validation of content involves elaborating and refining the data collection instrument (Hoppen, Lapointe, & Moreau, 1996). Theoretical propositions and hypotheses arising from the literature review on platforms and innovation diffusion guided the formulation of the questions, the internal consistency of the scale was performed through an exploratory factor analysis, and the Cronbach's alpha ensured content validation (Churchil, 1979). This sort of validation ensures that the indicators utilized consistently represent the phenomenon under evaluation. Following Perrien, Chéron, and Zins's (1984) guidelines, the researchers considered several factors in designing the questionnaire. Initially, we used a representative number of closed question options to cover all answers. Further, only questions strictly related to the research topic were applied. We also considered the questions' implications in the data tabulation and analysis procedures.

Pretesting

Subsequently, the authors performed a pretest for the data collection instrument. In this pretest stage, the authors considered the following aspects highlighted by Gil (2002): clarity and precision of terms; number of questions; the form of questions; the order of the questions; and the introductory text. The pretest comprised two stages. Initially, after the questionnaires were prepared and printed, 40 Uber users were approached to answer the first-stage questions. Considering the anxiety displayed by most users, the researchers developed a dynamic online questionnaire to improve the interview dynamics. The second pretest had structured questions available in an online and dynamic platform. It was operated via tablets and carried out with 25 respondents. The number of interviewees met the minimum criterion of 15 interviews for pretesting (Malhotra, 2011). This procedure was essential to evaluate the electronic platform, public acceptance to join the study, and to assess respondents' understanding of the wording.

Data collection

According to Malhotra (2012), in stratified probability samples, first the universe must be divided into subgroups, called strata. Then the elements must be selected from random criteria. Here, the research universe was stratified in terms of gender (for consumer users) and defined by the duration of interviews and the number of interviews expected. In total, 32 census sectors were selected in the city of Belo Horizonte. The structured interviews took place between May and August 2019 with people who traveled near schools, malls, and shopping centers in the census sectors. The researchers skipped five individuals before starting the next interview in order to ensure a random selection of interviewees. In the case of drivers, due to the application's confidentiality issues, the approach occurred in places where they usually wait to provide their service, e.g., airport pick-up points, bus stations, and malls within the boundaries of the census tracts, respecting the random selection of interviewees, i.e., skipping five individuals before starting the next interview. Respondents signed a free and informed consent form on the virtual platform to operationalize the study. A dialog box displayed at the beginning of the section on the user's data was used to gather respondents' demographic details. Ápice, a small company based at the Pontifical Catholic University of Minas Gerais, collaborated in the data collection.

A team of experienced professionals composed of four researchers, three coordinator-supervisors, and 55 technicians performed the data collection. All those involved received specific training to operationalize data collection and critically analyze the data. The team approached individuals in places selected by stratification, ensuring the randomness of the sample. Initially, the researchers questioned individuals regarding whether they were users of the Uber platform, inviting them to participate in the survey if the answer was positive. The authors performed the following procedures to check the quality of the data collection: (a) audit of transcriptions of the electronic research forms; (b) phone calls made to interviewees to confirm the provided information; and (c) evaluation of the research forms, analyzing whether they were complete and matched the electronic research system's registration.

Non-response and common method bias

Non-response (Depner, 2007) corresponds to 0.4% of the passengers; in the drivers' sample, non-response was not identified, which indicates, according to Batinic, Werner, Gräf, and Bandilla (1999), good research reliability and quality. Longford (2000, p.73) argues that less than 2% of non-response already indicates good research reliability. In the present study, the low non-response was achieved due to the face-to-face approach, the little time to respond (less than five minutes), the virtual platform used to operationalize the study, and the trained team involved. The occurrence of common method bias is frequent when scholars use the same type of scale with the same number of response options and when the analysis is transversal, i.e., at a specific moment (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The authors therefore used Harman's single factor test to check for common method bias, as well as exploratory factor analysis using all the study variables to generate a single factor. According to Podsakoff, MacKenzie, Lee, and Podsakoff (2003), when the variance explained in the factor analysis is less than 50%, common method bias is not an issue. Using SPSS v.25, we adopted the component extraction method and unrotated factor solution, as suggested by Podsakoff et al. (2003). The exploratory factor analysis outcome indicated an explained variance of 29.17% via Harman's single factor test, i.e., no significant evidence of common method bias. The authors also verified acquiescence bias indications, such as missing data, suspicious research response patterns, outliers, and survey straight-lining (Hair, Hult, & Ringle, 2013; Podsakoff et al., 2003). We also employed univariate outlier detection to detect outliers. This technique indicated values above four standard deviations as a reference to characterize an atypical observation.

Measurement instrument

The researchers used Cronbach's alpha (α) to verify the reliability of the scales. The objective was to indicate the percentage of the variance of the measures free of random errors (Malhotra, 2011). Landis and Koch (1977) asserted that values above 0.61 are acceptable; in this research, Cronbach's alpha was 0.71, which demonstrates the utilized scales' internal consistency. The researchers used the t-test for independent samples, associated with the Levene's (1960) test to verify whether, between 2014 and 2019, in Belo Horizonte city, the Uber expansion process occurred in balanced way between drivers and passengers. The software used to perform the test was SPSS v.25.

The following hypothesis tests were adopted:

H0 (Levene's test): The monthly driver adoption variance is equal to the monthly passenger adoption variance ($p > 0.05$).

H0 (t-test): The average monthly passenger adoption is equal to the average of the monthly drivers' adoption ($p > 0.05$).

Following the categories proposed by Rogers (1962; 2003) (innovative, early adopters, early majority, late majority, and laggards), the researchers, based also on Parasuraman and Colby's (2007) conceptualization, formulated the 'technological readiness indicator' to measure people's propensity to adopt and use innovative technologies using a Likert scale. This indicator checks whether there is a significant difference in technological readiness levels between drivers and passengers. Thus, several degrees of readiness would be present in the Rogers' curve continuum. Therefore, the indicator should provide different scores in each phase of the curve, with a higher score for innovators and early adopters and a lower score for the early majority, the late majority, and laggards. The following propositions and equation (1) were used to provide a value for the indicator.

P1. I am a person sensitive to novelties, able to try new things.

P2. I like to use and test novel technologies.

P3. I have used or use apps like Uber.

Despite the existence of a technology readiness index (Parasuraman & Colby, 2015), a custom scale and indicator were developed considering the P2P platform particularities described by Claussen and Halbinger (2021), Jong, Gillert, and Stock (2018) and Monaco, Oliveira, Torrance, Von Hippel, and Von Hippel (2019), thus reducing respondent burden. Parasuraman and Colby (2015, p. 18) affirm that "researchers have frequently opted to use a small subset of items to reduce the burden on respondents." Despite the updated model with TR2, Parasuraman and Colby's (2015) scale is still considered too generic for the P2P platform specificities.

The scale used was as follows: 1 = 'totally disagree,' 2 = 'partially disagree,' 3 = 'neutral, or indifferent,' 4 = 'partially agree,' and 5 = 'totally agree.' The values were converted into indices from –1 to +1, assigning –1 to 1, –0.5 to 2, 0 to 3, +0.50 to 4, and +1 to 5. The following equation was used:

$$Pt = \frac{\frac{\sum_{k}^{p}(\mathbf{P1})}{n} + \frac{\sum_{k}^{p}(\mathbf{P2})}{n} + \frac{\sum_{k}^{p}(\mathbf{P3})}{n}}{\mathbf{3}} \qquad (1)$$

where: Pt = technology readiness; P1, P2, P3 = Likert-scale data; n = sample size; and k = the user (k = 1, 2, ..., p).

The lower the indicator, the lower the user's readiness to adopt innovative technologies. In turn, the higher the indicator, the greater the user's readiness for technological adoption. Using the indicator data, it is possible to compare the technological readiness data between the sample of drivers and consumers for each of Rogers' (1962; 2003) categories, leading to the following hypothesis tests:

> *H0* (Levene's test): The driver sample's technological readiness indicator variance is equal to the variance of the technological readiness indicator in the passenger sample ($p > 0.05$).
>
> *H0* (t-test): The technological readiness indicator in the drivers' sample is equal to the technological readiness indicator in the passenger sample for each of Rogers' categories ($p > 0.05$).

Data analysis

The authors carried out a multidimensional analysis of the data (Hair et al., 2013), elaborated according to Rogers' (1962; 2003) criteria for the composition of the innovation's adoption and diffusion curve, to identify the adopters' profiles. The researchers simultaneously analyzed more than two variables to summarize the findings or perform more in-depth analysis. The analysis categories were established based on literature, thus facilitating data interpretation and codification. The analysis categories grouped the data collected through the questionnaires. The indicator was created based on the structured questions, with support from the Likert-scale questions. The test statistic considered in the hypothesis test was based on the Student's t-distribution; a normal distribution is expected once the population's mean and standard deviation is known.

By identifying the time (date) of Uber's adoption for each user, it was possible to describe the Uber innovation diffusion's evolution curve in the driver and passenger segments, distinguishing between the earlier and later users. Thus, all users were classified according to the date of adoption, that is, between 2014 and 2019. As previously noted, Rogers (1962; 2003) allocates users to a normal distribution curve and considers that half of them are among the innovators (2.5%), early adopters (13.5%), and the early majority (34%), while the other half of the curve comprises the late majority (34%) and laggards (16%). Based on Rogers' (1962; 2003) propositions, the researchers identified and analyzed each category of user profiles in the diffusion curve. The elaboration of the diffusion curve (cumulative distribution) proceeded as follows: the x-axis plotted the period since the launch of the innovation, while the y-axis plotted the percentage of adopters accumulated up to the x period.

RESULTS

Initially, based on the data collected, Uber's diffusion and adoption curves in Belo Horizonte were elaborated. Figure 1 shows the adoption curves per year.

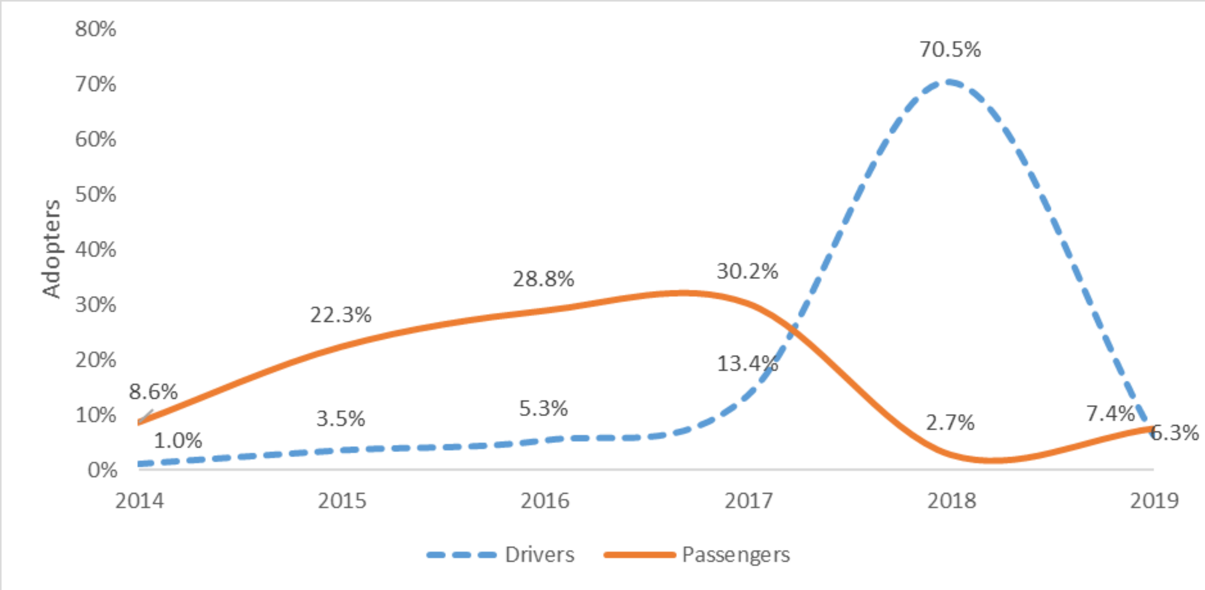

Figure 1. Passengers and drivers' adoption curve.

In order to facilitate the visualization of the adoption curve, we considered the same period for drivers and passengers. Source: Based on Rogers, E. M. (2003), Diffusion of Innovations (5 ed., p. 247). New York: Simon & Schuster.

For passengers, the diffusion occurred more quickly in the period between 2014 and 2017. A small portion (7%) had used the application for less than one year. If we add this portion to those who had started using the application one or two years ago (3%), the total rises to just over 10%. This percentage indicates that the platform's use continued to expand but with less intensity, with an inflection point starting in 2018. For drivers, from 2014 to 2016, the diffusion occurred much more slowly, accelerating from 2017. Most drivers (78%) had started operating from 2018 to 2019. Only 7% had started activities on the application from 2019 onward, demonstrating that the process was still in progress until the final data collection.

Although the consumer and driver curves look different, it is necessary to check whether there is a balance in the relationship between peers point to point. This balance is required to sustain the diffusion process. Therefore, the researchers carried out the independent hypothesis test considering monthly periods of drivers' and passengers' adoption (see Table 1).

Table 1

Adoption curve statistics

Group	*n*	Average	Deviation error	Mean standard error
Passengers	61	7.2787	5.40719	0.69232
Drivers	50	7.9400	10.43818	1.47618

Note. Descriptive statistics for average.

As shown in Table 1, the passengers' sample presents an adoption average of 7.3 per month with a standard deviation of 5.4 users. The drivers' sample presents a larger average (7.9 users per month) and a standard deviation of 10.4 users.

The Levene's test results for equality of variances indicate no equality of variance between the samples ($p < 0.05$). The t-test for equality of means revealed a p-value of >0.05, indicating no significant difference between the average of drivers' and passengers' adoption samples. Therefore, on average, the independent t-test showed that the monthly adoption rate is the same between passengers and drivers ($t(0.686) = -0.406$; $p > 0.05$) (see Table 2). Thus, the evidence demonstrates a balance between adoption among offerers (drivers) and demanders (passengers), which is necessary for disseminating point-to-point platforms, such as in the case of Uber. The second research question sought to understand whether there is a difference between drivers' and users' technological readiness levels, considering Rogers' categories. To answer this question, through the technological readiness indicator, the authors measured the predisposition levels present in the continuum of Rogers' (1962; 2003) curve.

Table 2

Adoption curve hypothesis tests

	Levene's test		t-test for equality of means						
								95% confidence interval of difference	
	Z	Sig.	t	df	Sig. (2-tailed)	Mean difference	Standard error of difference	Lower	Upper
Assumed equal variances	11.084	0.001	−0.430	109	0.668	−0.66131	1.53892	−3.71140	2.38878
Equal variances not assumed			−0.406	70.154	0.686	−0.66131	1.63047	−3.91305	2.59042

Note. Levene's test consider p < 0,05 for variance not assumed equal, and p > 0,05 for variance assumed equal; t-test considered p < 0.05.

Figure 2 compares the composition of the two curves. Although the differences in the evolution of the diffusion between them are visible at the beginning of the application's expansion phases, the two curves demonstrate Rogers' (1962; 2003) diffusion format. Both curves have a high growth stage, accelerating until reaching the early adopters and the early majority. The phase up to the early majority represents half of the individuals foreseen in the system. After the early majority phase, the number of adopters grows more slowly, reaching the late majority and, finally, the laggards.

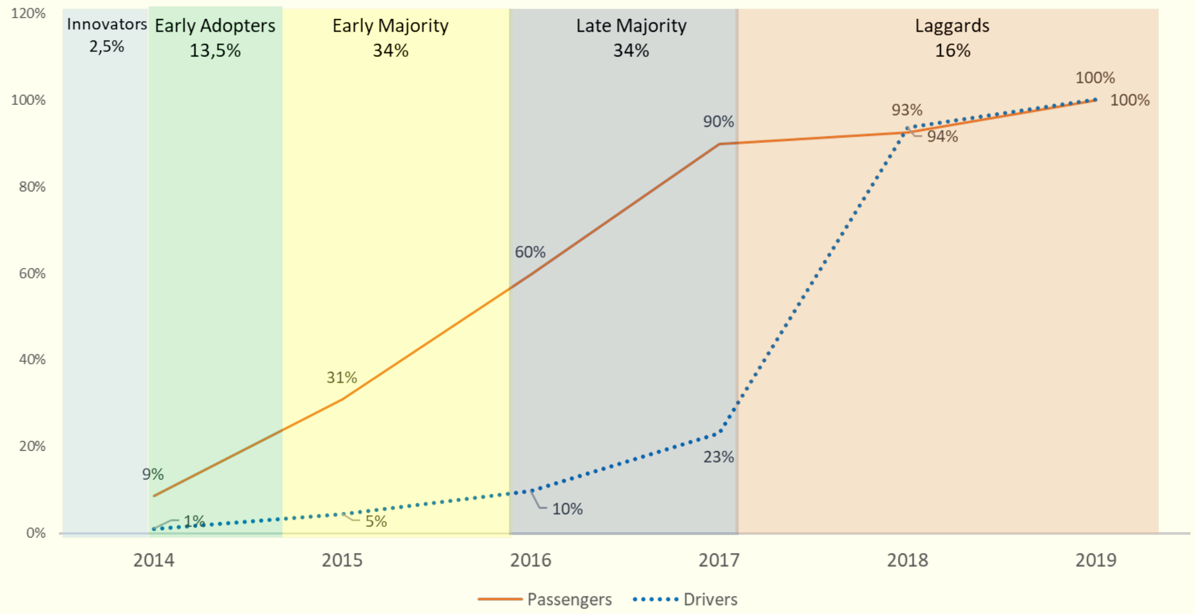

Figure 2. Passengers' and drivers' adoption curve according to user category.

To facilitate the diffusion curve of drives and passengers, the data were accumulated, describing the curve in each phase of the Rogers' concept. Source: Developed considering Rogers, E. M. (2003), Diffusion of Innovations (5 ed., p. 247). New York: Simon & Schuster.

Concerning the passengers' profile, among the innovators, 82% believed themselves to be sensitive to novelties, and 100% stated that they like testing novel technologies. Regarding the early adopters, most (77%) saw leadership as the primary reason for adopting innovation, thus highlighting the importance of influencers. Among the early majority, 93% believed that Uber increased the necessity of interaction with novel technologies and control systems. Only 11% of the late majority, described as conservative (Rogers, 1962; 2003), considered themselves inclined to test new technologies, which shows that social pressure for use is a crucial convincing factor for this group. Finally, the laggards, resistant to change, isolated, and stuck in the past (Rogers, 1962; 2003), had a different profile than expected. Among them, 48% were sensitive to novel developments.

Regarding drivers, 69% of the innovators considered themselves sensitive to novelties, and 82% like to test novel technologies. A total 94% of early adopters are leaders in adopting innovation in their networks, thus acting as influencers. Among the early majority, 70% felt Uber had intensified the necessity of interaction with novel technologies and control systems. In the late majority, 89% considered themselves inclined to test novel technologies. This shows that drivers are more open to novel technological experiences than passengers are. Finally, 85% of laggards showed sensitivity to novelties, reflecting the distinct profile described by Rogers (1962; 2003).

Uber consumers joined the platform very quickly in Belo Horizonte city. The first year already included innovative users and early adopters (16% of the total). By the end of the third year, the users' cumulative percentage was already 60%, comprising both the initial majority and the late majority. By the fourth year, the curve included 90% of adopters, dropping sharply in 2018 and 2019, which comprised only 10% of adopters. The adoption curve for drivers was slower compared to that of consumers. The early adopters appeared between 2015 and 2016, while the early majority appeared in 2017 and 2018. The year 2018 also showed the highest adoption rate, predominantly comprised of late majority and the laggards. Table 3 shows the Likert-scale data after conversion into scores and the calculations for the technological readiness indicator.

Table 3

Technological readiness indicator

	Likert scale questions							
	I am a person sensitive to novelties, able to try new things		I like to use/test new technologies		I've used, or use apps similar to Uber		Technological readiness indicator	
User type	Passengers	Drivers	Passengers	Drivers	Passengers	Drivers	Passengers	Drivers
Innovators	0.773	0.350	0.864	0.700	0.500	0.650	0.712	0.567
Early adopters	0.733	0.650	0.542	0.750	0.559	0.630	0.610	0.676
Early majority	0.583	0.620	0.553	0.726	0.130	0.581	0.421	0.643
Late majority	–0.083	0.660	–0.099	0.730	–0.159	0.544	–0.114	0.644
Laggards	–0.028	0.593	0.049	0.730	–0.190	0.484	–0.056	0.603

Note. For values higher than zero, the score is positive; for values lower than zero, the score is negative. Technological readiness considers the same logic.

The technological readiness indicator shows decreasing values for passengers, indicating that the predisposition to adopt innovation falls as one progresses through the profiles classified by Rogers (1962; 2003) in the diffusion curve. However, concerning drivers, the technological readiness values remained positive at all stages of the diffusion process, indicating that the profile of the drivers is distinct from that of the consumers. The researchers utilized t-test for independent samples, associated with Levene's test, to verify the hypothesis that the levels of technological readiness between the samples are different. The test was performed in each category of the Rogers' curve (see Table 4).

Table 4

Technological readiness indicator

Rogers' (1962; 2003) categories	Levene's test for equality of variances			t-test for equality of means						
	Variance	Z	Sig.	t	df	Sig. (2-tailed)	Mean difference	Standard error of difference	95% confidence interval of difference	
									Lower	Upper
Innovative passengers vs. innovative drivers	Assumed equal	2.440	0.135	1.157	19.000	0.261	0.145	0.126	–0.118	0.408
	Not assumed equal			1.175	18.224	0.255	0.145	0.124	–0.114	0.405

Continues

Table 4 (continued)

Rogers' (1962; 2003) categories	Levene's test for equality of variances			t-test for equality of means						
	Variance	Z	Sig.	t	df	Sig. (2-tailed)	Mean difference	Standard error of difference	95% confidence interval of difference	
									Lower	Upper
Early adopter passengers vs. initial adopter drivers	Assumed equal	5.225	0.024	–1.076	112.00	0.284	–0.066	0.062	–0.188	0.056
	Not assumed equal			–1.093	107.97	0.277	–0.066	0.061	–0.186	0.054
Early majority passengers vs. early majority drivers	Assumed equal	36.320	0.000	–5.514	284.00	0.000	–0.222	0.040	–0.301	–0.142
	Not assumed equal			–5.616	271.25	0.000	–0.222	0.039	–0.299	–0.144
Late majority passengers vs. late majority drivers	Assumed equal	4.861	0.028	–24.937	284.00	0.000	–0.758	0.030	–0.817	–0.698
	Not assumed equal			–24.704	263.70	0.000	–0.758	0.031	–0.818	–0.697
Laggard passengers vs. laggard drivers	Assumed equal	29.633	0.000	–8.621	132.00	0.000	–0.660	0.076	–0.811	–0.508
	Not assumed equal			–8.938	105.56	0.000	–0.660	0.074	–0.806	–0.513

Note. Levene's test considers $p < 0.05$ when equal variances are not assumed, and $p > 0.05$ for equal variances assumed; t-test considers $p < 0.05$.

In the categories of innovators and early adopters, the analysis of the t-test and Levene's test results compared to the indicator data, with a significance level of 5%, indicate no significant difference in technological readiness between the samples of customers and drivers. However, the other categories (early majority, late majority, and laggards) show significant differences, with a positive index for drivers in all Rogers' (1962; 2003) categories. The data show that drivers have a different profile than the one presented in Rogers' (1962; 2003) classifications, i.e., less technological readiness would be expected among the early majority and latecomers. This lower technological readiness among the early majority and latecomers occurred among passengers but was not evident among drivers.

DISCUSSION

The hypothesis test results show no significant differences in Uber providers' (drivers) adoption rate and that of passengers (consumers). Drivers and passengers had an average adoption of 7.9 and 7.3, respectively. Although the curves are also distinct in the average adoption and dispersion, considering the duality between passengers and drivers, the diffusion process occurred in a balanced way between passengers and drivers (Avital et al., 2014). This duality is crucial for the platform's operational synchronism. The drivers' adoption curve is also flatter than that of the passengers. This curve shows greater dispersion of data, with emphasis on the median point (between earlier users and later users) occurring two years after (mid-2018) the median point of consumers (mid-2016).

Regarding Rogers' category profiles, the technological readiness indicator shows different degrees of predisposition for adoption between drivers and customers. The sample of customers/passengers is more consistent than that of drivers regarding the technological readiness levels predicted by Rogers (1962; 2003). The indicator shows a high degree of technological readiness in the innovative (0.712) and early adopters (0.610) categories, decreasing among the early majority (0.421), late majority (−0.114), and laggards (−0.056). The latter have negative indices, indicating less predisposition. This result is consistent with that expected in Rogers' (1962; 2003) categories. In the drivers' case, however, the data are different from what is expected.

The predisposition to experiment and test novel technologies is always positive and constant on the diffusion curve: innovative (0.567); early adopters (0.676); early majority (0.693); late majority (0.644); and laggards (0.603). A total of 6% of drivers were unemployed before joining Uber, while for 3%, Uber was their first job. These data corroborate that Uber platforms can reduce unemployment, affecting companies, society, and the job offer. Passengers show greater adherence to Rogers' (1962; 2003) profiles for the innovative, early adopters, initial majority, and late majority categories. Regarding drivers, laggards and the late majority profiles show a new openness to innovation and new technologies, denoting a peculiar characteristic of the Belo Horizonte platforms market.

The research findings corroborate Rogers' (1962; 2003) propositions on the determinant characteristics for adoption. Before adopting an innovation, Rogers (1962; 2003) argued that the actors must perceive comparative advantages compared to existing products. The Uber platform offers low prices, convenience, and comfort, hitherto absent in the low-cost transportation market, such as buses and subways. By presenting such benefits, the platform demonstrates a competitive advantage over competitors. However, according to Rogers (1962; 2003), the innovation must also be compatible with values, norms, and particular needs for people to adopt it. In this regard, the Uber platform demonstrates adherence to the need for fast, less costly, and more efficient transportation among the individuals surveyed, including changing their beliefs, habits, and values.

Further, regarding people's propensity to adopt and use novel technologies, the early users' profiles are similar to those described by Parasuraman and Colby (2007). The data also point to similarities between the early users' profiles and those highlighted by Song et al. (2013) concerning the individual characteristics (drivers and customers) and platform particularities. Rogers (1962; 2003) highlighted another determining factor also observed in the Uber platform, i.e., the ease of evaluating the innovation after its use. The platform offers a service evaluation system immediately after the use of the service. In addition, it features service scores that serve as a reference both for platform managers and for users.

Uber presents the characteristics described by Rogers (1962; 2003) that give rise to the adoption and diffusion curve presented in this paper. The platform demonstrates an understanding of the complexity of users' innovation adoption and potential for expansion based on the ease of use. Indeed, to join the platform, consumers only need a smartphone with internet access, while, in addition to this, drivers only need a vehicle and a driving license.

IMPLICATIONS

Theoretical and methodological implications

This article has several theoretical and methodological implications. The first relates to incorporating the notion of innovation diffusion in the study of peer-to-peer technological platforms, such as Uber. Although previous research has addressed innovation diffusion, it has mainly considered the adoption of novel technologies only from the perspective of consumers (Lai, 2017; Meuter, Ostrom, Roundtree, & Bitner, 2000). Although a few studies have sought to understand mobile technologies' diffusion, including Uber (Min et al., 2019), these studies have disregarded the diffusion curve and its various impacts. This article explores both gaps, integrating them as well. It also investigates consumers (passengers) and providers (drivers), analyzing both actors' innovation adoption curves in the diffusion process. By doing so, this article highlights that research should incorporate the combined analysis of the various actors engaged in the process in the context of peer-to-peer platforms, since the P2P platform diffusion requires an adoption balance between consumers and providers. The combined analysis carried out allows a better understanding of the studied phenomenon. In other words, the process used to identify, map, and analyze the innovation and adoption cycle in each market can be adjusted and applied to other places and to various types of innovation.

The second implication relates to the creation of the technological readiness indicator, which can be used in different empirical contexts to understand the differences across users' profiles. The technology readiness indicator was developed with a customs scale considering two singularities of peer-to-peer platform's adoption: (a) engaging in pre-innovation, as similar platform activities can influence the adoption of the novelty (Claussen & Halbinger, 2021; Jong et al., 2018); and (b) the sensibility to test and use a new platform novelty since no producer is mediating the process of production and consumption (Monaco et al., 2019). Furthermore, the technology readiness scale by Parasuraman and Colby (2015), even the updated TR2 (focus on optimism, innovativeness, discomfort, and insecurity), provides an excellent way to have a broad perspective of the novelty predisposition. However, it does not focus on peer-to-peer platforms and does not address the P2P platform specificities. Thus, a custom scale is an opportunity to measure these specificities. Nevertheless, according to Parasuraman and Colby (2015), we have to be careful to use a small subset of items to reduce the burden on respondents. Based on the scales utilized in the present paper, it was possible to identify the different user profiles according to their willingness to adopt innovation at each stage of the diffusion process. The present paper made it possible to assess the pace and the current stage of Uber's entry into the Belo Horizonte market, in addition to assessing the application's diffusion cycle from its launch in 2014 to the completion of the survey in 2019.

The third implication relates to Rogers' diffusion theory application. Although there are many recent models to understand the factors that interfere in the decision to use a technology (e.g., TRA, TPB, TAM, UTAUT), these models are appropriate for explaining the variables that influence the use of technology (Lai, 2017; Scherer et al., 2019), despite their difficulty in accurately identifying all the variables that influence the decision process (Venkatesh et al., 2003). The original model of Rogers' theory has greater applicability with regard to describe and analyze the phases of the diffusion process, especially when the aim is to identify whether the adoption levels occur in a balanced way (Bresnahan & Greenstein, 2014; Matzler et al., 2015) in each of the phases of a peer-to-peer diffusion process. If the adoption among peers is not balanced, the system will become unbalanced and eventually collapse (Chen et al., 2004). Therefore, Rogers' original theory was still the most proper model for understanding the diffusion process of a peer-to-peer platform, like Uber, and the technology readiness indicator was essential to check the adoption user balance.

Practical implications

This article also has significant practical implications. Initially, it stresses the relevance and adequacy of Rogers' theory to innovation and diffusion research in relation to understanding several phenomena, including peer-to-peer technological platforms, such as Uber. In this context, Shrotriya, Dhir, and Sushil (2018) emphasized the importance of continuous innovation in obtaining a competitive advantage. Second, for entrepreneurs interested in benchmarking peer-to-peer platforms, this article demonstrates the Uber case's possibilities. The platform allows Uber to offer low prices, convenience, and comfort, leading to a competitive advantage over several other competitors. Enterprise owners interested in eliminating intermediaries by directly connecting suppliers to users can and should consider the possibility of peer-to-peer platforms. Uber is among the recent leading examples that can be used for benchmarking.

Further, such platforms can facilitate easy access for consumers and suppliers, with whom the responsibility for the required goods lies. Thus, such resources enable the low cost necessary for their management. The advent of technological platforms requires managers to conduct a more refined analysis of current consumers' needs as well as those of potential consumers, or other services' and products' users. Uber represents a good example of this, given its lower cost, convenience in the context of public transportation, and having a non-focused market compared to other private transportation providers, such as taxis.

Another element that managers cannot neglect is the speed of the platform's diffusion process. Even after five years of operation and Uber's rapid growth, the platform, until mid-2019 (data collection period), was continuing to expand, albeit at a slower pace. This demonstrates that marketing efforts in terms of dissemination are essential at the beginning of the curve when they reach innovators, early adopters, and the early majority. Simultaneously, the results suggest that managers must strengthen their efforts to reach users with a more conservative profile, i.e., the late majority and the laggards.

Policy implications

Although these research results are not representative of the entire Brazilian population, the quantitative method used here allows the generalization of Belo Horizonte's city results. In doing so, this article provides some relevant implications for public policies in the area of the development of urban transport. In addition to its own market, Uber has impacted an entire transport chain, including the auto industry, bus companies, taxis, and subways. Even other disconnected segments, such as car rental, fuel, maintenance, and vehicle assistance, among others, have also been impacted following the platform's arrival.

By focusing on the diffusion process of peer-to-peer technological platforms, with Uber as an empirical analysis object, this research expands our limited knowledge concerning the current diffusion of such innovations. Further, it provides managers with practical inputs capable of measuring the impacts that such platforms have in the general urban mobility market. As such application of technology platforms is complementary to traditional public transport offerings, this article estimates and suggests the significance and need for public policymakers to rethink public transport strategies and legislation and their direct and indirect effects. Indeed, Uber's adoption trajectory suggests, among other things, that traditional means of transportation, such as buses, subways, and taxis, do not fully meet the needs of the population. This poor service leads to a regulatory imbalance, where the existing institutional order does not provide sufficient support for actors to carry out their activities.

Although not the object of analysis in this article, it is impossible to disregard the fact that Uber's success may prove to be partly related to the population's unemployment rate. Some of the drivers who work on the platform may be doing so as a temporary alternative source of income. This suggests that the meso-macro levels radiate the impacts driven by the diffusion of innovation at the micro-level, and that macro-structural factors, such as unemployment, can impact the innovation diffusion's success rate. In this sense, public policymakers must pay attention to the legal and institutional factors that influence, for instance, the appropriate adjustment of service release versus its taxation.

Expectations caused by different types of technological platforms' emergence bring both potential benefits and threats. The benefits derive, for instance, from the hope that novel technologies will be able to help increase inclusion and improve the quality of life for many people. However, the risks, dilemmas, and challenges are enormous, encompassing the possibility of current crises multiplying and expanding, the expansion of reconversion and industrial relocation, increased unemployment, social polarization, and institutional weakening. Public policymakers must pay attention to both dimensions.

LIMITATIONS

The study is not without limitations. Although it presents the diffusion curve and gauges technological readiness for Uber drivers and passengers, it does not address the causes of user adoption; the study does not capture the reasons for users to adopt innovation. Although the technological readiness indicator provides a way to quantify the propensity to adopt an innovation, including more variables may allow the indicator to be adapted to other contexts, e.g., health.

SUGGESTIONS FOR FURTHER RESEARCH

Rogers' (1962; 2003) typology in the study of the diffusion of peer-to-peer technological platforms reveals several novel perspectives for investigating platforms that need to deal with both sides of the market simultaneously. Such platforms' success can impact the entire value chain. Therefore, future studies should apply Rogers' typology to several other peer-to-peer platforms. These studies could corroborate or expand the present findings regarding differences in the adoption curves between the distinct actors involved in the process. Further, the typology can also be used to analyze other processes of change triggered by other technological innovation types, opening up new possibilities for measurement and testing. Future studies could also: (a) aim to comprehensively understand, through qualitative methodological strategies, the impacts of peer-to-peer applications in different sectors; (b) assess cross-national data; such studies could assess the impacts of platforms on urban mobility and the macro-structural changes, which could improve the generalizability of the results; (c) test, corroborate, or expand the technological readiness indicator developed in this paper; (d) test the Parasuraman and Colby's (2015) technology readiness scale on peer-to-peer platforms studies; (e) investigate the influence of blockchain and the internet of things on the future development of such platforms; (f) examine the reasons for adopting such platforms, focusing on the variables involved in users' decision-making, such as, for example, culture and digital influencers; (g) investigate the influence that previous technology has on future behavior in relation to adopting novel technology.

CONCLUDING REMARKS

This article has sought to answer two fundamental questions that have been little explored in the literature, specifically how the innovation diffusion process occurs among Uber drivers and users, and whether there is a difference between drivers' and users' technological readiness levels. Field evidence allows us to conclude that: (a) despite the apparent differences with regard to the speed of adoption curves for drivers and passengers, there are no significant differences in the adoption levels between drivers and passengers; (b) regarding the adoption cycle, the process took place relatively quickly among passengers. During the first three years, about 60% of passengers had already joined the platform. Among drivers, the process occurred more slowly; only 23% had joined in the first four years.

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