
The impact of network externalities on acceptance and use of an app of peer-to-peer platform: a study with Uber users

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Abstract

In recent years, sharing business models have emerged based on the use of technology. Thus, this study used the constructs of UTAUT2 and Network Externalities, in order to analyze how the network externality moderates the acceptance of an app used in peer-to-peer platform. A survey was conducted with 243 Uber users and data were analyzed through the structural equation modeling. As a result, it has been found that all factors influence user acceptance in a positive way. However, the network externality moderates this influence when it comes to factors as facilitating conditions, habit, and social influence.

Keywords: UTAUT2; Network Externality; Uber; Technology; Structural Equation Modeling.

O impacto de externalidades de rede na aceitação e uso em aplicativo de uma plataforma peer-to-peer: um estudo com usuários da Uber

Resumo

Nos últimos anos, surgiram modelos de negócios compartilhados baseados no uso de tecnologia. Assim, este estudo utilizou os conceitos da UTAUT2 e Externalidades de Rede, com o objetivo de analisar como a externalidade de rede modera a aceitação de um aplicativo utilizado em plataforma *peer-to-peer*. Foi realizado um survey com 243 usuários Uber e os dados foram analisados por meio da modelagem da equação estrutural. Como resultado, verificou-se que todos os fatores influenciam a aceitação do usuário de forma positiva. No entanto, a externalidade de rede modera essa influência quando se trata dos fatores condições facilitadoras, hábito e influência social.

Palavras-chave: UTAUT2; Externalidade de Rede; Uber; Tecnologia; Modelagem de Equações Estruturais.

El impacto de las externalidades de red en la aceptación y el uso de una aplicación de plataforma peer-to-peer: un estudio con usuarios de Uber

Resumen

En los últimos años, han surgido modelos comerciales compartidos basados en el uso de la tecnología. Por lo tanto, este estudio utilizó los constructos de UTAUT2 y externalidades de red, con el fin de analizar cómo la externalidad de red modera la aceptación de una aplicación utilizada en la plataforma *peer-to-peer*. Se realizó una encuesta con 243 usuarios de Uber y se analizaron los datos mediante el modelo de ecuaciones estructurales. Como resultado, se ha encontrado que todos los factores influyen en la aceptación del usuario de una manera positiva. Sin embargo, la externalidad de la red modera esta influencia cuando se trata de factores que facilitan las condiciones, el hábito y la influencia social.

Palabras clave: UTAUT2; Externalidad de red; Uber; Tecnología; Modelado de ecuaciones estructurales.

1 Introduction

Over the past few years, a number of new and different sharing business models have emerged. In common, these business models operate in the “sharing economy” of collaborative consumption (Botsman & Rogers, 2011), where people or organizations offer and share resources in a creative and new way. Uber got media attention because of its market penetration, which has also attracted the ire of a number of stakeholders who claim that these models unfairly compete in an unregulated environment, fail to provide the minimum quality and safety standards, and exploit their on-demand workers (Muñoz & Cohen, 2017).

Created in 2009, Uber is a company with a high technology sharing platform, being considered one of the most valuable companies in the market nowadays (Watanabe, Naveed, Neittaanmäki & Fox, 2016). According to these authors, “it is seen as the jewel of information and communication technologies (ICTs), particularly the digital services platform and the sharing economy, because it brilliantly connects the transportation sector to ICTs through its sharing travel app and grab the sharing revolution”, named in the academic background as peer-to-peer (Watanabe *et al.*, 2016, p.2). Consequently, it fully enjoys the benefits of collaborative consumption characterized by (i) selling the use of a product rather than the ownership of a product, (ii) supporting customers in their desire to resell goods, (iii) exploiting unused resources and capacities, (iv) providing repair and maintenance services, and (v) using collaborative consumption (Matzler *et al.*, 2015, p.14).

It is now one of the fastest growing companies in the world and has been exploring the new frontier of the disruptive business model guided to the ICTs (IDBM) (Watanabe *et al.*, 2016). Based on this model, it has managed to globally expand to more than 479 cities in more than 75 countries around the world in June, 2016. Its value exceeds the value of the US cab and limousine industry. This rapid expansion can provide constructive information about this technology-based sharing market. However, this rapid expansion resulted in legal battles in almost every city around the world (Malhotra & Alstynne, 2014). Unlike licensed taxi drivers, private citizens who offer sharing travel services do not necessarily need a professional driver’s license; they do not do licensing examinations for that and do not buy commercial insurance.

According to Watanabe *et al.* (2016), Uber rapid expansion can be attributed to the construction of this disruptive business model based on ICTs. The authors complement that business models are shifting to platform structures based on this type of technology. As a social phenomenon, it is perceived that this expansion occurs despite the various controversies

surrounding this kind of disruptive business model based on technology. Such situation requires further research about the acceptance of this technology. Since it focuses on sharing urban mobility based on technology (through mobile devices), it is important to use one of many research models into technology adoption. This study used one of the most influential and comprehensive theories in technology adoption as the basis for the conceptualization and extended it with an important construct originating from studies on economic theories.

The Unified Theory of Acceptance and Use of Technology (UTAUT2) is an established model that used constructs in the quest to influence the intention to use a technology. The main four predictors of UTAUT are performance expectancy, effort expectancy, social influence and facilitating conditions. On the other hand, as the theories of technology adoption are technology-specific, it is important to think of other constructs related to technology or context. Thus, the proposed extension is related to the characteristic of the network of users and service providers that utilize a certain technological platform, it is, therefore, the network externality to moderate the adoption of technology. Considering this extension is also guaranteeing the theoretical originality of this paper. The use of network externalities can be explained by the notions of Chung et al. (2016), when they state that especially in developing countries, the economic status is influencing the users' choice of a mobile network, thus influencing the use of any app related to the technology. This kind of network externality is considered as "indirect network externality".

Therefore, the objective of this paper is to analyze how the network externality influences the acceptance and use of an app used in a peer-to-peer platform. This article is divided as follows: the subsequent section will explore the literature related to the theme and the main discussed constructs: UTAUT2 and network externalities. The third section will describe the method used to address the research question and the hypothesis. Section four will address data analyzes, while section five will discuss the results. Finally, the conclusions and suggestions for future research will be discussed at the end.

2 Theoretical framework

The research on technology adoption aims to understand the factors that predict people's decision in adopting a specific technology. One of the important models is the Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh *et al.* (2003) and further extended by Venkatesh *et al.* (2012). When exploring the technology adoption from

within a peer-to-peer platform is important to think about network externalities. The following two sections will explore the two dimensions of the proposed conceptual framework.

2.1 The Unified Theory of Use and Acceptance of Technology

The UTAUT model was originally presented with four main constructs: performance expectancy, effort expectancy, social influences and facilitating conditions. The model has presented an advanced understanding of technology acceptance, unifying multiple theoretical perspectives and incorporating dynamic influences, adding four moderating variables (age, gender, experience and willingness to use) that solidify the explanatory skills of the model (Wang et al., 2008). Nevertheless, it explained 70% of the variability of users' intentions for technology use. UTAUT has integrated eight theories and models in the field of technology acceptance and human behavior, including TRA (Theory of Reasoned Action), TAM (Technology Acceptance Model), MM (Motivational Model), TPB (Theory of Planned Behavior), C-TAM-TPB (combination of TAM and TPB), MPCU (Model of Personal Computer Utilization), IDT (Innovation Diffusion Theory) and SCT (Social Cognitive Theory) (Venkatesh *et al.*, 2003).

The empirical research has repeatedly shown that the UTAUT model aims to study factors that influence technology acceptance and behavioral intentions better than competing models (Venkatesh *et al.*, 2003; Park *et al.*, 2007; Zhou, 2013; Nysveen & Pedersen, 2016). Due to the sensitivity of the model to cultural aspects, it was considered as suitable for cross-country and cross-region studies, since UTAUT has the capacity to highlight and discover cultural differences, and may resist to translation problems (Oshlyansky *et al.*, 2007).

The model was then extended to include hedonic motivation (using technology with a sense of fun), price value, and habit. Users tend to behave more positively about using a technology in their interface or handling if it is fun (Brown & Venkatesh, 2005). Habits can be defined in two ways: habits can refer to past behavior (Kim & Malhotra 2005), or as an individual performs an automatically behavior using technology because of the learning process (Limayem *et al.*, 2007). The second definition fits to the use of information technology. The research indicated that the habit in the form of previous behavior was closely linked to the technology acceptance (Venkatesh *et al.*, 2012).

Although the UTAUT model has addressed most of the necessary variables to provide an understanding of the intentions of acceptance and use of technology, it is important to notice

that the results about the relative significance of the four main constructs of the model have widely and inconsistently ranged, without clear standards (Cheng *et al.*, 2011), especially when it comes to application in different countries. This is extremely important for research that seeks to reapply or extend the model to carefully choose which constructs include and choose the data analysis method that ensures valid results (Attuquayefio & Add, 2014). And it cannot be forgotten that the model may need to be adjusted to accommodate the differences between countries (Cheng *et al.*, 2011) and also between different social phenomena that surround the existence of a certain technology.

Regarding the constructs, the effort expectancy refers to how comfortable and easy the clients feel in adopting a technology. The effort expectancy usually results in greater significance in early adoption (Baron *et al.*, 2006), indirectly affecting behavioral intentions through performance expectancy. It means that if a customer feels that the use of a certain technology will require a lot of effort, his perception of that technology will be diminished (Zhou, 2011).

Performance expectancy encompasses other factors in technology acceptance, including perceived utility, relative advantage, and outcome expectation. Venkatesh *et al.* (2003) defined the term as the degree to which the user thinks that using a particular technology will improve overall performance. Previous research has emphasized this construct as one of the best predictors of technology acceptance (Al-Shafi & Weerakkody, 2009; Zhou, 2013). Hence, “facilitating conditions” refer to the degree to which the technical and organizational infrastructure that facilitates the use of a technology is already in operation (Attuquayefio & Add, 2014). As the technology adoption is a specific domain itself, the abundance and ubiquity of mobile technology will be considered important for the adoption process, which emphasizes the role of facilitating conditions as a predictor of behavioral intention (Peng & Mu, 2011).

“Social influence” is the pressure exerted by members of a social environment of an individual to perform or not the behavior under consideration (Taylor & Todd, 1995). Social influence was reported by research to significantly impact behavioral intentions (Hong & Tam, 2006). It is believed that the significance of social influence as influencing the technology acceptance stems from the presumption that individuals tend to consult important people in their environment to reduce the anxiety associated with the use of an innovation (Slade *et al.*, 2015). In addition to this conclusion, the researchers completed that external influences and social image have a great significant prediction of customer behavior (Liébana-Cabanillas *et al.*, 2014; Suntornpithug & Khamalah, 2010).

2.2 Network Externalities

The influence of network externalities occurs when the perceived value of the service or product increases as the number of users also increases (Economides, 1996), explaining how the utility of the product or service is linked to the number of its buyers. There are three types of network externalities that explain this relationship: direct effect of network externality, positive influence and indirect network effect.

The direct effect of network externality is felt when the number of users or customers for a product or service increases. The positive influence is directly felt as the user becomes able to interact with a larger number of users. The indirect effect of network externalities is felt when the result of an improvement in the product/service utility is induced by the increase in the number of users. The network externalities have also an indirect effect that can be felt by the user, because the increase in the number of buyers causes an improvement in the availability and quality of after-sale services (Katz & Shapiro, 1985).

The effect of externality has been studied as a factor that influences the acceptance of many information systems technologies, especially those sharing the characteristics of network assets (Shapiro & Varian, 1998). For sharing economy peer-to-peer platforms, service network externalities can have an impact on user's acceptance and use intentions.

3 Research method

This research is considered as quantitative. As a research method, the cross-sectional survey was used, being the survey defined by Bryman (1989, p.104) as a method of collecting data conventionally associated with questionnaires and interviews. Fink and Kosecoff (1998) consider the possibility of the survey to take the form of self-administered questionnaires and interviews. In this work, self-administered questionnaires via Internet were used. Respondents were invited by Facebook to participate in the survey.

The UTAUT2 model is suitable for the purposes of this study, since it has high explanatory abilities, consolidating several theories and models of the technology acceptance area (Venkatesh *et al.*, 2003). The model is used to study the factors that influence clients' behavioral intentions about the technology of a peer-to-peer platform. When examining the literature on the sharing economy market, it was not identified papers focused on predicting

how the technologies of these platforms are accepted and what factors influence the behavioral intentions of the adopters.

In order to extend the explanatory abilities of the UTAUT2 model and realizing that, in general, the services offered by the peer-to-peer platforms are submitted to the network externality effect, because the value of these services usually increases as the number of users also increases (Wang *et al.*, 2008a), this construct was inserted as moderator of the process of acceptance and use intention. Figure 1 illustrates the proposed research model.

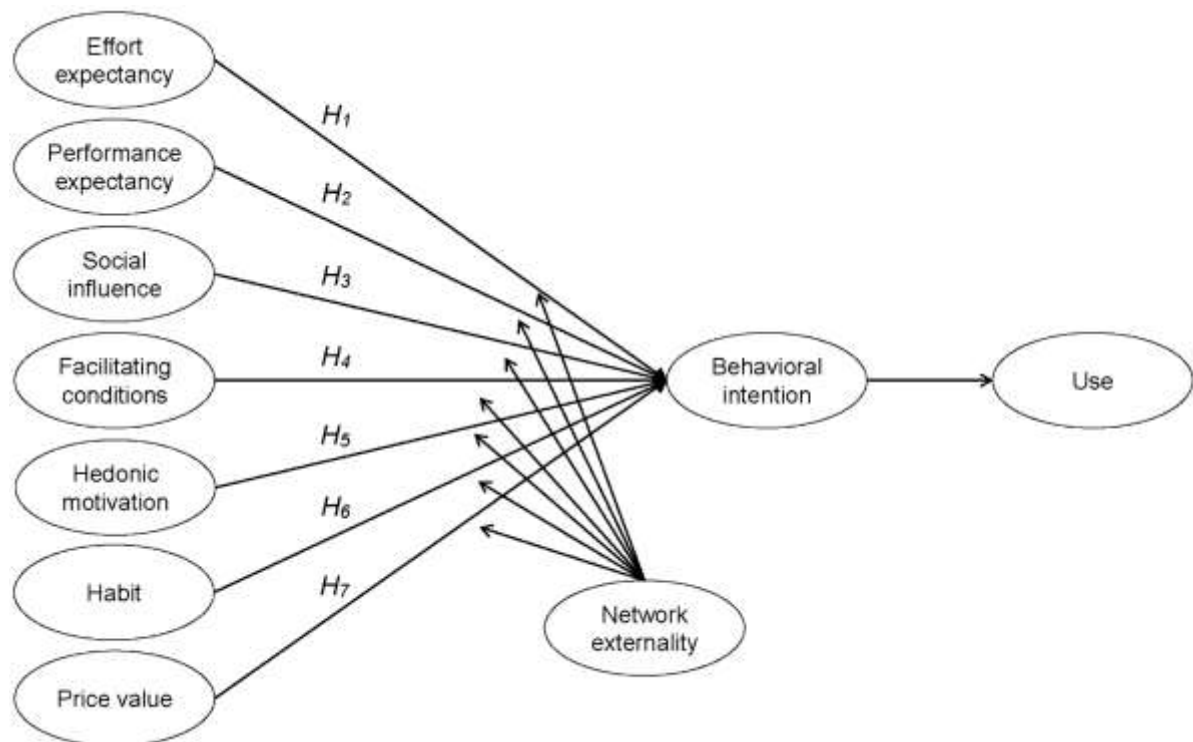


Figure 1: Proposed structural model

As all the constructs were in English, it was necessary to translate them, as explained below. Figure 2 shows the translated constructs and items.

Construct	Item	Authors
Effort Expectancy	Learning how to use Uber app was easy for me.	Venkatesh et al. (2012);
	The information Uber gives me is easy to understand (payment methods, car/passenger localization)	
	I think Uber app is easy to use.	
Performance Expectancy	I consider convenient to use Uber app.	Venkatesh et al. (2012);
	I consider that using Uber app saves my time.	
	I consider that using Uber app, I accomplish things from day-to-day faster.	
Social Influence	My friends/family tell me to use Uber.	
	My friends/family use Uber and I take this into account when using too	

	People whose opinions I value prefer to use Uber app, rather than other apps (Cabify, Will Go, Lyft, taxi apps, among others)	Venkatesh et al. (2012);
Facilitating conditions (formative)	I believe that I have the necessary resources to use Uber (Example: internet with adequate data transmission, compatible smartphone, among others) Uber app is compatible with other technologies I use and does not disrupt the performance of my mobile device. I ask for help from others when I have difficulties in using Uber app.	Venkatesh et al. (2012)
Hedonic Motivation	I feel motivated to use Uber. I consider pleasurable to use Uber app. I consider using Uber app is enjoyable.	Venkatesh et al. (2012)
Price Value	Uber is reasonably priced. The price of Uber's service is fair Compared to the usual price, Uber offers a good cost/benefit relation.	Venkatesh et al. (2012)
Habit	Using Uber has become a habit for me. I consider Uber to be essential in my day-to-day life. I often use Uber app.	Venkatesh et al. (2012)
Network externalities	I believe more drivers will want to provide Uber service if they realize that the number of people using the app is increasing. I believe that the most drivers use Uber app, the waiting time will be shorter when I request the service. (Assume that quality is shorter waiting for service). I believe that the most drivers use Uber app, the service will be cheaper.	Katz e Shapiro (1992)
Behavioral intentions	I intend to continue using Uber app in the future. I hope to continue using Uber app in my routine. I plan to use Uber more often.	Venkatesh et al. (2012);

Figure 2: Constructs and Items of the Questionnaire

3.1 Objective and Research Hypotheses

This study aimed to explore how the effect of network externalities influences technology acceptance. As highlighted, it is believed that as higher the network externality is (more individuals using a particular technology), as higher will be the perception of other people regarding the ease in using a technology. In this sense, when network externality (NE) increases, the effort expectancy (EE) becomes less important in explaining behavioral intentions (BI) to use peer-to-peer technology. Therefore:

H₁: The network externality moderates the significant and positive relation of the effort expectancy on the behavioral intentions.

Performance expectancy refers to the extent to which an individual believes that the use of a particular technology will improve his performance (Venkatesh et al., 2003). If a user thinks that using a specific innovation will improve his performance, it is more likely that he/she will use it (Morris & Venkatesh, 2000). As more drivers use the technology, higher will be the performance of the entire network. Therefore:

H₂: The network externality moderates the significant and positive relation of the performance expectancy on the behavioral intentions

Social influence is defined as the social pressure exerted on an individual by people close to him in the social environment to use or not an innovation (Venkatesh *et al.*, 2003). This factor proved its importance as a predictor of technology acceptance in several contexts. By inserting SI in a context with a strong network externality, it is proposed that the importance of SI to explain behavioral intentions increases. Therefore:

H₃: The network externality moderates the significant and positive relation of social influence on behavioral intentions.

The facilitating conditions refer to the degree to which the technical and organizational infrastructure facilitates the use of a certain technology that is already in use (Attuquayefio & Add, 2014). In a context where the network externality is strong, the relative importance of this construct to explain the behavioral intentions increases, therefore:

H₄: The network externality moderates the significant and positive relation of facilitating conditions on behavioral intentions.

The hedonic motivation (HM) construct was elaborated from Brown and Venkatesh (2005) conceptualizations about the fact that users have a more positive behavior regarding the use of a technology, especially if they think it is fun to use it (even if used for work). The influence of network externalities occurs when the benefit of using a product increases as the number of people using it also increases (Haruvy & Prasad, 1998). In the context of peer-to-peer platforms, users seem to feel happy and pleasant in using technology when the number of technology users increases. Therefore:

H₅: The network externality moderates the significant and positive relation of hedonic motivation on behavioral intentions.

The construct of habit is defined in two ways: i) habits can refer to past behavior among members of the same social group (Kim & Malhotra, 2005), or ii) how the individual automatically performs a behavior using IT because of the learning process (Limayem *et al.*, 2007). The second definition fits to the use of information technology. The research indicated that the habit, as previous behavior, was closely linked to the technology acceptance (Venkatesh *et al.*, 2012). In a scenario where the network externality is strongly established, individuals automatically use the technology (Limayem *et al.*, 2007), therefore:

H₆: The network externality moderates the significant and positive relation of habit on behavioral intentions.

The construct of price value (PV) is defined as the cost and monetary price of a particular technology regard to the benefit perceived by the consumer (Venkatesh *et al.*, 2012). According to these authors, the structure of costs and prices can have a significant impact on the use of technology. For example, there is evidence that the popularity of short message services (SMS) in China is due to the low price of SMS compared to other types of mobile Internet apps (Chan *et al.*, 2008). In marketing research, cost and monetary price are generally conceptualized along with the quality of products or services to determine the perceived value (Zeithaml, 1988). The price value is positive when the benefits of using the technology are perceived as greater than the monetary cost and have a positive impact on the intention. Thus, in this study, the value will be added to a predictor of behavioral intention to use technology. And also because it is believed that a strong network externality can influence on the relative importance of the PV construct in predicting behavioral intentions. Therefore,

H₇: The network externality moderates the significant and positive relation of price value on behavioral intentions.

3.2 Development of Data Collection Instruments

In order to guarantee the validity of the instrument, the items of the questionnaire were adapted from the literature. The writing of the items was modified to fit the context of peer-to-peer platforms (the researched technology). To ensure that the translated questions were intuitive and appropriate to the culture and social reality of Uber users, the questionnaire was submitted to a pre-test. The items were used in the research and presented to the respondents randomly. Three control variables were inserted in order to eliminate random responses and also a variable that could identify the passenger who used Uber service, but had never accessed the technology (or app), so he could also be eliminated from the sample. The objective is to analyze only users who have actually used the technology, not just the service provided by Uber.

3.3 Sampling and Questionnaires Distribution

For the definition of the number of respondents, the G*Power software was used. It was evaluated the construct that receive the largest number of arrows or has the highest number of predictors; in the case of the Behavioral Intent (BI) model, with 7 arrows indicating prediction, for the calculation, which was performed before collecting data, it was observed the parameters recommended by Hair et al. (2016): the use of power as 0.80, f^2 median = 0.15. The number of respondents was 77, however, in order to make the sample more robust, 243 valid questionnaires were answered (that also meets the assumptions of Hair et al. (2014) about the sampling) in the period from September 2017 to January 2018, with users of Uber technology, in 73 Brazilian cities, highlighting that the app is in operation in 94 cities of the country.

4 Data analysis

In this paper, we chose to follow Hair *et al.* (2016) due to the SmartPLS software approach, although Anderson and Gerbing (1988) are the main reference in structural equations modeling, as identified by Vieira *et al.* (2017). The structure of this research has 8 models of reflective measurement and one moderator. Reflective models are facilitating conditions, performance expectancy, effort expectancy, social influence, price value, habit, hedonic motivation and behavioral intention. The construct of network externality is a moderator. According to Hair *et al.* (2016), the decision about which is the appropriate model of measurement has been the subject of considerable debate in a variety of disciplines and is not fully determined.

The SmartPLS software was used. About the parameters to execute the PLS-SEM algorithm for when the maximum number of 300 interactions or the stop criterion of 1.0E-5 (that is, 0.00001) was reached. According to Hair et al. (2016), the selection of a maximum number of 300 interactions must ensure that convergence is obtained in the stop criterion of 1.0E-5. We applied the path weighting scheme, because according to Hair *et al.* (2016), it provides the highest R² value for endogenous latent variables. Figure 3 shows the model after the execution of PLS algorithm.

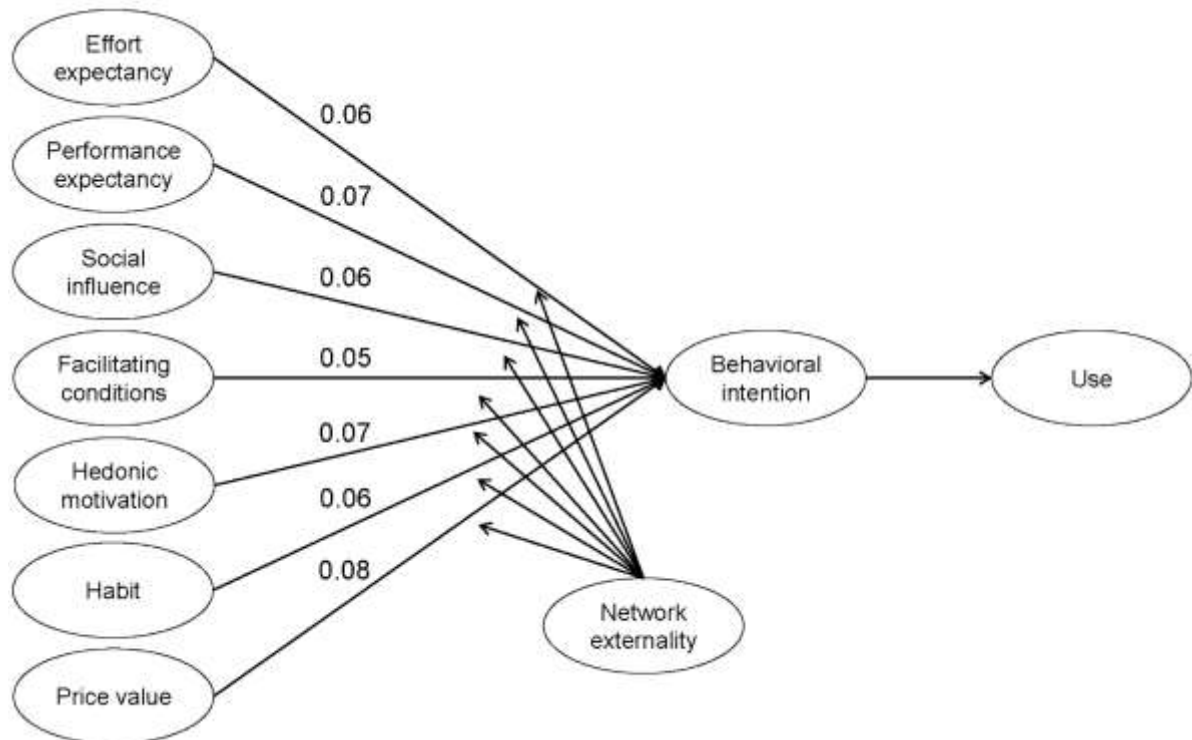


Figure 3: Path Coefficients

4.1 Preliminary analysis

The used stop criterion to measure the PLS algorithm was a maximum of 300 iterations and the criterion was reached after the iteration 3. The reflective measurement models are evaluated in their reliability and validity of internal consistency. According to Hair et al. (2016), specific measures include composite reliability (as a form to assess the reliability of internal consistency), convergent validity, and discriminant validity. To ensure convergent validity, it was necessary to eliminate one indicator of the construct “facilitating conditions”. This item was eliminated after a careful analysis of the effects of its removal, through the identification that its outer loading was below 0.70. The others obtained values above 0.70 and were considered as significant. Continuing the analysis, it is important to clarify that the composite reliability indicates that the sample is free of bias, that is, the answers are reliable, and the values are according to the definitions from Hair et al. (2016). Table 1 summarizes the results of the evaluation of the reflective measurement model.

Table 1
Measuring of Reflective Models

Latent Variable	Indicator	Loadings (Weights)	Composite Reliability	Average Variance Extracted (AVE)	Discriminant Validity
Facilitating Conditions	FC1	0.71 (0.43)	0.80	0.67	Yes
	FC2	0.92 (0.76)			
Performance Expectancy	PE1	0.80 (1.00)	0.87	0.69	Yes
	PE2	0.84 (0.38)			
	PE3	0.85 (0.39)			
Effort Expectancy	EE1	0.77 (0.44)	0.89	0.73	Yes
	EE2	0.90 (0.50)			
	EE3	0.90 (0.41)			
Network Externality	NE1	0.84 (0.44)	0.84	0.64	Yes
	NE2	0.83 (0.44)			
	NE3	0.72 (0.37)			
Habit	HA1	0.93 (0.39)	0.93	0.82	Yes
	HA2	0.88 (0.36)			
	HA3	0.91 (0.36)			
Social Influence	SI1	0.84 (0.44)	0.85	0.66	Yes
	SI2	0.86 (0.41)			
	SI3	0.74 (0.38)			
Behavioral Intention	BI1	0.85 (0.39)	0.89	0.73	Yes
	BI2	0.88 (0.42)			
	BI3	0.83 (0.36)			
Hedonic Motivation	HM1	0.83 (0.50)	0.83	0.62	Yes
	HM2	0.72 (0.38)			
	HM3	0.80 (0.39)			
Price Value	PV1	0.84 (0.33)	0.91	0.77	Yes
	PV2	0.89 (0.41)			
	PV3	0.89 (0.24)			

Still about Table 1, the average variance extracted (AVE) is a common measure to establish convergent validity at the level of the construct. AVE is an indicator of the adequacy of convergence when the values are higher than 0.5. It means that the variation is greater than the variance due to the error. AVE for all constructs is greater than 0.5. In turn, the convergent validity according to Hair et al. (2016) can be defined as the significant relation between two or more measures of the same construct or theoretically related constructs. In other words, AVE represents the fraction of data that is explained by each of the constructs, or, how much, on average, the variables correlate with their respective constructs. As the values are above 0.50, it is assumed that the model converges to a satisfactory result (Hair et al., 2016). Discriminant validity is the extent to which a construct is truly distinct from others by empirical standards. Thus, establishing a discriminatory validity implies that the construct is unique (Hair et al., 2016). For measuring the discriminant validity, it was applied the Fornell-Larcker criterion (the most conservative approach to assessing discriminant validity, based on the measure of “shared variance” suggested by Fornell and Larcker (1981) and to examine cross-loads (where the

external loading of an indicator in the associated construct should be greater than all its loads in the other constructs). Specifically, the square root of the AVE of each construct should be higher than its higher correlation with any other construct (Hair et al., 2016). According to Hair et al. (2016), the logic of this method is based on the idea that a construct shares more variance with its associated indicators than with any other construct. All the evaluation criteria of model were met, providing support for the reliability and validity of the reflective measures.

Considering that all reflective constructs exhibit satisfactory levels of quality, the evaluation of the structural model will be presented below. The evaluation of the results of the structural model allows one to determine how well the empirical data support the theory, deciding whether it was empirically confirmed (Hair et al., 2016). The first step is to evaluate the collinearity and so the latent variable scores will be used. For the collinearity test, the tolerance and variation inflation factor (VIF) is estimated. The variance inflation factor (VIF) indicates the amount that the variance of each coefficient is increased in relation to those with uncorrelated independent variables. Since all tolerance values and VIF are within acceptable limits, it is concluded that there are no multicollinearity problems and that the independent variable is not extremely predicting itself. Table 2 shows the colinearity evaluation. As can be seen, all VIF values are clearly below the limit of 5. Therefore, the collinearity between predictor constructs is not a problem in the structural model.

Table 2
Results of Variance Inflation Factor

Collinearity Statistics	
Construct	Variance Inflation Factor (VIF)
Facilitating Conditions	1.62
Performance Expectancy	1.70
Effort Expectancy	1.26
Network Externality	1.83
Habit	1.66
Social Influence	1.31
Hedonic Motivation	2.30
Price Value	1.64

Then, R² level was evaluated. According to Hair et al. (2016), the most commonly used measure to evaluate the structural model is the coefficient of determination (R² value). For researches on consumer behavior with attitudinal measurement scales, values above 0.20 are considered high. In this model, the R² value of Behavioral Intention (0.61) can be considered as being significantly substantial. The next step involves the evaluation of the path coefficients

of the structural model. To evaluate the meaning of the relations, we execute the bootstrapping procedure. Table 3 shows the path coefficients, the T-Value and their P-Values.

Table 3
Results of the Significance Test of the Path Coefficients of the Structural Model.

Paths Definition	Path Coefficient	T Value	P Value
Facilitating Conditions -> Behavioral Intention	0.06	0.09	0.93
Performance Expectancy -> Behavioral Intention	0.07	0.60	0.55
Effort Expectancy -> Behavioral Intention	0.05	1.17	0.24
Habit -> Behavioral Intention	0.05	7.64	0.00
Social Influence -> Behavioral Intention	0.05	3.18	0.00
Moderator Effect (FC->NE->BI)	0.05	0.65	0.52
Moderator Effect (PE-> NE-> BI)	0.07	1.12	0.26
Moderator Effect (EE-> NE-> BI)	0.06	0.85	0.39
Moderator Effect (HA-> NE > BI)	0.06	2.10	0.04
Moderator Effect (SI-> NE->BI)	0.06	2.31	0.02
Moderator Effect (HM-> NE->BI)	0.07	1.39	0.16
Moderator Effect (PV-> NE->BI)	0.08	0.33	0.74
Moderator Effect (FC-> NE->BI)	0.06	2.30	0.02
Price Value -> Behavioral Intention	0.06	2.04	0.04

Still regard to Table 3, it is relevant to clarify that the values and significance of the path coefficients indicate how much one construct relates to the other. These values vary from -1.0 to +1.0, indicating positive or negative relations respectively, being values equal to 0 considered weak. And, they indicate positive relations between the constructs. The significance of these relations can be measured by T-Student, where values above 1.96 are considered significant at 5% ($t \geq 1.96$ or $p \leq 0.05$), that is, the constructs and/or path coefficients are acceptable. In this case, significant relations are: Habit → Behavioral Intention, Social Influence → Behavioral Intention, Moderator Effect (Effort Expectancy → Network Externality → Behavior Intention), Moderator Effect (Habit → Network Externality → Behavior Intention), Moderator Effect (Social Influence → Network Externality → Behavioral Intention), Moderator Effect (Facilitating Conditions → Network Externality → Behavioral Intention) and Price Value → Behavioral Intention.

The evaluation of the size of effects and predictive relevance will be now presented. In addition to evaluating the magnitude of R^2 values as a criterion of predictive accuracy, Hair et al. (2016) indicate that researchers should also examine the Q^2 value of Stone-Geisser. The authors emphasize that this measure is an indicator of the predictive relevance of the model. Then, the blindfolding procedure was performed. Since there are 243 respondents, we chose an omission distance of $D = 7$. It can not be used an omission distance in which the division of the

number of observations used in the model estimation and the distance is a whole-number. In the presented path model, the predictive relevance Q^2 of behavioral intention (endogenous construct) has a value of 0.39, which implies that the model has great predictive relevance. Therefore, it can be inferred that all the exogenous constructs have great predictive relevance over the endogenous one. However, it is important to verify the predictive relevance of the exogenous construction. This measure refers to the size of effect q^2 (eq.1).

$$q^2 = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}} \quad (\text{eq.1})$$

In addition to evaluating the R^2 values of all endogenous constructs, the change in R^2 value when a specified exogenous construction is omitted in the model can be used to assess whether the omitted construction has a substantial impact on the endogenous construction (behavioral intention) (Hair et al., 2016). The value is obtained by the inclusion and exclusion of endogenous constructs of the model (one by one). It is evaluated how much each construct is “useful” for the model adjustment (Hair et al., 2016). This measure is referred as the size of effect f^2 (eq.2).

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}} \quad (\text{eq.2})$$

Table 4 summarizes the results of the size of f^2 and q^2 effect regard to significant relations in the model. The guidelines for evaluating f^2 and q^2 are the values of 0.02, 0.15 and 0.35, respectively, which represent small, medium and large effects of the exogenous latent variable.

Table 4:
Size of Effect

Exogenous Constructs	Size of Effect f^2	Size of Effect q^2
	Behavioral Intention	Behavioral Intention
Facilitating Conditions	0.00	0.00
Performance Expectancy	0.00	0.00
Effort Expectancy	0.01	0.00
Network Externality	0.04	0.05
Habit	0.26	0.11
Social Influence	0.05	0.03
Hedonic Motivation	0.02	0.02
Price Value	0.02	0.02

Thus, Table 4 shows that network externality (0.04), social influence (0.05), hedonic motivation (0.02) and price value (0.02) have a small substantial impact on behavioral intention, since its withdrawals have values where, $f^2 = \geq 0.02$ and ≤ 0.15 . Otherwise, habit has a medium substantial impact on behavioral intention (0.26). About the size of the effect q^2 , is possible to infer that the model presents a small effect for the constructs Network Externality (0.05), Habit (0.11), Social Influence (0.03), Hedonic Motivation (0.02) and Price Value (0.02).

4.2 Discussion of results

The objective of this study was to investigate how network externalities influence the acceptance and use of an app used in a peer-to-peer platform. To fulfill this objective, different factors and their influence on behavioral intention were explored. This topic will discuss aspects related to the hypotheses, constructs and their respective impacts on behavioral intentions. First, the hypotheses will be presented, emphasizing that H3, H4, H6 and H7 were supported. It is clear that the positive relation between social influence and behavioral intentions, between facilitating conditions and intentions, and habit and intentions are moderated by the network externality effect, as can be seen in Figure 4.

Hypotheses	Supported
H1: The network externality moderates the significant and positive relation of the effort expectancy on the behavioral intentions.	No
H2: The network externality moderates the significant and positive relation of the performance expectancy on the behavioral intentions	No
H3: The network externality moderates the significant and positive relation of social influence on behavioral intentions.	Yes
H4: The network externality moderates the significant and positive relation of facilitating conditions on behavioral intentions.	Yes
H5: The network externality moderates the significant and positive relation of hedonic motivation on behavioral intentions.	No
H6: The network externality moderates the significant and positive relation of habit on behavioral intentions.	Yes
H7: The network externality moderates the significant and positive relation of price value on behavioral intentions.	No

Figure 4: Research hypotheses

About the supported hypotheses, it is important to clarify that in H3 the perception about the positioning of other people concerning a technology defined as social influence (Venkatesh et al., 2012) and its relation to the intention of behavior is influenced by the increase of benefits of a technology from a larger number of users, characterized as network externality (Shapiro & Varian, 1989). In Chen, Salmanian and Akram's paper (2017), also carried out in the context

of sharing economy, the Social Influence factor showed a positive intermediate influence on the user acceptance of technology in China. It means that users are apparently more interested in the suggestions and opinions of their reference group (families, friends, co-workers) when deciding to use Uber. However, in this research the contributions go further, showing that the users' perception about the opinion from others on Uber app and their intention to use it is positively influenced by the increase of benefits (generated by the growth of the number of users) of this app.

Other important information concerns the relation of Facilitating Conditions and behavioral intention to be influenced by network externality effects. Facilitating Conditions are described by Venkatesh *et al.* (2012) as the degree to which the individual believes that there is an organizational and technical infrastructure to support the system use. In previous papers, this construct is essential for sharing economies based on digital platforms (Telles, 2016; Anderson *et al.*, 2013). Though, in this paper the contributions are expanded and it is possible to conclude that the influence of the facilitating conditions on the behavioral intentions is moderated by the network externality effects. In other words, the belief that there is a technical infrastructure that supports the use of Uber app influences the desire to use it, especially when users realize the increase of benefits generated by the growth of users.

Regarding the fact that the network externality moderates the significant and positive relation of the habit on behavioral intentions (H6), it is relevant to clarify that the habit was adopted from the definitions of Limayem *et al.* (2007), which refers to how an individual automatically performs a behavior using technology because of the learning process. The research of Venkatesh *et al.* (2012) indicated that the habit, as previous behavior, was closely linked to technology acceptance. In the recent research of Chen *et al.* (2017), the Habit construct showed to play a positive intermediary role in influencing users' acceptance of technology in a digital platform. In this paper, the influence of habit on intention and behavior is moderated by users' perception about the increase of the benefits of the products by the network effect.

Price value is strongly connected to existing sharing economy studies, in which it plays a role in defining relations between the use of idle resources and the reduction of offered prices (Benkler, 2004; Codagnone & Martens, 2016). And in this research, it imposes a significant positive effect on the behavioral intention of the users of Uber app; however, when it is inserted the network externality as moderator, this relation loses significance. It indicates that app's users carefully evaluate the monetary differences in this market. This result differs from

UTAUT first version of Venkatesh *et al.* (2003), in which they stated that employees do not pay attention to money. In the second version of UTAUT (Venkatesh *et al.*, 2012), price value was noted as a factor considered as imposing a significant influence on user's acceptance, similar to the findings of this study. But, the fact that the construct loses its significance from the insertion of the network externality as a moderator is a phenomenon that still deserves to be better studied.

5 Final considerations

Information and communication technologies and the possibility of connectivity from mobile devices have created new business models, such as sharing economy. In Brazil, Uber Tecnologias SA is one of the most representative companies of this new model. This new digitally enabled industry has experienced disruptions and drastic changes in market share among its competitors, such as Uber and Taxi. User's acceptance was analyzed using the UTAUT2 framework, which is a combination of several models of users' acceptance, and the externality construct was also used as moderator of the relation between exogenous and endogenous variables.

As a result, it was verified that all seven factors of UTAUT2, Network Externality, Habit, Social Influence, Hedonic Motivation, and Price Value positively influence user acceptance. However, the network externality moderates this influence when it comes to the factors facilitating conditions, habit, and social influence. After analyzing the results, practical and research implications are presented, especially managerial recommendations about the increase of market share and user acceptance of the analyzed peer-to-peer platform.

The varied sample of interviewed users grants this study a high quality for generalization. However, even though UTAUT2 is already a sophisticated framework, it is still under development and is being further improved and extended by researchers who are interested in understanding buying behavior and use of technology. Factors such as trust and risk are recommended to be included in additional studies about UTAUT2, also allied to the economic concept of network externality, once both can impact on the acceptance for certain users. As identified by Vieira *et al.* (2017), even facing so many conflicts, this business model continues to expand.

The expansion of this kind of peer-to-peer platform to cover other industries such as food delivery, car and home sharing, can clarify the performance of these factors to explain the acceptance of this market. Replications of this study are also recommended across different

countries and cultures to obtain information about the influence of culture or industries on UTAUT2 factors moderated by the network externality. Besides, a longitudinal study could be considered to investigate the change in user acceptance of these peer-to-peer technologies over time.

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