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ABSTRACT

The goal of our research study is to develop a hybrid instrument built on the revised Unified Theory of Acceptance and Use of Technology (UTAUT2) framework, which is reliable in predicting the behavioral intention to use the Uber ridesharing app. It focuses on extending the UTAUT2 in collaborative consumption, particularly from a consumer and ridesharing-app perspective. Our proposed framework, UTAUT-CC, preserves existing UTAUT2 constructs – performance expectancy, effort expectancy, social expectancy, and facilitating conditions. It also retains demographic moderating variables of age and gender, while maintaining some of the key integral relationships depicted in those models. We integrated three new constructs deemed relevant in linking collaborative consumption and a sharing economy – price, trust, and convenience. We incorporated elements of online and offline services (O2O) together from respective perspectives of mobile technology and ridesharing. Our overall model explained 70.5% of the variance of behavioral intention of Uber. We concluded the paper by exploring actionable implications for practitioners and scholars.

Keywords: Collaborative Commerce, Uber, Unified Theory of Acceptance and Use of Technology, UTAUT2, Price, Trust, Convenience

INTRODUCTION

Consumers are consistently seeking greater alternatives and more convenience when accessing goods and services in a cost-effective and collaborative manner. Collaborative commerce, known as 'C-Commerce', refers to a trading community and an innovative framework in which resources, goods, services, and information are exchanged between suppliers and consumers to maximize efficiencies. A more appropriate term of collaborative commerce is collaborative consumption, both of which highlight a sharing economy. In this environment, goods and services are exchanged in a peer-to-peer fashion in which the consumer can be either the provider or beneficiary of the resources. These transactional exchanges are typically facilitated through intermediaries or brokers who provide added value in the form of innovative technology services and platforms over which the peer exchange occurs. Companies like Airbnb, Uber, Lyft, and GrubHub have been fully established with this business model, and have connected consumers with suppliers in a peer-to-peer network (Botsman & Rogers, 2010). For example, Airbnb facilitates sharing by allowing individuals to rent their dwellings to paying customers for durations of time. Similarly, through its mobile application, Uber enables real-time location-based ride sharing and receive a fraction of the transaction fee (Cohen & Kietzmann 2014). One of the primary characteristics of collaborative consumption entails the reliance on internet technologies such as Web 2.0. Web 2.0 provides a medium, which facilitates the connection of users, collaboration, and sharing of content. Suppliers and consumers typically connect and communicate through the web or mobile device to share the exchanged resources. A second important attribute is that of temporary access and non-ownership of the resource from the consumer's perspective (Belk, 2014).

Collaborative commerce and consumption have several implications within business. The firm acts as an intermediary and provides a product, brand, and medium for connecting the supplier to the consumer for accessing the goods and services. Seeking convenience in certain products and services, consumers utilize the firm's product to acquire goods and services provided by suppliers sharing the same channel. Suppliers utilize the firm's product as an avenue to distribute their services, access consumers, market their brand, and attract new business. The facilitating firm contributes to the delivery of services and benefits by generating revenue per transaction, increasing brand awareness, and establishing an online community of consumers and suppliers around its products and services. However, the collaborating consumption firm does not incur the burden of ownership (Botsman & Rogers, 2010). Thus, collaborative consumption promotes a sharing symbiotic relationship where all parties involved in the transaction create and consume value. One of the most important benefits for consumers is a greater pool of "rated" product and service alternatives at lower costs. Consumers have an opportunity to review ratings and feedback from past consumers of the product/service, allowing them to form a conscious choice prior to making a selection. Having the ability to review feedback, reviews, and recommendations within the sharing community increases the chances that the consumer will make a purchase. On the other side of the spectrum, a top-performing supplier benefits from the marketing around high ratings and feedback from consumers, as well as increased sales potential and brand promotion/awareness. Feedback ratings also highlight opportunities and weaknesses for suppliers that are performing poorly. From this information, corrective action can be taken.

Collaborative consumption/commerce is on the rise and has provided new and proven ways of allowing companies to create communities around their brand, receive feedback on services, and

build deeper relationships with their customers (Cohen & Kietzmann, 2014). More and more companies are incorporating centralized digital, peer-to-peer networks and online communities into their business models to have better customer reach and brand marketing. Many of these companies have a business model solely based on a single digital channel interface with these online communities (Garrett et al., 2017).

Past studies have attempted to determine the factors leading to the adoption and use of collaborative commerce (Lin et al., 2017). However, minimal empirical research has been done around the collaborative commerce business models and the driving forces behind consumer use of such resources (Min et al., 2019). To date, a few studies have been conducted in the area of collaborative consumption, which leverage the Technology Acceptance Model (TAM) as the core framework of choice (Choi 2018). TAM emphasizes that behavioral intention is positively influenced by perceived usefulness and perceived ease of use. Furthermore, the innovative business model surrounding collaborative commerce has continued to expand, and ride sharing technology services such as Uber have been more widely adopted by consumers (Kietzmann et al., 2013). Although some studies have been successful in determining positive relationships between perceived usefulness and perceived ease of use with behavioral intention and usage (Lin and Yang 2018), very few researchers have extensively examined the adoption of the Uber mobile sharing platform (Mittendorf, 2017).

Other scholars have leveraged extensions of the revised Unified Theory of Acceptance and Use of Technology (UTAUT2), which has expanded the research in this area to an extent (Roy, 2017). However, very little empirical research on the use of different types of specific collaborative consumption such as hotel sharing, bicycle sharing, and ridesharing, have been performed (Lee et al., 2018). The few analyses have been limited in scope and context and failed to explore additional factors deemed relevant to a sharing economy. For instance, demographic moderator relationships have not been thoroughly and empirically explored in collaborative commerce. In addition, none of these studies have explored the elements of perceived uncertainty alongside the benefits of using collaborative commerce in the context of the Uber mobile application. Therefore, the primary purpose of our study is to examine factors that affect consumer adoption and use of collaborative consumption/commerce systems, specifically in the context of the ridesharing company, Uber Technologies. We will leverage the UTAUT2 model with an exhaustive list of measured constructs and relationships, with some slight modifications.

LITERATURE REVIEW

For this study, there are four pertinent bodies of literature that we draw upon. The first one is collaborative consumption leveraged by the Technology Acceptance Model (TAM). TAM emphasizes that behavioral intention is positively influenced by perceived usefulness and perceived ease of use (Venkatesh et al., 2003). This literature identifies TAM as a successful model in regards to collaborative commerce (Liu & Yang, 2018), as well as various modified versions of these models (Dishaw & Strong, 1999). The combination of these different studies allows us to gain a clearer picture of the different variables such as price, trust, and convenience, which we implement in our models. As well, this literature facilitates a deeper understanding of the effect that our chosen variables' modifiers (age, gender) have in regards to our hypotheses.

The second stream of literature focuses on different types of e-businesses throughout the world in relation to collaborative commerce. One important contribution of this collection of work has been to give us a clearer look into the focus and methodology of these studies (Hsu & Lin, 2016). Specifically, we used this literature to examine past research questions and models that appropriately fit with an e-business format in regards to collaborative commerce (Vidgen et al., 2004). By combining this set of literature with that identified in our Introduction, we were able to make a concrete decision that UTAUT would be the best model for our research purposes.

For our third focus, we draw upon literature concerning smartphone and mobile app usage. Reviewing this work was valuable in that it offered examples of research in the same realm, enabling us to examine the different variables and models that have been previously used (Weiss, 2013). This research not only exposed us to objectives from a number of perspectives, but also some good findings on usage behavior in regards to mobile applications. Moreover, while these examples were instructive for the aforementioned reasons, none of these studies on mobile applications dealt directly with our specific research context – ridesharing.

Finally, our literature review brought us to studies focusing directly on Uber. Past studies have examined both trust and price, and only a few studies modelled the projects using UTAUT (Zhu et al., 2017). By combining the three different bodies of knowledge indicated above, we were able to understand what research had previously been performed specifically on Uber, and to identify any gaps in the literature regarding this topic. Out of all of the past studies reviewed, we found no empirical studies that bring together our interests – the millennial generation, a modified UTAUT2, and the added variables of price, trust, and convenience.

THEORETICAL BACKGROUND

Unified Theory of Acceptance and Use of Technology (UTAUT) was built upon existing models to explain user intention and subsequent usage behavior. UTAUT can be broken into three core constructs: performance expectancy, effort expectancy, and social influence. These are related to behavioral intention and, ultimately, increasing use behaviour. In addition, facilitating conditions are directly related to use behavior, representing as the fourth construct. Experiences, voluntariness of use, gender, and age are also identified as moderators of the four core constructs (Venkatesh et al., 2003).

The Innovations Diffusion Theory (IDT) is another technology acceptance model, which has the objective of predicting and determining the factors that influence the adoption and utilization of computer systems over time across various groups. IDT looks deeper into how new forms of technology spread throughout different groups of individuals and tries to explain the human behavioral intention to use computer systems by employing the main constructs of Compatibility of Technology, Complexity of Technology, and Relative Advantage.

Our model will incorporate the UTAUT constructs (Venkatesh et al., 2003), as well as perceived risk (Lee et al., 2018) and relative advantage from IDT (Moore & Benbasat, 1991). Our model will

focus on collaborative commerce as it applies to the ride sharing industry and will specifically examine the Uber application.

HYPOTHESIS DEVELOPMENT

Performance Expectancy

Performance expectancy relates to how well an individual believes Uber will improve their life. Uber offers transportation and the ability to improve productivity and task achievement. Performance expectancy is considered as the stronger predictor of behavior intention. Research on gender indicates that men tend to be more task-oriented (Venkatesh et al., 2003). Age also plays an important factor, as attitudes differ with younger individuals placing more importance on rewards (Venkatesh et al., 2003), or in our case, Uber ratings and free/discounted rides.

> *H1: Performance expectancy is positively related to an individual's behavioral intention to use the Uber mobile app. The influence of performance expectancy is moderated by gender and age.*

Effort Expectancy

Effort expectancy is the degree of ease associated with the Uber app and riding experience. This is best evaluated during post-training. An increased usage of the app will diminish the effort expectancy over time. Thus, it is expected that if the Uber app is easier to use, then more customers will use the app. Gender also plays a role in effort expectancy (Venkatesh & Morris, 2000) with this factor being more salient in women than men. In addition, Venkatesh et al. (2003) notes that as age increases, the ability to handle complex stimuli becomes more difficult, which would indicate a required low effort expectancy rate for older ages.

> *H2: Effort expectance is positively related to an individual's behavioral intention to use the Uber mobile app. The influence of effort expectance is moderated by gender and age.*

Social Influence

Social influence is the extent to which an individual perceives that others believe in or recommend using the Uber app. Social influence is greatly impacted by someone of importance or someone whose opinion is valued. On a larger scale, social norms will also affect an individual's decision to use via social pressure. Social influence is said to be significant in mandatory settings compared to voluntary settings. Over time, the social pressure will diminish as experience with the application increases (Venkatesh et al., 2003). Theories suggest that women tend to be more sensitive to social influences when forming an intention to use (Venkatesh et al., 2000). Furthermore, studies have shown that as age increases, there is a greater need for acceptance (Morris &Venkatesh, 2000; Venkatesh & Morris, 2000). Again, similar to effort expectancy, the effect of social influences diminishes with continued interaction (Venkatesh & Morris, 2000).

> *H3: Social influence is positively related to an individual's behavioral intention to use the Uber mobile app. The impact of social influence is moderated by gender and age.*

Price

Price is a very important variable, especially when considering more recent studies in the current technological environment. Chong (2013) believed that a big driver of acceptance is the low cost of products. Uber is a free mobile application that requires no fee to download, unlike many other consumer applications. In terms of sharing economy services, Uber in this case, even though it is a pay-for-service available on a free application, it is much more flexible cost-wise. An Uber-like business model allows for lower prices than their more traditional competition, such as yellow cab companies. Lower prices further allow the possibility to attract greater user participation and increase the chances of positive behavioral intention (Lee et al., 2018).

> *H4: Lower price is positively related to individual's behavioral intention to use the Uber mobile app. The impact of price is moderated by gender and age.*

Trust

Trust is a very important and highly studied variable. It has been examined with respect to a wide variety of topics, including collaborative commerce. Research performed by Mittendorf (2017) reveals how trust stems from relationships through different parties, making it a crucial factor in a context where risk or uncertainty may exist. The use of Uber can be considered an act with potential risk, which could make an untrusting person wary. Trust alters how an individual perceives risk, which in turn, may affects the benefit they see from the platform. In their research study, Lee et al. (2018) discusses the idea that if a consumer has an increased level of trust with the platform, it will limit their perceived risk and lead to a more positive perception of the benefits from using the platform. The authors argue that trust is especially important in regards to online transactions due to the larger 'unknown' factors at play (Lee et al., 2018). We build on this understanding from past studies of our model, arguing that higher levels of trust will increase the tendency to use the ride sharing services.

> *H5: Trust is positively related to individual's behavioral intention to use the Uber mobile app. The impact of trust is moderated by gender and age.*

Convenience

Convenience is a variable that helps to facilitate an individual's experience of a product or service, which will ideally increase the frequency of their usage (Lee et al., 2018). Uber is increasing convenience for users by eliminating the middle party that was previously needed to connect with a driver for hire, such as the dispatcher who allocates taxicabs. A recent study by Roy (2017) explained that the unanticipated jump in the popularity of ride sharing applications is a product of extremely fast-paced lifestyles. Individuals are seeking both comfort and convenience in terms of their travel and commuting options that suit their fast and spontaneous lifestyles. Based on this literature, we believe that higher levels of convenience will increase an individual's behavioral intention.

H6: Convenience is positively related to individual's behavioral intention to use the Uber mobile app. The impact of convenience is moderated by gender and age.

Facilitating Conditions

Facilitating conditions are the degrees to which people believe an organizational and technical infrastructure exists to support the use of a system, or in the present case, mobile application (Venkatesh et al., 2003). Facilitating conditions will help integrate different ideas not previously included in our model. Many organizations have support issues and that is something that individuals take into consideration before using a technology. However, when this variable is included in a model that already contains both performance expectancy and effort expectancy, which account for similar factors, facilitating conditions can be considered a nonsignificant factor (Venkatesh et al., 2003).

H7: Facilitating conditions will have a significant influence on individual's behavioral intention to use the Uber mobile app. The impact of facilitating conditions is moderated by gender and age.

Experiences

Experience reflects an opportunity to use a target technology and is typically operationalized as the passage of time from the initial use of a technology by an individual (Venkatesh et al., 2012). Behavioral intention is defined as the users' perceived likelihood to make use of something in each situation (IOM, 2002). The experience of the new system also affects a user's behavioral intention whether to adopt and use the new system or not (Wang et al., 2006). Also, Kim and Malhotra (2005) found that prior use was a strong predictor of future technology use. Experience has been shown to moderate the effect of the core constructs on the intention to use a technology (Venkatesh et al., 2012).

H8: User experience will be positively related to individual's behavioral intention to use the Uber mobile app. The impact of experiences is moderated by gender and age.

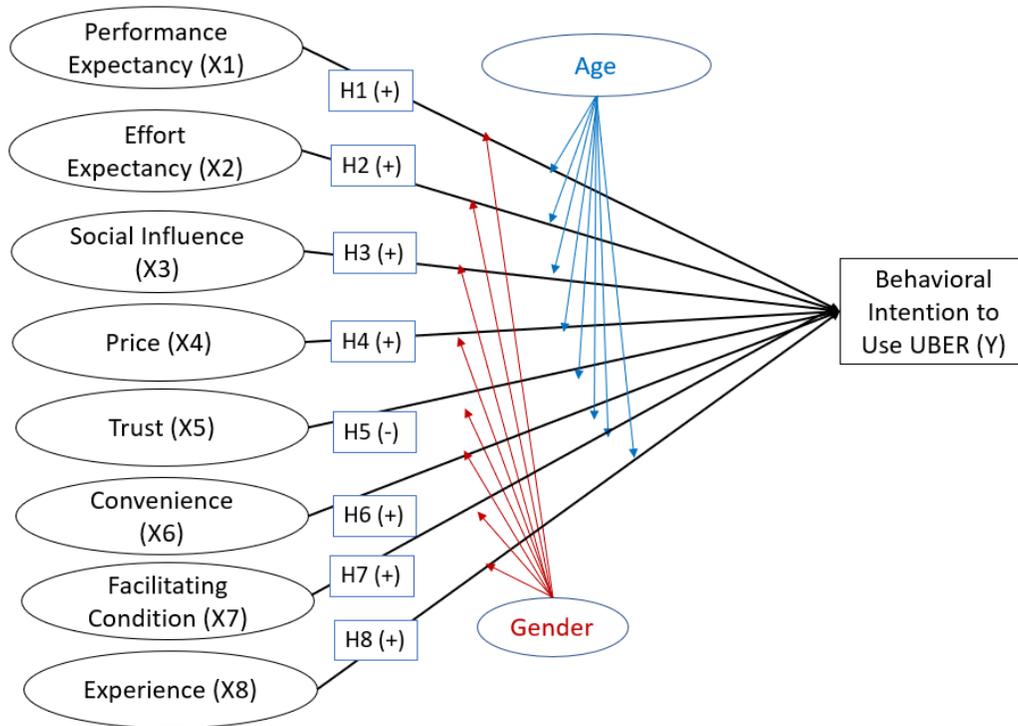Figure 1 displays our proposed research framework, UTAUT-CC.

Figure 1. Research Framework - UTAUT-CC Model

METHODOLOGY

Empirical data for the research study was gathered via paper-based questionnaires with a total of 43 questions. Respondents were allowed 5 to 10 minutes to complete the questionnaire in a single sitting. 250 undergraduate business major students at a public university in the New England area were randomly selected from the population of approximately 1,800 undergraduate students in the business school. Out of the 250 students, 180 surveys were collected. Research participants may or may not have used Uber services or the Uber mobile application in the past, but the latter were then removed from the sample. Such data screening led to a final sample size of 175, with a sampling rate of 13.9% (= 250 ÷ 1800) and a response rate of 72% (=180 ÷ 250).

Variables

In order to collect the needed data to test the above hypotheses, we developed a questionnaire that captures each of the following variables: performance expectancy, effort expectancy, social influence, facilitating conditions, price, trust, and convenience. Forty of the questions are structured around the focal constructs of this study, an average of 4-5 questions per construct. Two of the questions capture demographic related profile data such as age and gender. The remaining questions captured whether the respondent had utilized Uber ridesharing services in the past, which serves as a screening mechanism. A seven-point Likert scale was employed to capture responses that ranged from Strongly Disagree (1) to Strongly Agree (7). A number of the survey items were

adopted from prior studies, namely Venkatesh et al. (2012), Moore and Benbasat (1991), and Davis et al. (1989), and the questions were tailored for applicability to the current research context. Additionally, some questions were self-developed. Respondents who indicated that they had never used Uber services before were eliminated from the sample. In Table 1, we summarize the various original sources we used to select our survey items.

Analytical Model

We used a multiple regression approach to our research models in an effort to analyze the data, allowing us to examine several variables as compared to just one in linear regression. The goal is to predict user behavior and user intention to use the Uber app, using several variables to create the best fitting model for our study. Our analytical model focuses on behavioral intention as the dependent variable. To assess the dependent variable, we used performance expectancy, effort expectancy, social influence, price, trust, and convenience as predictors. In addition, age and gender serve as control variables.

$$Y_1 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8$$

where Y_1 = Behavioral Intention
   X_1 = Performance Expectancy
   X_2 = Effort Expectancy
   X_3 = Social Influence
   X_4 = Price
   X_5 = Trust
   X_6 = Convenience
   X_7 = Facilitating Conditions
   X_8 = Experiences

RESULTS

Descriptive Statistics

Out of our 175 received questionnaires our descriptive statistics show that 144 respondents were between the ages of 18-24 (82.30%), 27 were between the ages of 25-54 (15.30%), and only 4 respondents elected not to answer (2.40%). In terms of gender, 78 were females (44.60%), 87 were males (49.70%), 1 responded other (0.60%), and 9 respondents elected not to answer (5.10%).

Table 2 presents the results of a Cronbach's Alpha reliability test. For variables to be reliable, Cronbach's Alpha scores should be above 70%. The means, standard deviations, and correlations for all study variables are reported in Table 3.

Table 1. Cronbach's Alpha Reliability Test

Variable	Items	Cronbach's Alpha	Remarks
Performance Expectancy (X1)	Q1, Q2, Q3	0.902	Q4 dropped.
Effort Expectancy (X2)	Q5, Q6, Q7, Q9	0.933	Q8 dropped.
Social Influence (X3)	Q10, Q11, Q12, Q13, Q14	0.902	
Price (X4)	Q16, Q17, Q18	0.788	Q15 dropped.
Trust (X5)	Q19, Q20, Q21, Q22, Q23	0.909	
Convenience (X6)	Q24, Q25, Q26, Q27	0.849	
Facilitating Conditions (X7)	Q28, Q29, Q30, Q31	0.845	
Experience (X8)	Q32, Q33, Q34, Q35, Q36	0.751	
Behavioral Intention (Y1)	Q37, Q38, Q39, Q40	0.826	

The means, standard deviations, and correlations for all study variables are reported in Table 2.

Table 2. Variable Means, Standard Deviations, and Correlations

	Mean	SD	Y	X1	X2	X3	X4	X5	X6	X7	X8
Behavioral Intention (Y)	4.836	1.524	1	.546**	.725**	.555**	.514**	.609**	.671**	.561**	.682**
Performance Expectancy (X1)	3.219	1.759		1	.451**	.597**	.320**	.390**	.302**	.235**	.442**
Effort Expectancy (X2)	5.445	1.574			1	.351**	.469**	.587**	.615**	.623**	.775**
Social Influence (X3)	3.649	1.699				1	.350**	.410**	.388**	.238**	.372**
Price (X4)	4.511	1.333					1	.722**	.592**	.486**	.462**
Trust (X5)	4.663	1.267						1	.652**	.525**	.536**
Convenience (X6)	5.354	1.335							1	.736**	.589**
Facilitating Conditions (X7)	5.751	1.279								1	.589**
Experience (X8)	4.879	1.284									1

$**p < 0.01$

Overall Model

The results show significance in the overall multiple regression model with the dependent variable, behavioral intention [Adjusted $R^2 = 0.702$; $F(8, 164) = 51.552$; $p < 0.01$]. As shown in Table 4, our findings showed that performance expectancy (X1), effort expectancy (X2), social influence (X3), and convenience (X6) were all ($p < 0.05$) positively related to an individual's behavioral intention to use the Uber app. However, experience (X8) had a marginally positive relationship with an individual's behavioral intention to use the Uber app, and facilitating conditions (X7), price (X4), and trust (X5) showed no significant relationships. Thus, Hypothesis 6 was supported, whereas Hypothesis 4 and 5 were not.

Table 3. Overall Multiple Regression Model with Behavioral Intention

Dependent Variable (Y) = Behavioral Intention to Use Uber;
$R^2 = 0.705$, Adjusted $R^2 = 0.702$; $F(8, 164) = 51.552**$

	B	Std. Error	Beta	t-statistic
Constant	-0.479	0.321		-1.490
Performance Expectancy (X1)	0.119	0.048	0.138	2.478*
Effort Expectancy (X2)	0.293	0.070	0.303	4.164**
Social Influence (X3)	0.176	0.049	0.197	3.590**
Price (X4)	0.008	0.071	0.007	0.111
Trust (X5)	0.099	0.083	0.082	1.195
Convenience (X6)	0.271	0.085	0.239	3.194**
Facilitating Conditions (X7)	0.000	0.083	0.000	-0.003
Experience (X8)	0.154	0.082	0.131	1.872#

#$p < 0.10$, *$p < 0.05$, **$p < 0.01$

Reduced Model

Our results revealed that three variables (facilitating conditions, price, and trust) had no significant relationship with an individual's behavioral intention to use the Uber app. In an attempt to strengthen the fit of our initial regression model, we dropped two of those variables (facilitating conditions and price) to create our first reduced model. This revised model showed even greater significance [Adjusted $R^2 = 0.705$; $F(6, 166) = 69.567$; $p < 0.01$], as adjusted R^2 and the *F*-value both increased. Our findings indicate that performance expectancy (X1), effort expectancy (X2), social influence (X3), and convenience (X6) all had statistically significant ($p < 0.05$) relationships with an individual's behavioral intention to use the Uber app. Experience (X8) had a marginally positive relationship with an individual's behavioral intention to use the Uber app, whereas trust (X5) displayed no significant relationship (see Table 4). This is our best-fit model.

Table 4. Reduced Regression Model with Behavioral Intention

Dependent Variable (Y) = Behavioral Intention to Use Uber;
Adjusted $R^2 = 0.705$; $F(6, 166) = 69.567**$

	B	Std. Error	Beta	t-statistic
Constant	-0.476	0.290		-1.641
Performance Expectancy (X1)	0.119	0.048	0.138	2.502*
Effort Expectancy (X2)	0.293	0.069	0.303	4.247**
Social Influence (X3)	0.176	0.048	0.197	3.652**
Trust (X5)	0.104	0.070	0.086	1.474
Convenience (X6)	0.272	0.069	0.240	3.927**
Experience (X8)	0.155	0.081	0.131	1.919#

#$p < 0.10$, *$p < 0.05$, **$p < 0.01$

Reduced Model Moderated by Age

The above results uncovered which of our variables have statistical significance in regards to individual's behavioral intention to use the Uber app. To take a deeper look into the moderating

effects of age, we performed two separate regression models based on age. Results in Table 5 show that, for the subgroup with ages 18-24, performance expectancy (X1), effort expectancy (X2), social influence (X3), convenience (X6), and experience (X8) were positively related to an individual's behavioral intention to use the Uber app, whereas trust (X5) was not.

Table 5. Reduced Regression Model with Ages 18-24

Dependent Variable (Y) = Behavioral Intention to Use Uber; Adjusted R^2 = 0.685; $F(6, 137)$ = 52.88**				
	B	*Std. Error*	*Beta*	*t-statistic*
Constant	-0.581	0.360		-1.615
Performance Expectancy (X1)	0.130	0.054	0.154	2.403*
Effort Expectancy (X2)	0.312	0.077	0.309	4.74**
Social Influence (X3)	0.173	0.054	0.200	.3177**
Trust (X5)	0.077	0.077	0.061	1.000
Convenience (X6)	0.280	0.081	0.227	3.432**
Experience (X8)	0.172	0.091	0.139	1.892[#]

[#]$p < 0.10$, *$p < 0.05$, **$p < 0.01$

However, for the subgroup with age 25-54, performance expectancy (X1), effort expectancy (X2), social influence (X3), and convenience (X6) and experience (X8) were not significantly related to individual's behavioral intention to use the Uber app. Only trust (X5) was marginally related to the behavioral intention ($p < 0.10$). Refer to Table 6.

Table 6. Reduced Regression Model with Ages 25-54

Dependent Variable (Y) = Behavioral Intention to Use Uber; Adjusted R^2 = 0.769; $F(6, 22)$ = 16.541**				
	B	*Std. Error*	*Beta*	*t-statistic*
Constant	0.101	0.632		0.160
Performance Expectancy (X1)	0.152	0.129	0.161	1.177
Effort Expectancy (X2)	0.175	0.187	0.209	0.932
Social Influence (X3)	0.031	0.162	0.027	0.192
Trust (X5)	0.539	0.266	0.519	1.99[#]
Convenience (X6)	0.152	0.159	0.167	0.960
Experience (X8)	-0.024	0.216	-0.023	-0.109

[#]$p < 0.10$, *$p < 0.05$, **$p < 0.01$

Reduced Model Moderated by Gender

To take a deeper look into the moderating effects of gender, we did two separate regression models based on gender. Results in Table 7 show that, for female customers, performance expectancy (X1), effort expectancy (X2), social influence (X3), and convenience (X6) were positively related to an individual's behavioral intention to use Uber app, but trust (X5) and experience (X8) did not show significant relationships.

Table 1. Reduced Regression Model (Female Only)

Dependent Variable (Y) = Behavioral Intention to Use Uber; Adjusted R^2 = 0.674; $F(6, 71)$ = 27.543**				
	B	*Std. Error*	*Beta*	*t-statistic*
Constant	-0.596	0.493		-1.209
Performance Expectancy (X1)	0.151	0.075	0.191	2.007*
Effort Expectancy (X2)	0.286	0.121	0.283	2.369*
Social Influence (X3)	0.167	0.079	0.199	2.115*
Trust (X5)	0.088	0.101	0.072	0.863
Convenience (X6)	0.397	0.103	0.320	3.853**
Experience (X8)	0.050	0.127	0.046	0.394

$^\#p < 0.10$, $^*p < 0.05$, $^{**}p < 0.01$

For male customers on the other hands, results show that effort expectancy (X2), social influence (X3), convenience (X6), and experience (X8) were positively related to individual's behavioral intention to use Uber app. However, trust (X5) and performance expectancy (X1) did not have statistically significant relationships. Refer to Table 8.

Table 8. Reduced Regression Model (Male Only)

Dependent Variable (Y) = Behavioral Intention to Use Uber; Adjusted R^2 = 0.680; $F(6, 79)$ = 31.115**				
	B	*Std. Error*	*Beta*	*t-statistic*
Constant	-0.867	0.484		-1.79#
Performance Expectancy (X1)	0.069	0.068	0.080	1.006
Effort Expectancy (X2)	0.283	0.093	0.277	3.034**
Social Influence (X3)	0.168	0.067	0.193	2.508*
Trust (X5)	0.127	0.104	0.105	1.222
Convenience (X6)	0.229	0.110	0.189	2.075*
Experience (X8)	0.320	0.127	0.230	2.517*

$^\#p < 0.10$, $^*p < 0.05$, $^{**}p < 0.01$

DISCUSSION

The purpose of this study was to develop a model that can empirically test factors that influence the intention to use the Uber app. A few past studies have examined the behavioral intention to use ride sharing services from the consumer's perspective. However, most have done so using the Technology Acceptance Model (TAM) as a framework with limited scope and only a few constructs included, such as perceived ease of use and usefulness as drivers. We developed an instrument that utilizes the theoretical framework of the unified UTAUT and UTAUT2 models with some of its existing variables and relationships to provide the necessary explanation, fill any gaps, and to build on the body of knowledge in this area. We preserved the key variables of performance expectancy, effort expectancy, and social influence from UTAUT/UTAUT2 in

furthering this research and its applicability to collaborative commerce. We also retained moderating variables, such as age, gender, and experience, to give a holistic view of the changing perceptions of consumers regarding the intention to use technology. The developed hybrid variant introduced a few previously relevant but unmeasured constructs in the area of collaborative consumption and ridesharing from the consumer technology utilization perspective: price, trust, and convenience. Similar to predecessor models UTAUT and UTAUT2, our final UTAUT-CC unified model displayed strong statistical results and applicability to consumer intention to use and ultimate use of the Uber app. Our overall UTAUT-CC model explained 70.5% and 43.4% of the variance of behavioral intention and use of the Uber app, respectively. UTAUT and UTAUT2 concluded with 70% and 74% in explaining behavioral intention to use, respectively. When related to explaining variance in eventual use, UTAUT and UTAUT2 concluded with R2 values of 48% and 52%, respectively. Three of the four key constructs from the UTAUT model (performance expectancy, effort expectancy, and social influence) were found to be highly significant predictors of the behavioral intention to use Uber.

Performance Expectancy

We adopted the key performance expectancy construct and existing relationship links from the UTAUT2 model to represent the elements of productivity benefits and usefulness obtained from utilizing the Uber ridesharing services. In a prior study on mobile internet technology, it was hypothesized and later confirmed that performance expectancy is a significant predictor of behavioral intention to use, specifically in younger males (Venkatesh et al., 2012). Our hypothesis on performance expectancy was closely aligned to that of the UTAUT2 model. We hypothesized that performance expectancy influences behavioral intention to use Uber with a more significant impact in the younger population with low experience in using Uber. The results of our study provided empirical evidence that performance expectancy is significantly correlated with user behavior and Intention to use the Uber app.

Differences in age groups were in line with our expectations, with the younger age group of below 24 showing a significant correlation with performance expectancy as compared to the 24 and above age group, who did not have a significant relationship. This coincides with younger individuals' intrinsic desire for rewards, whether it is an Uber Passenger Rating, the ability to connect others to the Uber app to receive free rides, or potential social benefits. We also attribute these results to the increased value added and benefit of making it easier to find rides and get to destinations more quickly when leveraging the Uber ridesharing services.

While age was in line with expectations, it was the female group, not the male group as hypothesized, that showed a significant correlation. Venkatesh et al. (2012) distinguishes that men are more willing to overcome obstacles while women focus on the magnitude of effort required to perform the task. We can conclude that the level of effort to use the Uber app is lower than the perceived benefits and therefore carries a larger impact in females.

Effort Expectancy

We also adopted another key construct from UTAUT and UTAUT2, effort expectancy, to represent the elements of ease of utilizing the Uber app. Our results on effort expectancy was

closely aligned to that of the UTAUT2 model. The results show that effort expectancy positively influences behavioral intention to use the Uber app, especially for younger population. However, we did not find any significant differences in gender. The lack of difference in gender is attributed to the relative ease of use for the Uber app. Overall, our results confirmed that effort expectancy is a significant predictor of young people's behavioral intention to use the Uber app.

Social Influence

Social influence was expected to be a significant factor in the behavioral intention to use the Uber app. Social influence is based on the perception of others rather than on the intended user. Our hypothesis suggests that women tend to be more sensitive to social influences when forming an intention to use (Venkatesh et al., 2000). The effect of social influence on behavioral intention was hypothesized to be more prevalent with females and older people. According to our findings, gender showed no statistical differences and the 24 and underage group showed significant correlation as compared to the 24 and over age group. We attributed the conflicting data to be due to our population. The survey was taken at a New England region state university with the majority of participants being around the 24-year age mark. The sample was too narrowly focused on one subset of the population. We believe a more diverse population could generate alternative results which would align with our hypothesis.

Price

We adopted one of the key variables of UTAUT2, price, due to its relevance in decision making regarding technology from a consumer perspective. In our hypothesis (H4), we proposed that lower prices will have a positive impact on the behavioral intention to use Uber ride sharing services. Chong (2013) also believed that a big driver of acceptance is the low cost of the product or service. While Uber has proven to be a cheaper alternative than taxis, other comparable ride sharing services exist to compete with Uber. Uber also can price surge during peak times. Because of the relatively low-priced option compared to taxis and the similar cost to other ride sharing services, we believe that the price of Uber services would be a significant indicator to use them.

Within our overall model, the price was found to not be reliable and was therefore removed. Some misunderstanding on the part of respondents with respect to survey items in deciphering perceived benefit/value vs. monetary expenditure may help explain these nonsignificant findings. Another explanation could be due to the desensitization of payment of the ride sharing services. Users are notified of the cost of the ride, but payment is automatic through the phone, diluting the concept of actually paying in contrast to the traditional physical exchange of money. It is also possible that Uber's price is not a remarkable factor considering the saturated market for ride sharing services.

Trust

We replaced two of the constructs from UTAUT2, hedonic motivation and habit, with variables more relevant to consumer adoption of ridesharing services: convenience and trust. In our hypothesis (H5), we proposed that increased levels of trust in Uber will increase the consumer's behavioral intentions to use the Uber ride sharing services. Historically, prior research performed in the area of collaborative commerce postulate that trust is an integral factor in fostering a

successful sharing environment (Mittendorf, 2017). Unexpectedly, the results show that trust was not a significant predictor of behavioral intention to use the Uber app.

From existing literature related to trust in online shopping and e-commerce, it was proposed that trust reduces the social complexity faced by consumers in participating in commerce, allowing them to rule out inappropriate use of purchase information and obtain the services from an honest vendor as expected (Gefen et al., 2003). In their study, Gefen and co-authors hypothesized that trust in a vendor will positively affect the intention to use the vendor's services. Prior research has had difficulty in effectively predicting the implications of trust on intentions to use in a collaborative environment (Mittendorf, 2017). The construct measures trust in the company itself and its service quality. However, it did not effectively measure trust in the Uber app facilitating a collaborative exchange in sharing a ride with other consumers, trust in Uber drivers, and surrounding uncertainty on the other side of the collaborative transactional exchange. To this end, trust in the company itself may not have been perceived by respondents as a significant determinant in intention to use the Uber services. This could be because consumers have some degree of control in determining, by choice, if they want to share a ride with the voluntary option of either accepting or rejecting any uncertainty or risk associated with the intention to use, thus reducing the level of trust.

Convenience

Convenience relates to the consumer's perception of ease and flexibility in accessing and using the Uber ridesharing services via the mobile application. This construct specifically captures the consumer's perception of accessibility of the services through the Uber channel versus conventional means of access, such as traditional cab services. In a sharing/collaborative environment, one of the prime benefits for consumers in adopting a service is ease of access and the convenience that it offers. As such, we hypothesized that convenience would have a positive impact on the intention to use Uber ridesharing services.

In prior literature, it was hypothesized and realized that convenience (a perceived benefit) was a predictor of willingness to use electronic self-service delivery methods (Gilbert et al, 2004). Choudhury and Karahanna (2008) hypothesized and subsequently concluded that convenience, a dimension of relative advantage, was positively related to the behavioral intent to use electronic channels. Our results were closely aligned with those of the two studies noted above. Convenience was found to be a very significant predictor of the behavioral intention to use Uber ride sharing services. We attribute our findings to convenience being one of the primary benefits of utilizing a sharing economy where consumers have control of accessing resources, whenever needed. Incorporating convenience expanded the breadth of the UTAUT model to include elements of consumer technology use in a collaborative sharing environment.

Facilitating Conditions

In UTAUT2, facilitating conditions was hypothesized to have a positive influence on the behavioral intention to use and a direct positive influence on the eventual use of information technology. Past research provided evidence that if consumers had optimal conditions surrounding the technology in question, they would most likely exhibit an intention to use the technology

(Venkatesh et al., 2012). This was hypothesized to be more prominent in older women with less experience in utilizing the technology. In our study, we predicted that conditions facilitating the use of Uber ride sharing services (i.e. knowledge, resources, and app compatibility) would not have a significant influence on the consumer's behavioral intention to use the services.

Contrary to prior studies, our results were not aligned with our hypothesis and we found that facilitating conditions was not a significant predictor of the behavioral intention to use Uber ridesharing services. We attribute our results to the belief that most consumers have a mobile phone and will quickly download the Uber app on demand when needed, with little to no knowledge, assistance, or training.

Behavioral Intention

Similar to prior studies predicting technology usage based on behavioral intention, our model had results that aligned and were consistent. We found that the eventual use of the Uber ridesharing services was directly attributed to and affected by behavioral intentions to use the Uber app. Overall our model of the relationship between behavioral intention and subsequent use explained 43.4% of the variance of the use of Uber ride sharing, a reasonably high level in human behavior research. We believe we have tapped into a new niche of explaining usage behavior in collaborative commerce and sharing environments. However, to have a richer explanation of usage, further research could entail possibly incorporating the supplying user side of the sharing environment, such as Uber drivers.

Managerial Implications

In summary, convenience, social influence from others, performance expectancy, and effort expectancy were found to be the most important drivers of consumer intentions to use the Uber ride sharing platform and services. The results of our study provide some key implications for managers as it relates to fostering and mediating a successful collaborative transacting environment from a technology perspective. First, it comes as no surprise that convenience is a critical determinant in the consumer's use of the Uber platform. This is one of the core value propositions of Uber Technologies in sustaining a competitive advantage. Uber should continue to deliver on its existing value proposition, while expanding these offerings where possible. In addition, supporting resources to continuously build 24/7 high availability into their platform to ensure high consistency rates in driver (supplier) availability, reduction of waiting times for consumers, and fast pickup times should all be priorities. Knowledge of the estimated cost, duration of rides in advance, and cashless transactions are other elements of convenience embraced by consumers. Due to the fact that consumers are always on the go, they need an app that is easy to use and understand, with transparency in accomplishing mission-critical tasks, such as finding and booking a ride. Convenience goes hand in hand with performance gains attributed to using the app for quickly and effectively accessing ride sharing services. As such, product managers should take this into consideration and build this into the application removing any potential barriers to use. Marketing campaigns and segmentation strategies can be structured at targeting the younger population (male and female) where convenience is found to be more significant in predicting usage behavior. Additionally, one of the strategies that can be adopted is to encourage and incentivize users of the Uber app to invite others to the community to gain more participants

utilizing their services. This can be done through marketing and promotional coupon offers where referral discounts can be issued for each sign up targeting the younger population (male and female). In addition, engaging in collaborative partnerships with social networking communities can promote the increase of social influence, awareness, and increased collaboration among consumers. By keeping users in the community engaged, Uber can elicit ongoing collaboration, fostering an environment of continued participation on their mobile app. Lastly, engaging in data mining techniques capturing the in-app preferences, choices, feedback, and survey responses with demographics can provide actionable insight for further optimization and prompt sustained future use.

CONCLUSION

The goal of our research study is to develop a hybrid instrument built on the revised Unified Theory of Acceptance and Use of Technology (UTAUT2) framework, which is reliable in predicting the behavioral intention to use and subsequent use of the Uber ridesharing app. Our proposed framework preserves existing UTAUT2 constructs – performance expectancy, effort expectancy, social expectancy, and facilitating conditions. It also retains demographic moderating variables of age and gender, while maintaining some of the key integral relationships depicted in those models. We integrated three new constructs deemed relevant in linking collaborative consumption and a sharing economy – price, trust, and convenience.

One of the limitations of the study was the geographic region where it was conducted. This may not have represented a true depiction of some relevant constructs. We believe that the results may have been different if the survey was conducted in a major metropolitan area where use of Uber ride sharing was more ubiquitous. Second, we predicted that trust would be a significant determinant of the intention to use Uber services from a collaborative environment perspective. However, the results showed otherwise, which could be due to the scale items not effectively capturing trust centred on the overall collaborative exchange experience (e.g. trust in Uber drivers). Similar to trust, findings of price also did not meet our preconceived expectations. Scale items may not have effectively conveyed the trade-off between the benefits and the monetary costs of utilizing Uber. We believe that further studies, scale item re-evaluation, and refinement could assist with filling these identified gaps representing these constructs.

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Appendix 1. Variables & Items

Variable	Items	Item References
Performance Expectancy (X1)	Q1: I find that using *Uber* is useful in my daily life.	Venkatesh et al. (2012)
	Q2: Using *Uber* helps me accomplish things more quickly.	Venkatesh et al. (2012)
	Q3: Using *Uber* increases my productivity.	Venkatesh et al. (2012)
	Q4: Using the Uber app makes it easier to find rides.	Moore & Benbasat (1991)
Effort Expectancy (X2)	Q5: Learning how to use *Uber* was easy for me.	Venkatesh et al. (2012)
	Q6: My interaction with the *Uber* app is clear and understandable	Venkatesh et al. (2012)
	Q7: It is easy for me to become skillful at using *Uber*.	Venkatesh et al. (2012)
	Q8: I find it easy to get the *Uber* app to do what I want it to do.	Davis (1989); Davis et al. (1989)
	Q9: I find the *Uber* app to be flexible to interact with.	Davis (1989); Davis et al. (1989)
Social Influence (X3)	Q10: People who are important to me think that I should use *Uber*.	Venkatesh et al. (2012)
	Q11: People who influence my behavior think that I should use *Uber*	Venkatesh et al. (2012)
	Q12: People whose opinions that I value prefer that I use *Uber*.	Venkatesh et al. (2012)
	Q13: To a large extent I was motivated to use *Uber* because so many other people were using *Uber* at the time.	Ajzen & Fishbein (1980)
	Q14: I was motivated to use *Uber* for the first time because I knew that my friends, family or workmates approved of my use.	Ajzen and Fishbein (1980)
Price Value (X4)	Q15: *Uber* is reasonably priced.	Venkatesh et al. (2012)
	Q16: *Uber* is a good value for the money.	Venkatesh et al. (2012)
	Q17: At the current price, *Uber* provides a good value.	Venkatesh et al. (2012)
	Q18: Price of the ride and getting a good deal is the number one factor for me when using *Uber*.	Zo and Ramamurthy (2009)
Trust (X5)	Q19: *Uber* makes good-faith efforts to address most customer concerns.	Gefen et al. (2003), Bhattacherjee (2002)
	Q20: *Uber* is a competent service provider.	Gefen et al. (2003); Bhattacherjee (2002)
	Q21: *Uber* cares about its customers.	Gefen et al. (2003), Bhattacherjee (2002)
	Q22: I believe that *Uber* is consistent in quality and service.	Fang et al. (2014)
	Q23: Overall, I trust *Uber*	Stewart (2003); Pennington et al. (2003)
Convenience (X6)	Q24: *Uber* would enable me to ride sharing services anytime, day or night.	Gilbert et al., (2004); Meuter et al., (2000)
	Q25: It would be convenient for me to access rides services using *Uber*.	Gilbert et al., (2004); Meuter et al., (2000)
	Q26: I would find it more convenient to use *Uber* rather than a cab.	Choudhury and Karahanna (2008)
	Q27: It is important to minimize personal hassle when looking for a ride	Torkzadeh and Dhillon (2002)
Facilitating Conditions (X7)	Q28: I can get help from others when I have difficulties using Uber.	Venkatesh et al. (2012)
	Q29: I have the resources necessary to use the Uber app.	Venkatesh et al. (2012)
	Q30: I have the knowledge necessary to use the Uber app.	Venkatesh et al. (2012)
	Q31: The Uber app is compatible with other technologies I use.	Venkatesh et al. (2012)
Experience (X8)	Q32: I feel that I am a novice using the Uber app.	Carlson and Zmud (1999)
	Q33: I am very experienced using the Uber app.	Carlson and Zmud (1999)
	Q34: I feel that the Uber app is easy to use.	Carlson and Zmud (1999)
	Q35: I understand how to use all of the features of the Uber app.	Carlson and Zmud (1999)
	Q36: I feel comfortable using the Uber app.	Carlson and Zmud (1999)
Behavioral Intention (Y1)	Q37: I intend to continue using Uber in the future.	Venkatesh et al. (2012)
	Q38: I plan to continue to use Uber frequently.	Venkatesh et al. (2012)
	Q39: If I was in the market for a ride, I would be likely to use Uber.	Campbell et al. (2013)
	Q40: To the extent possible, I would use Uber for finding rides.	Turel et al. (2008)