The Role of Social and Technological Predispositions in Participation in the Sharing Economy

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This study contributes to the growing body of research on drivers of participation in the sharing economy. We extend the well-established technology acceptance model and include layers of personality architecture related to the social nature of these markets (extraversion) and their technology intermediation (technology proclivity). Findings from a cross-sectional survey (n = 292) show that extraversion is related directly to the intention to use sharing economy applications, such as in-home gig services, and related indirectly to likelihood to use these technologies and to engage as a provider of such services, through technology proclivity and the technology's perceived usefulness.

Keywords: extraversion, peer-to-peer service, sharing economy, technology acceptance, technology proclivity, personality prediction

INTRODUCTION

Brands such as Uber and Airbnb have become iconic examples of the sharing economy. According to the World Economic Forum, thousands of sharing economy platforms operate around the world, touching almost every business sector and activity (Rinne, 2019). These two-sided markets use governing algorithms to bring together consumers and service providers (Hamari et al., 2016; Perren & Kozinets, 2018). Market success and longevity of these platforms rely on attracting sufficient participants on both sides: hence, there is a growing body of empirical research identifying predictors of participation in the sharing economy.

Many scholars connect the sharing economy to the idea of sharing access to assets such as physical goods, space, time, or skill (Belk, 2014; Botsman & Rogers, 2010; Schor & Attwood-Charles, 2017). This sharing element underscores the collaborative nature of these consumption practices (Hamari et al., 2016; Piscicelli et al., 2015; Jiang & Tian, 2018). In fact, numerous sharing economy services such as ride-hailing or short-term vacation rentals exhibit high levels of consociality, defined as human interaction that is either physical, virtual, or both (Perren & Kozinets, 2018). In addition to sustainability (Hamari et al., 2016; Möhlmann, 2015; Styvén & Mariani 2020) and economic motives (Böcker & Meelen, 2017; Bucher et al., 2016; Hwang & Griffiths, 2016), the social element is quintessential to the sharing economy (Bucher et al., 2016; Eckhardt et al., 2019; Zhang et al., 2019). Social connection (Tussyadiah, 2016), social influence, trust (Möhlmann, 2015), or social closeness (Frechette et al, 2020) are crucial drivers or deterrents to participation.

Adopting the view of personality as a complex self-regulatory system (Caprara et al., 2009), this research investigates the role that basic psychological characteristics and self-related beliefs play in participation in sharing economy markets, answering the call for more research into how psychological constructs impact consumer behavior in contemporary contexts (Michaelidou & Siamagka, 2021). Since markets in the sharing economy exhibit a high degree of consociality (Perren & Kozinets, 2018), individuals' natural propensity to engage with others—their degree of extraversion—is likely to affect participation (Fligstein & Dauter, 2007; Hawlitschek et al., 2016).

In addition, technology platforms like Uber that enable these markets typically exhibit a high degree of technological intermediation (Eckhardt et al., 2019; Gerwe & Silva, 2020) so predisposition towards technology, or technology proclivity, (Ratchford & Barnhart, 2012) may also play an important role. Extant literature suggests consociality and technology intermediation are salient components of the sharing economy (Eckhardt et al., 2019; Gerwe & Silva, 2020; Perren & Kozinets, 2018). Surprisingly, little research has addressed how individuals' predispositions toward others (i.e., extraversion) or toward technology (technology proclivity) affect participation in the sharing economy (Benoit et al., 2017; Mai et al., 2020).

To address this gap, we examine whether and how extraversion, one's tendency to approach, engage, and be energized by others on a social basis (Soto & John, 2017) and general proclivity toward technology, one's optimism about and perceived proficiency with technology, affect participation in sharing economy platforms for both providers and consumers. We incorporate these predictors into the technology acceptance model (TAM) (Davis, 1989), a well-established model in the literature on technology acceptance (Jamšek & Culiberg, 2019; Lacan & Desmet, 2017; Liu & Yang, 2018; Wang et al., 2012; Wang et al., 2020; Yu et al., 2018). Our empirical study extends the research on the psychology of technology acceptance in two key ways. First, we examine how extraversion and technology proclivity affect participation in the sharing economy. Second, we investigate how these facets of personality might affect differently the behavioral intentions *to use* and *to provide* services in the sharing economy, given that individuals can participate in these markets as both consumers and providers (Jiang & Tian, 2018). For example, an Uber driver or Airbnb renter can use Door Dash to order food.

We begin with a review of existing research, which leads to the development of a theoretical model on the role that extraversion and technology proclivity play in participation in the sharing economy. Then we describe the data collection, which relied on scenarios featuring ride-hailing and in-home gig services, and the structural equation modelling analysis designed to test the model. We conclude with a discussion of our empirical findings and their future research and managerial implications.

LITERATURE REVIEW

Sharing Economy

The term sharing economy has been widely used to describe the rapidly growing peer-to-peer market activity, where individuals share their assets or provide services to others (Andreotti et al. 2016; Belk, 2014; Eckhardt, 2019). Recognizing that the sharing economy is not a monolithic phenomenon (Gerwe & Silva, 2020), scholars have developed several concepts of what sharing means. For example, the concept of access-based consumption focuses on non-ownership exchanges (Bardhi & Eckhardt, 2012). Collaborative consumption encompasses sharing access to goods as well as obtaining services or acts of giving, made possible by internet-based electronic platforms (Hamari et al., 2017; Piscicelli et al., 2015). Additionally, scholars have suggested categorizations based on definitional characteristics. For example, studying the phenomenon as communities for alternative consumption, Albinsson & Perera (2012) proposed categorization based on a collaborative lifestyle (i.e., sites connecting individuals with similar interests to share assets, such as Airbnb) and transaction characteristics: fee-based access (i.e., product service systems in which fees can be paid to access to a resource, such as Rent the Runway) and redistribution (i.e., marketplaces where goods can be sold, swapped, or gifted, such as eBay or Freecycle).

Taking a broad-based view, Perren and Kozinets' (2018) six-year ethnographic investigation of a wide range of manifestations across these "peer-to-peer, sharing, and access-based markets" (p. 20) identified two common underlying structural patterns. First is the degree of physical or virtual social interaction (consociality) and second, the degree to which technology is used to manage exchanges (platform intermediation). Similarly, recent reviews of the sharing economy literature identify the mediated technology component and relational peer-to-peer component as vital characteristics of the sharing economy, and distinguish business-to-consumer models (such as bike-sharing systems) which do not rely on crowdsourced resources (Eckhardt et al., 2019; Gerwe & Silva, 2020). Our research focuses on the sharing economy platforms with high consociality and a high level of technology intermediation, also known as *matchmakers* (Perren & Kozinets, 2018), in which extraversion and technology proclivity are likely to be important drivers of market participation. As sharing economy participants can take on roles from both sides of the exchange (demand and supply) (Jiang & Tian, 2018), we include both roles to determine if psychological characteristics and self-related beliefs might affect behavioral intentions *to use* and *to provide* services differently (Bocker & Meelen, 2017).

A Brief Review of the Technology Acceptance Model

The Technology Acceptance Model (TAM, 1989) is the most widely used model for investigating technology acceptance (Lee, Kozar, & Larsen, 2003; Legris, Ingham, & Collerette, 2003; Marangunić & Granić, 2015; Turner et al., 2010). Davis's (1989) TAM applied Ajzen and Fishbein's (1980) theory of reasoned action (TRA) to technology adoption. TRA postulates that individuals consider available information and the consequences of their actions to form their *behavioral intentions*. Thus, TAM includes two key user motivation variables: *perceived ease of use* and *perceived usefulness*. Perceived ease of use is defined as the extent to which a person believes that using a particular system is free of difficulty or significant effort. Perceived ease of use is reflected in the question, "Is *this* new technology difficult for me to use?" Perceived usefulness is defined as the extent to which a person believes that using a particular system is beneficial. Perceived usefulness is reflected in the question, "Is using *this* new technology beneficial to me?" A few studies have examined business-to-consumer exchanges in the sharing economy through the TAM lens. For example, in the context of commercial bike-sharing systems in China, both Yu et al. (2018) and Liu and Yang (2018) found that perceived usefulness and perceived ease of use positively relate to consumers' behavioral intentions.

The perceived ease of use and perceived usefulness constructs assist individuals in making decisions, as choices are a function of the perceived trade-off between the effort and the resulting benefit (Payne, 1982). Accordingly, Davis (1989) proposed perceived usefulness as having an independent effect on behavioral intentions and perceived ease of use as having both a direct effect on behavioral intention and an indirect effect through perceived usefulness. Thus, ease of use is conceived as a hurdle that users need to overcome before they can accept, adopt, and use a system (Venkatesh, 2000). However, as argued by Keil, Beranek, and Konsynski (1995), "no amount of perceived ease of use will compensate for low usefulness" (p. 89).

Personality as an antecedent of behavioral intention has been incorporated into the TAM, but both the traits examined as well as the related findings vary. For example, Barnett et al. (2015) found that conscientiousness was positively related to the use of learning management systems, but neuroticism and extraversion were negatively associated. In another academic context (eLearning programs), Punnoose (2012) also found that extraversion, conscientiousness, and neuroticism were significant drivers of technology use. Conversely, Lacan and Desmit (2017) examined social sensitivity as a TAM antecedent in crowdfunding platforms and found no significant direct effect on perceived usefulness, participation intentions, or word-of-mouth intentions. In a more recent study in the ride-sharing context, Wang et al. (2020) found personal innovativeness to be directly related to perceived usefulness.

Extraversion

The personality trait of extraversion "implies an energetic approach toward the social and material world" (John et al., 2008, p. 138). Extraversion is especially relevant to contexts high in social presence (Short et al., 1976). Most models define and measure extraversion based on sociability, assertiveness, and positive emotions or activity (Hills & Argyle, 2001; McCrae & Costa, 2010). Sociability reflects "the desire to socially approach and engage with others," assertiveness is the "willingness to express personal opinions and goals in social situations," and energy level involves "especially positively aroused states such as enthusiasm and excitement" (Soto & John, 2017, p. 121).

Given the central role of extraversion in how individuals navigate social contexts, it is unsurprising that a growing body of research has explored the relationship between extraversion and technology in a range of contexts and focal technologies (see Appendix A for a summary of the literature). In the context of social networks, extraverts disproportionally go online to strengthen and extend their social networks (Huang, 2019; Kraut et al. 2002; Wang et al., 2012), have more friends (Amichai-Hamburger & Vinitzky, 2010), belong to more groups (Ross et al., 2009), and therefore are more actively engaged on these networks (Shen et al., 2015). Extraverts perceive wearable technology as a means for social assimilation (Rauschnabel et al., 2015), expected visibility, and self-expressiveness, positively affecting attitudes toward use (Krey et al., 2019). The extraversion-introversion dimension is a significant predictor of internet use generally (McElroy et al., 2007), but extraverts also tend to use the internet for more goal-oriented motives such as sharing music with others, searching, and voicing their opinions to others (Amiel & Sargent, 2004; Hamburger & Ben-Artzi, 2000).

Extraversion and Participation in the Sharing Economy

Table 1 contains an overview of the literature on the role of extraversion in the TAM, with just one study focused on the sharing economy. The relationship between extraversion and elements of the TAM varied across contexts. For instance, extraversion was found to be related directly to perceived ease of use in the context of computer-based learning management systems (Punnoose, 2012; Tran, 2016) and social networks (Chuang et al, 2017; Rosen & Kluemper, 2008), but no relationship was found for location-based social networks (Bouwman et al., 2014). The relationship between extraversion and perceptions of the usefulness of Facebook also varied as a function of the country of study (Chuang et al., 2017; Rosen & Kluemper, 2008). To date, only one study has focused on the sharing economy: Jamšek and Culiberg (2020) examined a commercial bike-sharing platform and found that extraverts were more likely to start a conversation about environmental issues, take the initiative in conversations about environmental issues, and boast about using the bike-sharing platform.

TABLE 1
RELATIONSHIPS BETWEEN EXTRAVERSION AND TAM

Study	Focal technology	Extraversion relationship to TAM constructs		
Jamšek & Culiberg (2020)	commercial sharing			Loyalty*
Terzis et al. (2012)	eAssessment	Ease of use	Usefulness	
Barnett et al. (2015)	eLearning			Use intention
Punnoose (2012)	eLearning	Ease of use*		
Tran (2016)	eLearning	Ease of use*		
Zhou & Lu (2011)	mobile commerce		Usefulness	
Behrenbruch et al. (2013)	social event app		Usefulness*	
Bouwman et al. (2014)	social network	Ease of use	Usefulness	Use intention
Chuang et al. (2017)	social network	Ease of use*	Usefulness	
Rosen & Kluemper (2008)	social network	Ease of use*	Usefulness*	
Svendsen et al. (2013)	software tool	Ease of use*	Usefulness*	

Note. *Denotes study's finding of significant statistical relationship.

Building on the growing body of research of extraversion's relationship with technology acceptance, we assessed whether and how one's degree of extraversion relates to participation in the sharing economy for both consumer and provider roles. Although extraverts tend to prefer face-to-face interaction (McElroy et al., 2007), they are positively inclined toward technologies that enable social exchange (Amiel & Sargent, 2004; Shen et al., 2015). Given that extraverts are sociable individuals who seek activity and excitement (Soto & John, 2017), they should be more likely to engage in "new forms of social connection and experience" that the sharing economy creates (Perren & Kozinets 2018, p.23). Hence, we hypothesize that extraverts would be likelier to want to use as well as provide services in sharing economy platforms. In other words:

H1a, b: *Extraversion is positively related to intention to participate in sharing economy platforms (a) as a consumer and (b) as a provider.*

Technology Proclivity

One's general predisposition toward technology is a logical prerequisite toward accepting and adopting new forms of technology-enabled services. Indeed, scholars have identified optimism toward and perceived proficiency with technology as two key factors that predispose people toward new technology (Parasuraman, 2000; Ratchford & Barnhart, 2012). Individuals optimistic about technology believe it generally makes life easier, affords flexibility, and allows more control in life (Carver & Scheier, 2014; Walczuch et al., 2007), and these perceptions make them likelier to embrace technology applications (Lee et al., 2003; Mick & Fournier, 1998; Parasuraman, 2000; Ratchford & Barnhart, 2012). Optimists are more inclined to focus on technology's positive aspects and perceive it to be more beneficial, i.e., more useful, compared to pessimists (Blut & Wang, 2020). This positive inclination toward technology also makes optimists more willing to expend time and effort using it, consequently perceiving it to be easier to use than pessimists (Blut & Wang, 2020).

Perceived proficiency is also a key driver: Although learning to use new, complex technology often triggers frustration and even anger (Wood & Moreau, 2006), those individuals who are naturally able to master skills and develop self-efficacy (Terry, 1993) should be more likely to perceive the technology as easy to use and be more confident in their ability to use it (Howard, 2019; Venkatesh, 2000; Venkatesh & Davis, 2000). Moreover, one's sense of technological competence should reduce expectations of the amount of time and effort required to use it, thus leading to heightened belief in its usefulness. Thus, optimism and perceived proficiency towards technology, which together reflect an individual's *technology proclivity*, should be related to adoption.

Given the high level of technological intermediation in the sharing economy, the trait-like technology proclivity is a logical antecedent of the processes underpinning technology acceptance (Ratchford & Barnhart, 2012). Thus, in line with the recent meta-analysis findings that one's predisposition toward technology is strongly related to adoption of technology (Blut & Wang, 2020), we expect technology proclivity to be positively related to perceptions of ease of use and usefulness (Stern et al., 2008). Therefore, we hypothesize:

H2: *Technology proclivity is positively related to the perceived usefulness of sharing economy platforms.*

H3: *Technology proclivity is positively related to the perceived ease of use of sharing economy platforms.*

Extraversion, Technology Proclivity, and Technology Acceptance

The literature on extraversion also suggests that extraversion may be related to technology proclivity and, through it, to the processes of technology acceptance inherent in the TAM. Extraverts are generally described as more optimistic (Marshall et al., 1992; Williams, 1992), and optimists are more generally confident in their coping ability in novel and challenging settings (Scholz et al., 2002). Thus, extraverts may be more open to using new technologies.

Caprara et al. (2009) argue that the architecture of personality can be conceived as layers: Whereas personality traits are enduring behavioral tendencies, self-efficacy-related beliefs such as technology proclivity mediate the effect between broad personality traits and judgments about one's situational abilities. In the context of technology adoption, extraversion is related directly to self-efficacy beliefs and enactive mastery (Saleem et al., 2011), and extraverts have a more immersive tendency in technology-mediated environments (Parsons et al., 2015). Extraversion, perhaps because of its association with high energy levels and assertiveness, is associated with goal orientation and a strong motivation to learn (Barnett et al., 2015; Barrick & Mount, 1991; Major et al., 2006; Payne et al., 2007). Given this, we hypothesize extraversion as an antecedent of technology proclivity:

H4: *Extraversion is positively related to technology proclivity.*

The final set of hypotheses captures the relationships in the TAM model applied to the sharing economy. We include the individual's intention to participate as both a consumer and as a provider:

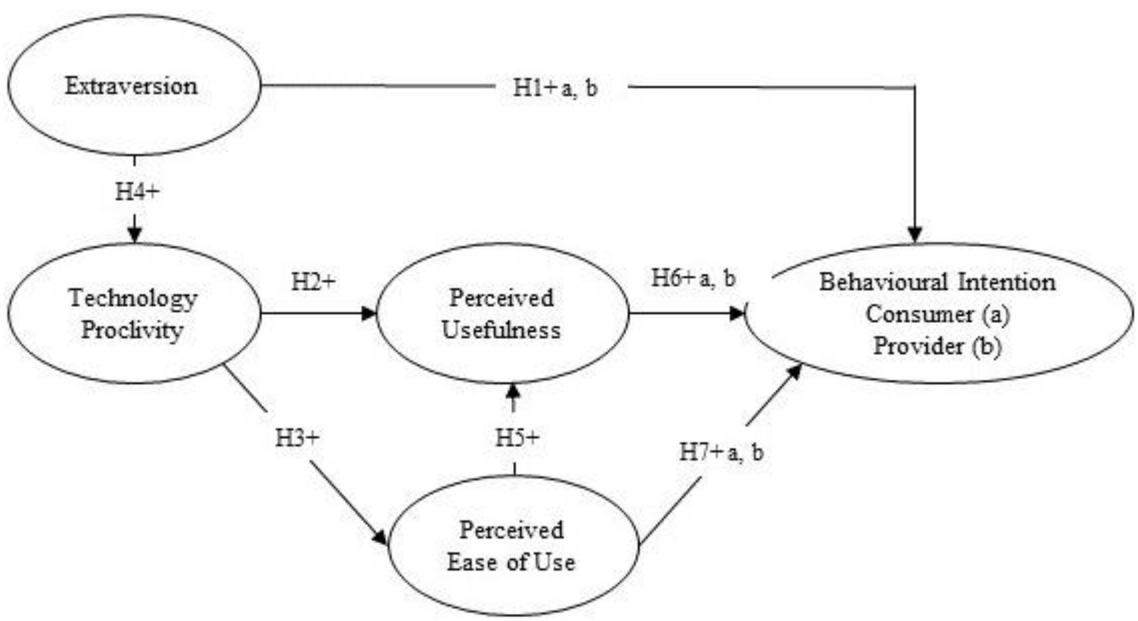
H5: *Perceived ease of use is positively related to the perceived usefulness of sharing economy platforms.*

H6a, b: *Perceived usefulness is positively related to the intention to participate in sharing economy platforms (a) as a consumer and (b) as a provider.*

H7a, b: *Perceived ease of use is positively related to the intention to participate in sharing economy platforms (a) as a consumer and (b) as a provider.*

The proposed empirical model in Figure 1 incorporates extraversion and technology proclivity into the TAM based on the above hypotheses.

FIGURE 1
CONCEPTUAL MODEL AND HYPOTHESES



RESEARCH METHODOLOGY

Study Design

In recognition that sharing economy platforms vary in social intensity (Mittendorf et al., 2019), we tested the model with two scenarios and similar sets of questions for cross comparison. Each scenario featured a sharing economy platform high in consociality and technology intermediation, in line with Perren and Kozinets' (2018) matchmaker categorization. The first scenario depicted a peer-to-peer ride-hailing service (e.g., Uber or Lyft), and the second one focused on a peer-to-peer gig service that purported to match individuals to in-home tasks (e.g., TaskRabbit, Takl, or Handy) (see full descriptions in Appendix B).

Measures of the Constructs

Participants responded to each scenario on instruments adapted from prior research (see Appendix B). Scales for the TAM were adapted from Davis's (1989) original work: 2-item behavioral intentions, 4-item perceived usefulness, and 4-item perceived ease of use. Extraversion was measured as a three-facet construct comprised of sociability, assertiveness, and energy level, consistent with Soto and John's (2017) recommendation to model it as three substantive factors (versus 12 individual items).

Technology adoption propensity measures have included both affinity and aversion aspects of one's predisposition toward technology. While the affinity aspects show consistent association with technology propensity, the results for the aversion aspects are mixed (Blut & Wang, 2020), likely due to the inherently positive nature of 'propensity.' Given the focus here on how one's disposition toward technology relates to the adoption of sharing economy platforms that exhibit high technological intermediation, we concentrate on the affinity facets of technology propensity. As such, we define technology proclivity as the trait-like construct that emerges from the combination of two affinity facets—optimism and perceived proficiency, in line with Ratchford and Barnhart (2012). We used Ratchford and Barnhart's 4-item technology optimism subscale and the 4-item perceived technology proficiency subscale. All items were measured on a five-point scale, where 1 = *disagree strongly* and 5 = *agree strongly* (see Table I for reliability of all scales in the model).

Study Sample

Participants were recruited from Amazon's Mechanical Turk (MTurk) online panel and received a small monetary reward for participation. Three hundred responses were collected. Eight responses with missing data for two of the extraversion measures (assertiveness and energy level) were removed via listwise deletion (van Ginkel et al., 2010), resulting in a total sample size of n = 292. The sample skewed male (55.8%), younger (75.3% were 25-44 years), and generally more educated than the general U.S. population (55.8% of the participants had a bachelor's degree or higher) (U.S. Census, 2018; U.S. Census, 2019a). The sample represented a broad range of employment industries. The urban concentration of the sample was comparable to the U.S. population (U.S. Census, 2019b), with 87.2% living in urban areas.

RESULTS

Measurement Validation

Using SPSS 26.0, we checked each scale's validity and inherent dimensionality (see Table 2). Cronbach's alphas ranged from 0.88 to 0.95, exceeding the recommended level of 0.80 (Field, 2018). Convergent validity, tested via the average variance extracted (AVE: Fornell & Larker, 1981), revealed that AVEs ranged from 0.55 to 0.90, exceeding the recommended level of 0.50 (Hair et al., 2006). To assess discriminant validity, we followed Voorhees et al. (2016) using the average variance extracted versus shared variance (AVE-SV) method and the heterotrait-monotrait (HTMT) ratio (Henseler et al., 2015). The square roots of AVE values (see diagonal in correlation matrix in Table 3) exceed the correlations among constructs and HTMT ratios (shown in parentheses) were under the .85 cutoff, supporting discriminant validity.

TABLE 2
RELIABILITY AND CONVERGENT VALIDITY

Construct	Mean	SD	Item	SFL	CA	CR	AVE
Extraversion	3.068	0.958	SOCB	0.900	0.914	0.858	0.733
			ASTV	0.854			
			ENGL	0.813			
Technology propensity	4.203	0.681	OPTM	0.881	0.875	0.843	0.776
			PROF	0.881			
Scenario One: Ride-Hailing							
Perceived usefulness	4.177	0.869	PU1	0.893	0.897	0.911	0.769
			PU2	0.868			
			PU3	0.866			
			PU4	0.881			
Perceived ease of use	4.524	0.701	PEU1	0.873	0.901	0.912	0.772
			PEU2	0.855			
			PEU3	0.903			
			PEU4	0.882			
Behavioral intent consumer	3.721	1.223	BIC1	0.961	0.917	0.957	0.924
			BIC2	0.961			
Behavioral intent provider	3.091	1.408	BIP1	0.974	0.945	0.972	0.949
			BIP2	0.974			
Scenario Two: In-Home Gig Service							
Perceived usefulness	4.097	0.914	PU1	0.912	0.925	0.937	0.819
			PU2	0.897			
			PU3	0.926			
			PU4	0.884			
Perceived ease of use	4.450	0.721	PEU1	0.884	0.912	0.924	0.793
			PEU2	0.886			
			PEU3	0.891			
			PEU4	0.902			
Behavioral intent consumer	3.471	1.285	BIC1	0.975	0.947	0.973	0.951
			BIC2	0.975			
Behavioral intent provider	3.164	1.359	BIP1	0.974	0.945	0.972	0.949
			BIP2	0.974			

Note: All measures on a 5-point scale, 1 = *disagree strongly* and 5 = *agree strongly*. Abbreviations: AVE, average variance extracted; CA, Cronbach's alpha; CR, composite reliability; SD, standard deviation; SFL, standardized factor loading.

Structural Model Analysis and Hypothesis Testing

We tested the proposed model in Figure 1 for each scenario using structural equation modeling with AMOS 26.0. Overall fit indices demonstrated good fit for both the ride-hailing scenario ($\chi^2(107) = 338.415$; $p \approx .000$; CFI = .932; IFI = .932; NNFI = .913; RMSEA = .086) and the in-home gig services scenario ($\chi^2(108) = 252.585$; $p \approx .000$; CFI = .960; IFI = .961; NNFI = .950; RMSEA = .068). Age and sex were also modeled as control variables but they had no influence on the overall findings so they were excluded for parsimony.

Scenario One Hypothesis Testing

The analysis for scenario one (ride-hailing service) revealed that the direct effect between extraversion (**EXT**) and intention to participate (**BI**) as either a consumer ($\beta = 0.04$, $p = 0.38$) or as a provider ($\beta = 0.01$, $p = 0.81$) in a ride-hailing service is not significant, thus H1a and H1b are not supported. The direct effects of technology proclivity (**TP**) on the sharing economy exchange's perceived usefulness (**PU**) ($\beta = 0.57$, $p < 0.00$) and perceived ease of use (**PEU**) ($\beta = 0.75$, $p < 0.00$) are significant, so we find support for H2 and H3. In line with H4, EXT is significantly related to TP ($\beta = 0.15$, $p = 0.04$). As expected, TP is related directly to the antecedents of TAM, PEU and PU, while EXT is related indirectly. EXT and TP explicated a significant portion of the variances of PU ($R^2 = 0.40$) and PEU ($R^2 = 0.55$).

As for the relationships within the TAM model, PEU is not significantly related to PU ($\beta = 0.07$, $p = 0.53$), so H5 is rejected. The relationship between PU and BI is significant, both as intention to use as a consumer ($\beta = 0.87$, $p < 0.00$) and as a provider ($\beta = 0.43$, $p < 0.00$) in support of H6a and H6b. The relationship between PEU and BI is significant, but it is negative in both consumer ($\beta = -0.15$, $p < 0.01$) and provider roles ($\beta = -0.18$, $p < 0.01$). Thus, neither H7a nor H7b are supported.

TABLE 3
FACTOR CORRELATIONS AND SQUARE ROOTS OF AVE

Constructs	EXT	TP	PU	PEU	BIC	BIP
Extraversion (EXT)	**0.783**					
Technology proclivity (TP)	0.165** (0.221)	**0.745**				
Scenario One: Ride-Hailing						
Perceived usefulness (PU)	0.104 (0.125)	0.494** (0.625)	**0.832**			
Perceived ease of use (PEU)	0.075 (0.093)	0.606** (0.756)	0.467** (0.521)	**0.835**		
Behavioral intent consumer (BIC)	0.118* (0.139)	0.367** (0.453)	0.702** (0.769)	0.256** (0.281)	**0.921**	
Behavioral intent provider (BIP)	0.065 (0.076)	0.152** (0.453)	0.270** (0.289)	0.008 (0.008)	0.367** (0.394)	**0.947**
Scenario Two: In-Home Gig Service						
Perceived usefulness (PU)	0.089 (0.105)	0.440** (0.550)	**0.872**			
Perceived ease of use (PEU)	0.093 (0.112)	0.583** (0.722)	0.433** (0.470)	**0.851**		
Behavioral intent consumer (BIC)	0.183** (0.209)	0.294** (0.359)	0.661** (0.704)	0.206** (0.220)	**0.949**	
Behavioral intent provider (BIP)	0.047 (0.054)	0.185** (0.227)	0.329** (0.350)	0.065 (0.068)	0.505** 0.534)	**0.947**

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
Note. The bold numbers represent the SQRT of AVE and the HTMT ratio is shown in parentheses.

Scenario Two Hypothesis Testing

Results are similar in the two exchange scenarios (in-home gig service), with one exception. Unlike in the ride-hailing scenario, for in-home gig service, the direct effect between EXT and BI is significant, as hypothesized in 1a ($\beta = 0.14$, $p < 0.01$). All other relationships in the model are consistent across scenarios in terms of coefficients and significance, providing further evidence of technology proclivity as a direct antecedent of TAM, and of extraversion as an indirect effect. In the in-home gig scenario, EXT and TP explain about one-third of perceived usefulness ($R^2 = 0.33$) and about half of the variance of perceived ease of use ($R^2 = 0.51$). The relationships within the TAM model are also consistent with scenario one, so overall, the results are robust in terms of consistency across the two sharing economy applications.

Although not hypothesized, the direct effects of EXT on the TAM beliefs were also tested in both scenarios, and no significant relationships were found. Therefore, the indirect effects of EXT on PU and

PEU are mediated through TP: scenario one EXT→TP→PU (β = 0.09, $p < 0.05$) and EXT→TP→PEU (β = 0.11, $p < 0.05$); scenario two EXT→TP →PU (β = 0.10, $p < 0.05$) and EXT→TP→PEU (β = 0.13, $p < 0.05$).

In summary, as Table 4 shows, the analysis reveals that extraverts have higher TP, and the positive relationship between TP and BI is mediated through PU. EXT is only directly related to BI to use in-home gig services in the consumer role. The predictors explain about the same amount of variance across scenarios: 65% of BI in the consumer role in the ride-hailing scenario and 55% in the in-home gig scenario; 14% of the variance in BI in the provider role in ride-hailing and 16% in the in-home gig scenario.

Post-Hoc Analysis

The counterintuitive negative relationship between PEU and BI prompted further analysis. The values of skewness and kurtosis for PEU were acceptable to represent normal distributions, but mean PEU scores in both scenarios approached the upper limit of the 5-point scale (scenario one M = 4.52, SD = .70 and scenario two M = 4.45, SD = .72). This signals a possible ceiling effect, where there is not enough variance in PEU to affect the model. Indeed, the direct path from PEU to PU was not significant in the model, although the two constructs were correlated.

TABLE 4
RESULTS OF HYPOTHESIS TESTING

	Scenario One (Ride-Hailing)		Scenario Two (In-Home Gig Service)	
Hypothesis	Path β	Support	Path β	Support
H1a: Extraversion→Behavioral intent consumer	0.040	No	0.135**	Yes
H1b: Extraversion→ Behavioral intent provider	0.014	No	0.034	No
H2: Technology proclivity→Perceived usefulness	0.574***	Yes	0.455***	Yes
H3: Technology proclivity→Perceived ease of use	0.745***	Yes	0.714***	Yes
H4: Extraversion→Technology proclivity	0.145*	Yes	0.162*	Yes
H5: Perceived ease of use→Perceived usefulness	0.070	No	0.155	No
H6a: Perceived usefulness→Behavioral intent consumer	0.869***	Yes	0.781***	Yes
H6b: Perceived usefulness→Behavioral intent provider	0.434***	Yes	0.445***	Yes
H7a: Perceived ease of use→Behavioral intent consumer	-0.154**	No	-0.167**	No
H7b: Perceived ease of use→Behavioral intent provider	-0.177**	No	-0.145*	No

Note. Standardized regression weights reported for path coefficient; *p<0.05, **p<0.01, ***p<0.001

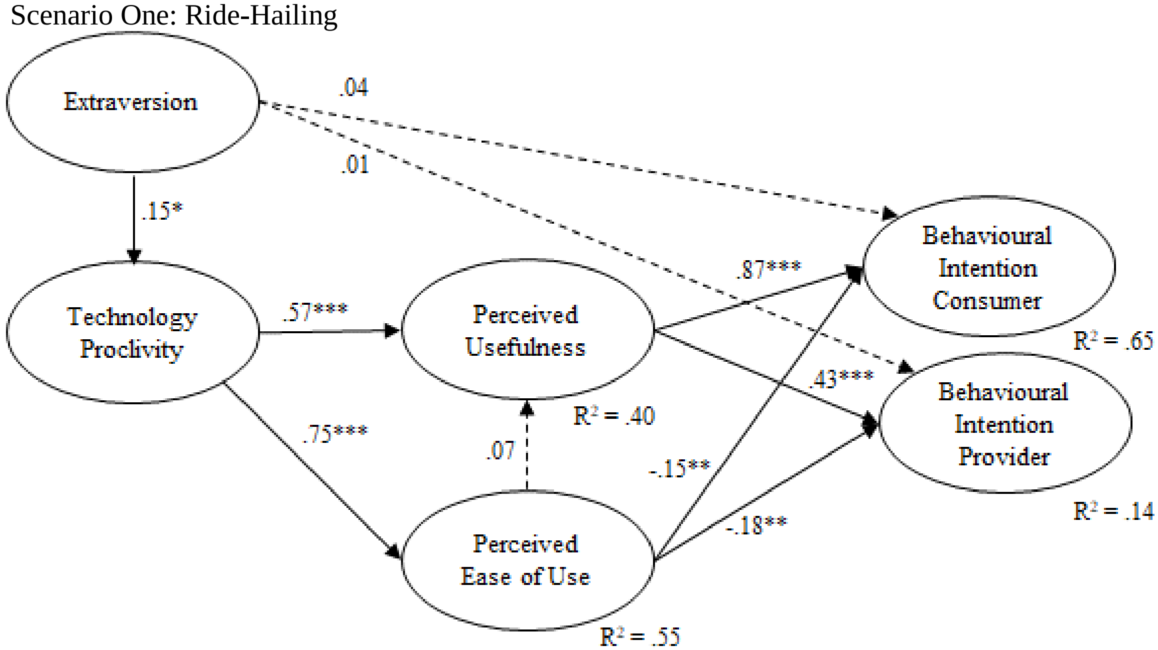
Because ceiling effects can create statistical aberrations, we tested reduced models that did not include PEU. These reduced models demonstrated good fit in both scenario one ($\chi^2(58) = 147.979$; $p \approx .000$; CFI = .962; IFI = .962; NNFI = .949; RMSEA = .073) and scenario two ($\chi^2(58) = 141.894$; $p \approx .000$; CFI = .968; IFI = .969; NNFI = .957; RMSEA = .071).

All the results of the reduced model remain consistent in magnitude and significance with respect to the full model. In particular, the variance in BI explained in the reduced models is similar to the original model: ride-hailing (R^2_consumer = 0.63; R^2_provider = 0.11) and in-home gig services (R^2_consumer = 0.52; R^2_provider = 0.14). The results for the full and reduced models are provided in Figure 2 and Figure

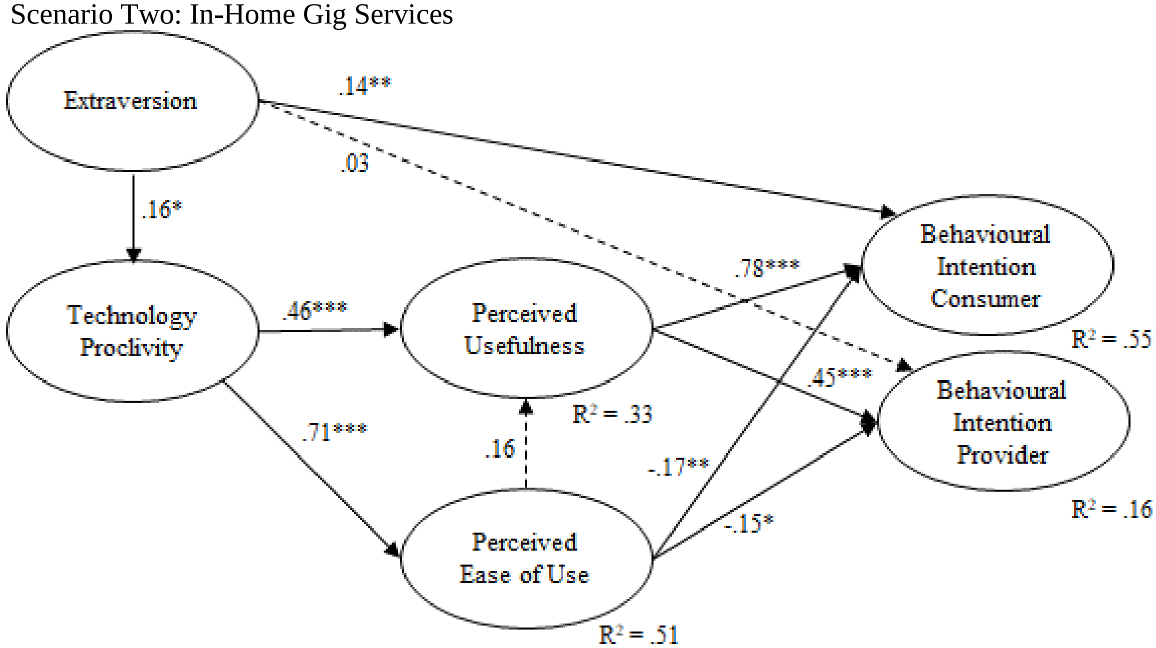
3, respectively. The consistent results bolster the model's robustness but also highlight PEU's lack of explanatory power.

FIGURE 2
FULL MODEL ANALYSIS RESULTS

Scenario One: Ride-Hailing

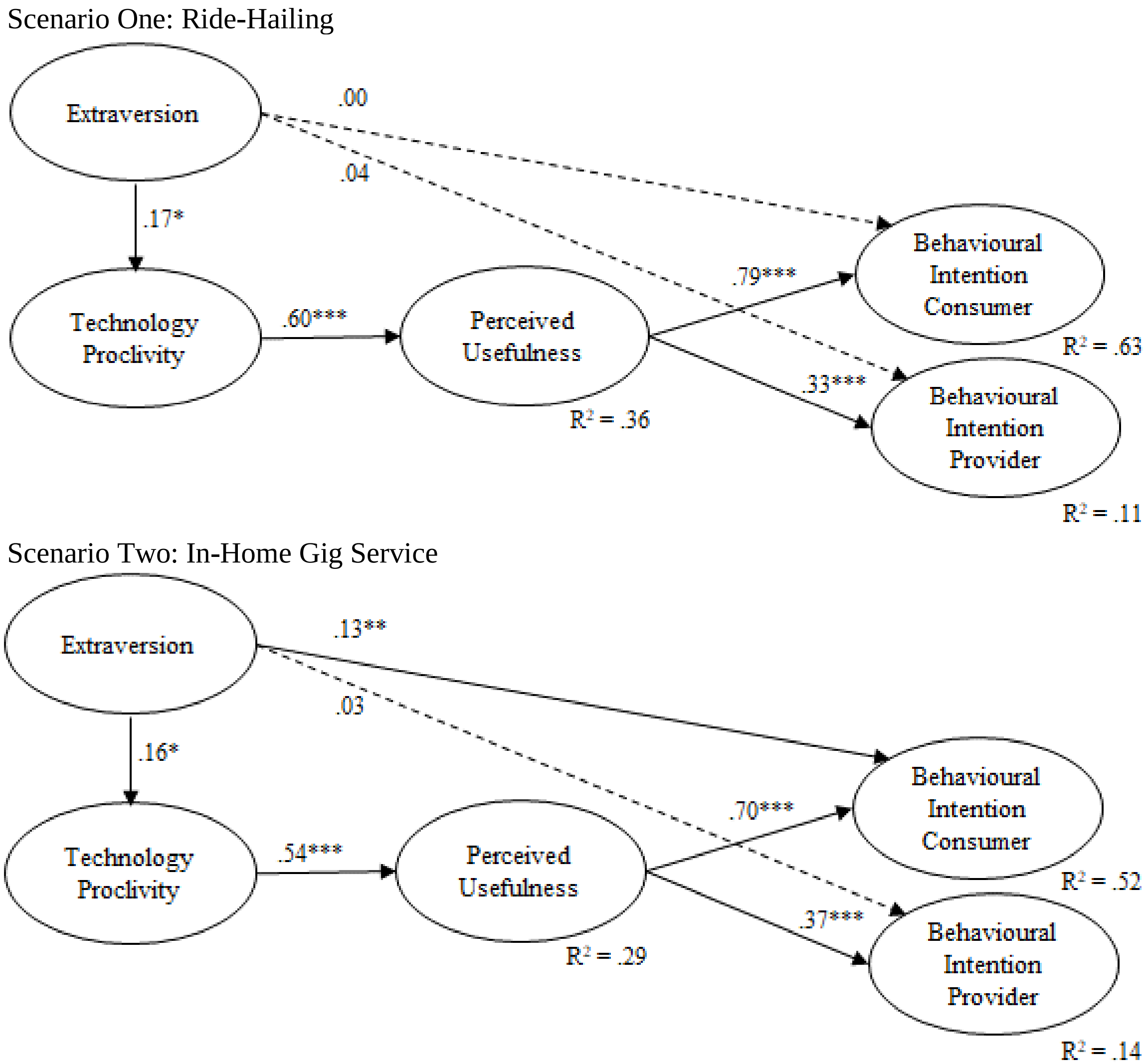


Scenario Two: In-Home Gig Services



Note. Standardized regression weights are provided along the paths; **p* < .05, ***p* < .01, and ****p* < .001; squared multiple correlations are denoted (R^2).

FIGURE 3
REDUCED MODEL ANALYSIS RESULTS



Note. Standardized regression weights are provided along the paths; **p* < .05, ***p* < .01, and ****p* < .001; squared multiple correlations are denoted (R^2).

DISCUSSION

This research contributes to extant literature in several ways. First, this study adds to the growing number of extensions of TAM that incorporate personality constructs (Gbongli et al., 2019; Gessl et al., 2019; Kim & Forsythe, 2008; Manis & Choi, 2019; Svendsen et al., 2013; Wang et al., 2020). Our contribution extends the TAM in the sharing economy by considering two of its distinct features: the high degrees of consociality and technology intermediation. In doing so, we also answer the call for research aimed at understanding how broad predictors, such as extraversion, affect participation in the sharing economy (Mai et al., 2020). Specifically, extraversion *and* technology proclivity emerge as important layers of personality architecture that affect perceived usefulness (R^2_ridehailing = 0.40; R^2_gig-service = 0.33) in sharing economy platforms.

With regard to consociality, our research reveals an important role of the extraversion personality trait on individuals' intention to engage in the sharing economy as both consumers and providers, although the role is mostly indirect, through technology proclivity. We do find a direct effect of extraversion on consumers' intention to adopt in-home gig services and not in the ride-hailing sector. A possible explanation is that consociality is more accentuated for an in-home service compared to that of a ride-hailing service because the consumer might place greater value on the social interaction that occurs with in-home gig services. After all, the in-home service provider is likely to enter the privacy of the consumer's home. Technology scholars have suggested that the influence of personality on technology acceptance likely depends on the technology or service investigated (Svendsen et al., 2013). Indeed, the lack of a direct relationship between extraversion and intention to provide in-home gig services may reflect that consociality might moderate the relationship in this context (Lee et al., 2003).

With regard to technological intermediation, technology proclivity emerges as a key antecedent to technology acceptance. This finding suggests that for the sharing economy, and possibly for other technologically intermediated markets, technology proclivity is an important predictor of adoption. A novel finding is the role of extraversion as an antecedent of technology proclivity (Marshall et al., 1992; Williams, 1992). The high energy inherent in extraverts and an associated optimistic disposition translates into a greater desire to engage with technology (Marshall et al., 1992; Williams, 1992; Scholz et al., 2002).

The findings also inform the TAM's applicability to the sharing economy. Perceived usefulness emerges as a tried-and-true antecedent of technology adoption in the sharing economy. By contrast, the consistently high perceptions of ease of use suggest that, as applications are increasingly graphical, simple, and user-friendly, their ease of use is no longer discriminant in the adoption process.

Theoretical Contributions

From a theoretical perspective, this study contributes to the technology adoption literature in two important ways. First, it provides evidence that personality influences adoption intentions in technology-mediated markets characterized by peer-to-peer exchange (Perren & Kozinets, 2018). Extraversion and technology proclivity emerge as important individual predispositions to engage in such markets for both consumers and providers. These two layers of personality architecture are directly related to technological intermediation and consociality, two central characteristics of the sharing economy (Benoit et al., 2017; Mai et al., 2020). The findings thus add to the emerging literature on the role of personality facets in technology adoption (Fox & Connolly, 2017; Stern et al., 2008).

Because the sharing economy is both a technological and social phenomenon, our research suggests that both cognitive processes and interpersonal abilities may play important roles in predicting individual intentions and participation in these markets. This study's findings add to the emerging literature suggesting that extraversion is an especially key personality antecedent for participation in the sharing economy (Acar & Toker, 2019; Mai et al., 2020).

Second, the study provides new insights as to the relevance of TAM. Although the individual TAM constructs performed well psychometrically, our study calls into question their interrelationships, especially the role of perceived ease of use. As applications become easier to use, it makes sense that ease of use is less of a driver of adoption, which is consistent with King and He's (2006) meta-analysis of TAM studies that suggests perceived ease of use might be an unstable measure in predicting behavioral intentions, and it's also consistent with other studies where perceived ease of use is absent (Zhou & Lu, 2011). Other authors have even questioned the overall effects of perceived ease of use in TAM, given the inherent ease of use of certain types of technology (Gefen & Straub, 2000; Keil et al., 1995; Kim & Forsythe, 2008). More generally, our findings add to the growing body of evidence that even classic theoretical models like TAM must continually evolve and adapt, especially in the fast-changing technology field.

Practical Implications

It is intuitive to think that one's affinity for consociality might influence participation in markets with high social interaction. Indeed, Perren and Kozinets (2018) recommend that "matchmakers should emphasize consociality and its tendency to lead to social connection … fostering brand community engagement" (p. 34). However, this research reveals that individual differences may affect participation. This is consistent with Hong et al. (2020) in the ride-hailing context. They found that drivers in ride-hailing platforms value privacy and safety in their interaction with riders. Consequently, their focus will be on providing the service, thus limiting social interaction to provide a courteous, professional service. Our findings also suggest that, to increase adoption, managers should focus on developing better solutions for users who are less extraverted and those who are less prone to adopt technology, also known as technology laggards. As such, our findings align with scholars who have suggested that marketers need to use varied strategies to uniquely address users and providers (Hartl et al., 2020).

LIMITATIONS AND FUTURE RESEARCH

More research is warranted to assess the generalizability of our findings on the role of extraversion on technology proclivity on the use of technology in general, and specifically on participation in the sharing economy. The slightly different results between scenarios suggest that the dynamics of engagement may differ across different categories of applications (Albinsson & Perera, 2012). The sampling strategy may also be a limitation as the MTurk sample population may be inherently more favorably inclined toward the use of technology: hence, high perceptions of ease of use. Thus, developing studies for less tech-savvy segments of the population is a promising avenue for future research.

Notwithstanding the novel insights into extraversion, this study is limited by its reliance on scenarios, not actual behavior, to understand behavioral intentions. These scenarios do resemble the adoption process for a new product (Svendsen et al., 2013) and are consistent with the fact that, in many situations, a consumer must decide to buy a product before actually having tried it. Future research might incorporate specific brands to investigate the effect of personality on technology acceptance and participation in the sharing economy.

The rapid expansion and continued relevance of the sharing economy is unmistakable, with consumer participation in the U.S. estimated at 89.6 million users in 2020 and forecast to top 100 million users by 2023 (eMarketer, 2020). This research's dual focus on intention to participate as a consumer and as a provider paves the way for more studies of willingness to engage as a service provider in the sharing economy. According to one of the company's cofounders, Uber had about 65 million consumers (riders) and 2 million providers (drivers) in 2017 (Camp, 2017). Future growth hinges on achieving enough drivers to serve new markets (Teece, 2018), so future research could examine personality traits of providers that may increase their intention to participate.

Research focused on service providers is still in its infancy, so more studies are needed to understand their motivations to participate in the sharing economy. This research paves the way for extensions of the model to incorporate many of the social and/or technological facets of the exchanges within sharing economy platforms. For instance, technology proclivity may affect the development of trust that consumers may develop with providers or with the platforms that support the exchanges (Abdar & Yen, 2020). Extraversion may play a role in whether and how consumers respond to any additional information service providers may share, such as recommendations of things to do, places to visit, or where to eat (Kong et al., 2020). Based on findings that a personal profile image can impact behavior in the sharing economy (Fagerstrøm et al. 2017), the way in which consumers and providers present themselves on the platform may also moderate the dynamics of how personality characteristics relate to participation in the sharing economy. We hope that the insights presented herein can motivate further research into the sociopsychological factors that underpin participation in the sharing economy.

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APPENDIX 1

Relationships Between Extraversion and Technology (Alphabetically Organized by Context)

		Extraversion as directly affecting …			
Study **Context**	Focal Technology (Sample)	Beliefs	Attitude	Behavior / Intention	Main findings
Barnett et al. (2015) **Academic**	web-based course management system (382 students, US)			Use intention Use*	extraversion *negatively* related to course management system use

Study **Context**	Focal Technology (Sample)	Extraversion as directly affecting … Beliefs	Attitude	Behavior / Intention	Main findings
Hunsinger et al. (2008) **Academic**	individual response classroom technology (452 students, US)	Enjoyment*			extraversion positively related to enjoyment of technology in classrooms
Parsons et al. (2015) **Academic**	online course management system (1671 students, US)	Immersive Tendency*			extraversion related to greater tendency to immerse in web-classroom environments
Punnoose (2012) **Academic**	eLearning (249 students, Thailand)	Enjoyment* Ease of use*			extraversion positively related to interaction, stimulation, and capacity for enjoyment; and to perceived ease of use
Saleem et al. (2011) **Academic**	self-checkout library system (143 students, Canada)	Self-efficacy*			extraversion is an antecedent of computer self-efficacy for females (but not males)
Terzis et al. (2012) **Academic**	computer-based assessment (117 students, Greece)	Importance* Usefulness Ease of use Playfulness Goal expectance Social influence			extraversion positively related to perception of importance of computer-based assessments and use intentions
Tran (2016) **Academic**	blended e-learning system (396 students, Vietnam)	Ease of Use*	Attitude		extraversion increases belief that blended a e-Learning system is easy to use, and produces a more positive attitude toward system
Jamšek & Culiberg (2020) **Commercial sharing**	bike-sharing system (185 users, Slovenia)			Loyalty*	extraverts who like talking about sustainability more loyal to bike-sharing systems
Amichai-Hamburger et al. (2002) **Communication**	online chat (40 hi-tech workers, Israel)			*Real Me* social interactions*	extraverts reveal more about themselves in face-to-face social environments versus online interaction
Hamburger & Ben-Artzi (2000) **Communication**	internet services (72 students, Israel)			Leisure usage* Social usage*	extraversion positively related to males' use of internet leisure services (i.e., random surfing and

Study **Context**	Focal Technology (Sample)	Extraversion as directly affecting … Beliefs	Attitude	Behavior / Intention	Main findings
					sex sites) and negatively associated with females' use of internet social services (i.e., chat, discussion groups)
Kraut et al. (2002) **Communication**	internet and web activities (208 Pittsburgh family members, US)	Social involvement* Well-being*			extraverts internet use associated with increases in community involvement and self-esteem and declines in loneliness, negative affect, and time pressure
Brenner et al. (2016) **Communication**	async video interviewing (106 students, Germany)		Attitude		extraversion not related to students' attitudes toward synchronous video interviewing
Butt & Phillips (2008) **Communication**	mobile phone functions (115 mobile phone owners, Australia)			Use*	extraversion related to patterns of mobile phone use (greater SMS use, incoming calls, and time spent changing ring tones or wallpaper)
Miller et al. (2012) **Communication**	mobile phone functions (1036 teenaged twins, Australia)			Use*	positively related to frequency of mobile phone talking and texting
Wang (2010) **Communication**	instant messaging (228 students, China)	Enjoyment*			extraversion positively related to perceived enjoyment from using instant messaging
Landers & Lounsbury (2004) **Communication** **Leisure** **Academic**	internet and web activities (117 students, US)			Use*	extraversion positively associated with internet communication usage, leisure, and academic activities
Amiel & Sargent (2004) **Communication** **Leisure** **Social**	internet and web-based activities (210 students, US)	Comfort*		Voice opinion* Doing research* Sharing music* Group belonging*	extraverts motivated to use the internet for sharing music, voicing one's opinion, and doing research, but not use internet as substitute for personal interaction; extraversion

Study **Context**	Focal Technology (Sample)	**Extraversion as directly affecting …** Beliefs	Attitude	Behavior / Intention	Main findings
					negatively related to group belonging and comfort talking to people online
Chipeva et al. (2018) **ICT-general**	information and communications technologies (498 students, Bulgaria and Portugal)			Use intention Use*	extraversion positively related to ICT usage behavior (i.e., e-banking, social networks, e-government, e-commerce, info search)
Picazo-Vela et al. (2010) **Leisure**	online review (171 students, US)			Use intention	no relationship between extraversion and intentions to provide online review
Turkyilmaz et al. (2015) **Leisure**	online impulse shopping (612 online shoppers, Turkey)			Online impulse buying*	extraversion positively related to online impulse buying
Xu et al. (2016) **Leisure**	mobile game and social apps (2043 Android mobile app users, Germany)			Mobile game app use* Social app use	extraversion positively related to use of mobile game apps, but not of social apps
McElroy et al. (2007) **Leisure**	buying and selling products online (132 students, US)			Use	no relationship between extraversion and use of internet to buy or sell products online
Zhou & Lu (2011) **Leisure**	mobile commerce (268 adults, China)	Trust* Usefulness			extraverts more trusting of service providers; trust affects perceived usefulness; both factors determine intention to adopt mobile commerce
Amichai-Hamburger & Vinitzky (2010) **Social network**	Facebook (237 students, Israel)			FB friends* FB groups	extraversion positively related to number of Facebook (FB) friends; no relationship between extraversion and use of FB groups
Bouwman et al. (2014) **Social network**	Feest.je (200 users, Netherlands)	Enjoyment Usefulness Ease of use		Use intention	no relationship between extraversion and perceived usefulness, perceived enjoyment, perceived

Study **Context**	Focal Technology (Sample)	Extraversion as directly affecting … Beliefs	Attitude	Behavior / Intention	Main findings
					ease of use, nor location-based social network use intention
Chuang et al. (2017) **Social network**	Facebook (324 students, Taiwan and Thailand)	Usefulness Ease of use*			extraversion positively related to perceived ease of use of FB, but not perceived usefulness
Deng et al. (2013) **Social network**	Qzone (221 users, China)	Critical mass* Supplemental entertainment*	Satisfaction*		extraversion positively related to social network perceived satisfaction, supplementary entertainment, and critical mass; indirectly related to playfulness and social network continuance intention
Kuo & Tang (2014) **Social network**	Facebook (500 students, Taiwan)			FB friends* FB time spent* FB photos*	extraverts like to socialize on FB (more time, friends, and photos) and in real life (more time on team sports and leisure activities)
Rosen & Kluemper (2008) **Social network**	Facebook (552 students, US)	Usefulness* Ease of use*			extraversion positively associated with perceived FB usefulness and ease of use
Ross et al. (2009) **Social network**	Facebook (97 students, Canada)			FB groups* FB features FB friends FB time spent	extraversion only related to more FB group memberships
Shen et al. (2015) **Social network**	Facebook (1327 adults, US)			FB photos* FB friends* FB videos* FB comments* FB likes* FB tags*	extraversion positively related to FB interactions, (e.g., number of friends, photos, posts, comments, likes in photos, tags in photos, and length of videos)
Wang et al. (2012) **Social network**	Renren (265 students, China)			Friends* Social presence* Play games* Status updates* Comments*	extraversion positively related to number of friends on Renren, making comments on Renren, and using status updates.

Study **Context**	Focal Technology (Sample)	Extraversion as directly affecting … Beliefs	 Attitude	 Behavior / Intention	Main findings
Conti et al. (2017) **Socially Assistive Tech**	socially assistive robotics (114 special education teachers, EU)	Usefulness* Social influence* Social pressure* Enjoyment* Adaptability* Facilitating conditions*	Attitude*	Use intention*	extraverts perceive socially assistive robots more useful, enjoyable, adaptive, and a social entity; have more positive attitude toward and intent to use robots in teaching activities; extraversion strongly correlated with others perceptions of robot use
Behrenbruch et al. (2013) **Tool**	mobile app for organizing meetings with friends at events (344 students, Germany)	Trust* Usefulness*			extraversion positively associated with perceived usefulness and trust for new mobile application technology
Svendsen et al. (2013) **Tool**	Software tool/digital content management (1004, age 15+ Norwegians)	Subjective norm Ease of use* Usefulness*			relationship between extraversion and use intentions mediated by perceived usefulness and ease of use

		Extraversion as moderating … Beliefs	 Attitude	 Behavior /Intention	
Devaraj et al. (2008)	**Academic** e-project collaboration system (180 students, US)	Subjective norm →		Use intention*	extraversion positively moderates relationship between subjective norms and intentions to use e-project collaboration system
Li (2016) **Academic**	learning information systems (331 students, Taiwan)	Subjective norm → Usefulness*			extraversion positively moderates relationship between subjective norms and perceived usefulness of learning information systems
Krey et al. (2019) **Wearables**	smartwatches (999 nonusers, Malaysia)	Expected visibility →	Attitude*		extraversion positively moderates symbolic value–attitude relationship for non-smartwatch users
Rauschnabel et al. (2015) **Wearables**	Google Glass (146 students and 201 adults, Germany)	Social conformity →		Use intention*	extraversion positively moderates relationship between social conformity and adoption intention of Google Glass

Note. *Denotes study's finding of significant statistical relationship.

APPENDIX 2

Measurement Scales

Construct	Item	Description
Sociability (SOCB)	SOCB1	Is outgoing, sociable.
	SOCB2	Tends to be quiet. (R)
	SOCB3	Is sometimes shy, introverted. (R)
	SOCB4	Is talkative.
Assertiveness (ASTV)	ASTV1	Has an assertive personality.
	ASTV2	Is dominant, acts as a leader.
	ASTV3	Finds it hard to influence people. (R)
	ASTV4	Prefers to have others take charge. (R)
Energy Level (ENGL)	ENGL1	Rarely feels excited or eager. (R)
	ENGL2	Is less active than other people. (R)
	ENGL3	Is full of energy.
	ENGL4	Shows a lot of enthusiasm.
Optimism (OPTM)	OPTM1	Technology gives me more control over my daily life.
	OPTM2	Technology helps me make necessary changes in my life.
	OPTM3	Technology allows me to more easily do the things I want to do at times when I want to do them.
	OPTM4	New technologies make my life easier.
Perceived Proficiency (PROF)	PROF1	I can figure out new high-tech products and services without help from others.
	PROF2	I seem to have fewer problems than other people in making technology work.
	PROF3	Other people come to me for advice on new technologies.
	PROF4	I enjoy figuring out how to use new technologies.
Scenario One: Ride-Hailing		
	consumer	Imagine you needed to go somewhere and the possibility existed for you to be matched with a person in your neighborhood who could give you a lift for a fee. Your pick up location, drop off location, cost for the ride and fee payment would all be handled through a software application that you downloaded on your mobile phone ("app").
Perceived Ease of Use (PEU)	PEU1	Learning to operate the mobile ride sharing app would be easy for me.
	PEU2	It would be easy for me to become skillful at using the mobile ride sharing app.
	PEU3	I would find the mobile ride sharing app easy to use.
	PEU4	I would find it easy to get the mobile ride sharing app to do what I want it to do.
Perceived Usefulness (PU)	PU1	Using the mobile ride sharing app would be a convenient way to go somewhere.
	PU2	Using the mobile ride sharing app would increase my efficiency in getting somewhere.
	PU3	Using the mobile ride sharing app would be an effective way to go somewhere.

Construct	Item	Description
	PU4	I would find the mobile ride sharing app to be useful when trying to get somewhere.
Behavioral Intention Consumer (BIC)	BIC1	Assuming that insurance issues would be all taken care of and the transaction is 100% secure, I intend to use the mobile ride sharing app.
	BIC2	Given that insurance issues would be all taken care of and the transaction is 100% secure, I predict that I would use the mobile ride sharing app.
	provider	Now, imagine a person in your neighborhood needed a ride and you are able to use the same app to let someone drive with you for a fee.
Behavioral Intention Provider (BIP)	BIP1	I intend to use the mobile ride sharing app to let someone drive with me for a fee.
	BIP2	I predict that I would use the mobile ride sharing app to let someone drive with me for a fee.
Scenario Two: In-Home Gig Service		
	consumer	Imagine you needed to perform a task in your home and the possibility existed for you to be matched with a person in your neighborhood who could perform the task for a fee. The details of your task, communication with the person, fee amount and payment would all be handled through a software application on your mobile phone (“app”).
Perceived Ease of Use (PEU)	PEU1	Learning to operate the mobile tasker matching app would be easy for me.
	PEU2	It would be easy for me to become skillful at using the mobile tasker matching app.
	PEU3	I would find the mobile tasker matching app easy to use. (PEU3)
	PEU4	I would find it easy to get the mobile tasker matching app to do what I want it to do.
Perceived Usefulness (PU)	PU1	Using the mobile tasker matching app would be a convenient way to perform a task in my home.
	PU2	Using the mobile tasker matching app would increase my efficiency in performing a task in my home.
	PU3	Using the mobile tasker matching app would be an effective way to perform a task in my home.
	PU4	I would find the mobile tasker matching app to be useful when trying to perform a task in my home.
Behavioral Intention Consumer (BIC)	BIC1	Assuming that insurance issues would be all taken care of and the transaction is 100% secure, I intend to use the mobile tasker matching sharing app.
	BIC2	Given that insurance issues would be all taken care of and the transaction is 100% secure, I predict that I would use the mobile tasker matching app.
	provider	Now, imagine a person in your neighborhood needed a task performed and you are able to use the same app to perform the task for a fee.
Behavioral Intention Provider (BIP)	BIP1	I intend to use the mobile tasker matching app to perform a task in someone else’s home for a fee.
	BIP2	I predict that I would use the mobile tasker matching app to perform a task in someone else’s home for a fee.

Note. All measures on a 5-point scale, 1= disagree strongly to 5= agree strongly. The order of the items within each scale was randomized. R = reverse coded.