The Role of Demographics, Trust, Computer Self-efficacy, and Ease of Use in the Sharing Economy

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ABSTRACT

The digital sharing economy has introduced opportunities for economic growth, productivity, and technological innovation. However, the adoption of sharing economy applications may be inaccessible to certain demographics, including older adults, low-income adults, and individuals who are not college educated. This research investigates how the demographic factors: trust, computer self-efficacy, and perceived ease of use, impact participation in the sharing economy. Drawing on survey data with 508 participants, we found that trust in institutions, computer self-efficacy, and perceived ease of use positively correlate to individuals' past use of and willingness to pay for future sharing economy services, but age is negatively correlated. Surprisingly, we do not find that sharing economy users are more likely to have higher trust in strangers, higher incomes, or more education. We compare our findings to existing research, discuss why institutional trust might negate other concerns about sharing economy use, and explore opportunities to support broader participation in the sharing economy.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in collaborative and social computing**; • **Information systems** → *Collaborative and social computing systems and tools*; • **Social and professional topics** → *User characteristics*;

KEYWORDS

Sharing economy; Age; Income; Education; Trust; Self-efficacy; Survey; Quantitative Analysis

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1 INTRODUCTION

The digital sharing economy refers to peer-to-peer exchange via online marketplaces [13] and provides opportunities to exchange resources and services within a society or between individuals. The sharing economy can promote economic growth, technological innovation, environmental sustainability, and social inclusion, factors that are central to the United Nations' Sustainable Development Goals (SDGs) [58]. Key sectors of the digital sharing economy such as car sharing, travel, and finance could potentially increase global revenues from approximately $15 billion to another $320 billion by 2025 [2]. The number of idling, or unused, resources available [41] and the number of people willing to share or rent their items [25] suggests the potential for continued growth [31]. In addition, research suggests that in areas where on-demand ride services such as Uber and Lyft operate, consumers take fewer trips and buy fewer cars [28], which may promote environmental sustainability. To individuals, the sharing economy applications not only lead to financial resources but also emotional support and cultural knowledge [19, 32].

However, the benefits of the sharing economy are uneven in society and limited to certain populations. Past research suggests that sharing economy participants are typically populations with higher incomes [1, 2, 61, 65], higher education [1, 2, 61], younger adults [1], and those who have higher levels of proficiency with technology [69]. We refer to these individuals as *represented users* of the sharing economy. *Underrepresented users*, such as those who have lower incomes and education, who may be older, and who have lower levels of proficiency with technology are often excluded and unable to access the benefits of the sharing economy [19, 20, 65]. Past research has also found that sharing economy platforms may be associated with racial discrimination [23] and geographic bias [65]. Therefore, understanding how sharing economy technologies could be designed to be more inclusive can further support economic equality, social mobility, and economic growth [33], and further contribute to the SDGs.

The present study builds on an emerging line of research that seeks to understand whether and how underrepresented users participate in the digital sharing economy. We examined how three demographic variables—age, income, and education—are associated with individuals' participation in the sharing economy. We also investigated three other factors regarding sharing economy participation: trust [29], computer self-efficacy, and ease of use of technology [19]. We hypothesize that underrepresented demographics—higher age, lower income, and lower education—are negatively associated with sharing economy participation, while trust, computer self-efficacy, and technology ease of use are positively correlated.

To test these hypotheses, we conducted an online survey (N=508). Prior work has largely taken an in-depth qualitative focus on a single sharing economy platform or a single type of service (see [21] for a systematic review). The present study takes a quantitative approach that seeks to confirm and extend prior work by covering multiple sharing economy services.

We find that age, trust in institutions, computer self-efficacy, and perceived ease of use correlate with sharing economy participation. However, perhaps surprisingly, trust in strangers has no significant effect. Furthermore, our results do not show that sharing economy users are more likely to have high incomes or more education, which differs from past findings [2, 61]. We explore explanations for these results, such as how people's trust in technology companies may eclipse their lack of trust in the strangers using them. We also explore opportunities for promoting self-efficacy and perceived ease of use and suggest directions for future work.

2 RELATED WORK

While the sharing economy broadly refers to the exchange of goods and services between peers in marketplaces, its definition and scope varies in prior literature [12, 21, 29]. The term "sharing economy" has been used as a synonym of the peer-to-peer (P2P) economy [9] and a model covering both the P2P economy and the business-to-consumer (B2C) economy [12]. It has also been used as an umbrella term to include a broader scope of economic concepts such as collaborative economy[1], collaborative consumption[2], and gig economy[3] [20, 21, 65].

In this paper, we refer to *the sharing economy* in the sense of the umbrella term, which refers to "an economic model based on sharing underutilized assets between peers without the transfer of ownership, ranging from spaces, to skills, to stuff, for monetary or non-monetary benefits via an online mediated platform, thereby encompassing all the different kinds of activities that take place on the various sharing platforms" [29, p.2]. This definition of the sharing economy allows us to cover its impact across domains such as renting space via Airbnb, ridesharing via Uber or Lyft, performing physical tasks such as painting via TaskRabbit, and sharing educational resources via Massive Open Online Courses (MOOCs) platforms.

Participation in the sharing economy, either as a worker/provider or consumer, offers a range of potential benefits. Consumers gain access to convenient services, while workers/providers acquire economic benefits [9, 22]. Participation also offers the opportunity to strengthen one's community [9, 44] and environmental benefits [28, 54]. The beneficiaries of the sharing economy are relatively well off [1, 2, 61] and there are opportunities to understand how to extend these benefits to populations historically disadvantaged by the mainstream economy [18, 20]. In this work, we refer to those users who typically benefit from the sharing economy as *represented* users. These users are typically younger, well educated, and have higher incomes. We refer to atypical users of the sharing economy as *underrepresented* users—older users, those who have less than a bachelor's degree, and low incomes.

Here we describe how demographics, trust, and computer self-efficacy intersect with technology use more broadly and identify open questions and hypotheses with respect to sharing economy participation.

2.1 Participants in the Sharing Economy

A 2016 Pew study of the "new digital economy" shows that 72% of American adults have been consumers of at least one of 11 popular services in the sharing economy, though roughly the same amount—73%—were unfamiliar with the term "sharing economy" [61]. This report found that the most avid users, or those using four or more of these services, were well educated (college graduates), had higher incomes, and lived in urban areas. In fact, those with household incomes greater than $100,000 have used four or more of sharing economy applications, which is three times the proportion of those households earning less than $30K per year. Regarding age, approximately 33% of 18- to 44-year-olds had used four or more of these services; on the other hand, 56% of those ages 65 and older (and 44% of those 50 and older) had not used *any* of the services. The Pew report focused on a limited number of services, namely ridesharing, home sharing, and crowdfunding; however, there is a much wider range of services that can benefit and address the needs of underrepresented users, including learning (MOOCs and Skillshare) [52], item exchange (Neighborgoods), health-related services (CrowdMed and HelpAround), and gig work (Etsy, Fiverr, Freelancer's Union, TaskRabbit).

Given the potential for these less popular services to address the needs of underrepresented demographics, we investigated whether those representing underrepresented demographics would be willing to pay for a *broader* selection of sharing economy services. Therefore, to assess past use and potential use of these less popular services in the future, we investigated both 1) past use of sharing economy services and 2) willingness for underrepresented users to pay for a broader set of sharing economy services in the future (e.g., grocery delivery, lending, teaching new skills, and selling used items). Our hypotheses were:

- *H1a-b*: Individuals who are older than 44 years of age (underrepresented user age groups) are a) less likely to have used sharing economy applications than those who are 44 and

[1]Collaborative economy: This concept depicts an economic model in which individuals have the equal power as companies to provide assets and services [12, 53]. This term has also been used as an umbrella term to cover other concepts and models regarding the sharing economy [12].

[2]Collaborative consumption: This term is focused on the consumption behavior in exchanges of unused goods and services [8, 12]. In other words, the collaborative consumption only covers sharing activities with explicit compensations, either monetary or non-monetary.

[3]Gig economy: The term refers to an economic model that online platforms match requesters and labors for gigs, i.e., on-demand works such as transportation and cleaning services [17, 24]. The gig economy emphasizes that individuals provide services by using their idle labors and time, while unused assets are not the main focus.

younger, and are b) more willing to pay for sharing economy services in the future than those who are 44 and younger.

- *H1c-d*: Individuals with household incomes that are less than $35,000 USD (underrepresented users incomes) are c) less likely to have used sharing economy application than those who have higher incomes than $35,000 USD per year, and are d) more willing to pay for future sharing economy services than those who have higher incomes than $35,000 USD per year.
- *H1e-f*: Individuals who have *not* completed a college education, bachelor's degree or higher (underrepresented user education), are e) less likely to have used sharing economy applications than those who have completed a college education, and are f) more willing to pay for future sharing economy services than those who have completed a college education.

2.2 Trust in the Sharing Economy

Trust has been defined as the "willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" [43, p. 715]. Prior work has highlighted the role that trust plays in overcoming these perceived vulnerabilities in peer-to-peer exchange or consumer-to-consumer e-commerce [5, 20, 36, 37, 46, 56, 63].

Exchanging goods and sharing homes, cars, and other resources with strangers requires trust from both the consumer and the provider [29, 64]. Indeed, "trust between strangers" is considered a key requirement for success in the sharing economy [13]. A review of the scholarly research on trust and the sharing economy identified "trusting beliefs" as a major theme, with trusting beliefs toward sellers and buyers being one of the most researched aspects of trust in the sharing economy [29]. For example, prior work has found that concerns for personal safety and distrust toward a provider (e.g., a host on Airbnb) can act as a barrier to participation [67]. Other work has also explored how "trust in strangers" affects participation in the sharing economy by low-income communities [20]. Following this prior work, we hypothesized that:

- *H2a-b*: Individuals who have higher trust in strangers are a) more likely to have used sharing economy applications and b) more willing to pay for future sharing-economy services than those who have lower trust in strangers.

Prior work has also demonstrated the role that institutional trust plays in the sharing economy [29]. Trust in institutions captures the degree to which an individual trusts entities such as large companies, public authorities, churches, and the legislature [47]. Trust in institutions is conceptually related to Luhmann's [39] "system trust" where, for example, "we do not really have to trust the bus driver as long as we can trust the system he presents: namely the bus company" [34, p. 143]. Keymolen [34] argues that in the sharing economy context, trust operates not just on an interpersonal level (i.e. trust in strangers) but also on a system level (i.e. trust in the platform that mediates the user's experience). Prior work supports this assertion. Airbnb hosts overcome the perceived risks of transacting with strangers by relying on the assurances provided by the platform—namely ensuring secure payment and helping to resolve disputes between hosts and guests [35]. Finally, Dillahunt et al.'s study of underrepresented demographics' use of real-time ridesharing services [19] suggested that key factors to sharing economy acceptance included building users' initial trust in the platform, working with trusted community organizations, and promoting trust in a brand. Therefore, we assert that those who have a greater trust in institutions, such as large companies, are more likely to trust the institutional assurances promised by those companies, and as such will be more likely to participate in those platforms. We hypothesized:

- *H2c-d*: Individuals who have higher trust in institutions are c) more likely to have used sharing economy applications and are d) more willing to pay for future sharing economy services than those who have lower trust in institutions.

2.3 Computer Self-efficacy and Perceived Ease of Use

Self-efficacy is an individual's belief that she has the capability to perform a certain behavior or accomplish a specific task [6]. Computer self-efficacy is an individual's belief about her ability to skillfully use computers in their decision to use them [15]. Prior research in the field of virtual banking has found that in addition to factors such as age and education, computer self-efficacy had a significant impact on whether someone adopted technology [71]. Wang et al. also found that computer self-efficacy led to significant changes in behavioral intention through perceived ease of use, perceived credibility, and perceived usefulness [71]. However, this study did not investigate applications of the sharing economy.

Dillahunt et al. found that some individuals living in the Detroit-metropolitan area, who were primarily underrepresented users of the sharing economy, chose not to participate in their real-time ridesharing study due to limited comfort with technology [19]. They also found that participants were comfortable with technology if they had someone in their network, such as a family member, who could provide support if they encountered difficulties using the application (e.g., "individuals needed some hand holding" [19]. We aim to add some specificity to their findings by investigating self-efficacy, specifically computer self-efficacy [15]. We hypothesized that:

- *H3a-b*: Individuals who have lower computer self-efficacy in using sharing economy applications are a) less likely to have used sharing economy applications and are b) less willing to pay for future sharing economy services than those who have higher computer self-efficacy.

Similarly, perceived ease of technology use describes an individual's belief that using a specific system is simple, or easy to do [16]. In a mixed methods study to understand the consumer potential of collaborative consumption among Dutch citizens, van de Glind found that users of the sharing economy needed some proficiency with technology to take advantage of such applications [69]. While this study suggests a need for computer proficiency, it is unclear whether this is a measure of how easy it is to use a system (perceived ease of use), or some other factor related to the use of technology. Theoretically, perceived ease of use is a factor that influences computer self-efficacy and a key predictor. Computer self-efficacy, which we also evaluate, is slightly more complex because people can develop confidence in using technology based on their perception of support from others. Therefore, we hypothesized the following:

- *H3c-d*: Individuals who have lower perceived ease of use in technology are c) less likely to have used and are d) less willing to pay for future sharing economy services than those who have higher perceived ease of use.

3 METHODS

We conducted an online survey with a national sample of adults in the U.S. to test our hypotheses. Participants were recruited through a Qualtrics[4] panel, which is an online survey platform allowing researchers to screen the sampling process. We used a screening process to capture respondents' gender, age, income, ethnicity, and education before continuing to the survey. This allowed us to manage respondent demographics. The survey contained 42 questions and was completed in a median of 715 seconds (approximately 12 minutes). Participants were compensated $5 through Qualtrics. The Likert scale questions used reversed response ordering from ascending to descending to minimize bias toward the response category. The survey was sent to 796 panelists. After removing incomplete responses, invalid responses, and responses that were completed too quickly to be reliable, we had a total of 508 robust responses.

3.1 Selection of Sharing Economy Services

In total, we selected fourteen existing sharing economy applications to examine participants' past use. Our selection process included choosing well-known sharing economy services based on popular press and past surveys of sharing economy usage [2, 61]. Given the rise of the gig economy and freelance labor, we aimed to include a diversity of applications in this domain [62] as well. The six applications we selected were also applications that had been used in a recent Pew report: Airbnb, Etsy, Fiverr, Lyft, TaskRabbit and Uber [61].

While these six applications represented past usage, we identified eight more applications that could address future usage, and could particularly address underrepresented users' needs concerning health, education, and economic growth[5]. We aimed to investigate whether underrepresented users would use, or be willing to pay for these applications in the future. We included CrowdMed and HelpAround, which provide services for users' health. These applications could be especially helpful for addressing health needs of older adults.

We included MOOCs and SkillShare (classified as sharing economy applications per [52]), which are services that provide knowledge and teach new skills; WeWork allows individuals to lease shared workplaces, which could also provide knowledge and skills. We selected these services because they could potentially address the needs of individuals without a formal education. For people with lower incomes, NeighborGoods enables individuals to exchange items with others to save money, and Kiva provides small business loans.

[4]http://www.qualtrics.com
[5]For more on these sustainability development goals see http://www.un.org/sustainabledevelopment/sustainabledevelopment-goals/

Application Category	Nonuser % (N)	User % (N)
Ridesharing	31.10% (158)	58.86% (299)
Spacesharing	43.11% (219)	15.75% (80)
Knowledge & Skill	19.88% (101)	15.16% (77)
Gigwork	38.58% (196)	28.94% (147)
Other	18.11% (92)	11.02% (56)

Table 1: Participants' past use of the five categories of existing sharing economy applications. The percentage means the portion of the entire dataset (N=508). Definition of Nonuser: "have heard about all applications in the category but haven't used any of them." Definition of User: "have used at least one application in the category."

3.2 Measures

Survey instruments were created based on past research on trust [27, 47, 72], computer self-efficacy [15, 38], and perceived ease of use [70]. We developed scales for constructs related to respondents' demographics, prior knowledge of the sharing economy, and their participation in the sharing economy. We also developed scales that would help us to understand respondents' levels of trust, self-efficacy with the sharing economy, and ease of use. Details and examples are provided next.

3.2.1 Dependent Variables. The survey was designed to measure how trust, computer self-efficacy, and perceived ease of use impact participation in the sharing economy. To gauge past and potential future participation, we asked respondents about their: "*past use of sharing economy applications*" and "*willingness to pay for future sharing economy services*", which are two sets of dependent variables.

Past Use of Sharing Economy Applications: We asked respondents about their experience using the fourteen existing sharing economy applications. For each application, we asked participants to choose among four choices: "*I have not heard of the application*"; "*I have heard of the application, but I have not used it*"; "*I have used the application, but not to earn money*"; and "*I have used the application to earn money.*" In the analyses, we focused on what factors were related to the differences between *nonusers* (had heard about the application but not used it) and *users* (had used the application).

We collapsed the fourteen applications into five service categories: Ridesharing (Lyft and Uber), Spacesharing (Airbnb and WeWork), Knowledge and Skill (MOOCs and SkillShare), Gigwork (Etsy, Fiverr, Freelancers' Union, and TaskRabbit), and Other (CrowdMed, HelpAround, Kiva, and NeighborGoods). See Table 1 for details. We also excluded those respondents in each of the five categories in Table 1 who had not heard about any of the corresponding applications.

Willingness to Pay for Sharing Economy Services in the Future: As described earlier, we selected nine non-application-specific services, given their potential to assist underrepresented users. These included: delivering groceries, teaching skills, tools and appliance lending, ridesharing, buying and selling used items, sharing workspaces,

Willingness to Pay for Future Service	Mean (SD)
Teach you skills	**3.29** (1.24)
Drive you to your destination	**3.06** (1.37)
Sell you used items	**3.03** (1.29)
Deliver your groceries	2.99 (1.31)
Complete tasks for you	2.95 (1.29)
Help you with minor health issue	2.82 (1.30)
Loan you tools/appliances	2.72 (1.30)
Lease you a shared workspace	2.66 (1.31)
Rent you extra space in a home	2.51 (1.33)

Table 2: Participants' willingness to pay for nine conceptual sharing economy services (N = 508). Scale: 5-point Likert scale, ranged from 1 (very unlikely) to 5 (very likely). The bold services are services that have scores higher than 3.

completing tasks, helping with minor health difficulties, and renting an extra room on a short-term basis (see Table 2). We chose not to use specific sharing economy services such as Lyft or Airbnb. Instead, we included less known services such as health and education because they might be appealing to underrepresented users of the sharing economy. Therefore, we asked participants to rate their willingness to pay for nine conceptual sharing economy services: "*How likely are you to pay a person you find on a sharing economy application to...* (use the service)."

3.2.2 Independent Variables. Age, Income, and Education: We used U.S. census data to recruit a representative sample of participants in the U.S. for age, ethnicity, and income[6].

Therefore, we divided household-income level into three segments using [40] as a guide: low-income (< $35,000), mid-income ($35,000 - $99,999), and high-income (≥ $100,000). We divided age into six segments: 18-24, 25-34, 35-44, 45-54, 55-64, 65 and over. The latter range is larger because prior work shows that people in this demographic are not yet heavy sharing economy participants and we anticipated we would still have a small sample in this bucket. We used the annual household income as an income measurement. We also divided educational background into six groups: high school degree or less, some college but no degree, associate's degree, bachelor's degree, graduate degree (master's, Ph.D, JD, and MD), and prefer not to say (see Table 3).

To compare our demographic results with existing results [2, 61], we further collapsed age, income, and education into binary groups into represented and underrepresented groups based on [61]. The definition of a underrepresented user is as follows: in age dimension, underrepresented users are people who are older than 44 years old; in education dimension, underrepresented users are those who have no bachelor's degree; in the income dimension, underrepresented users are those who have annual incomes less than $35K (see Table 4).

Trust: Drawing from the results of Glaeser et al. [27] and of Hurne's systematic literature review [29], we measured the level of trust between respondents and thirteen different groups of people, including strangers, family, and neighbors: "*How much trust do you have in...*" [47]. We adapted questions from several surveys on measuring trust [10, 27, 47, 72]. The trust factor included thirteen 4-point Likert scale instruments, and the results are shown in Table 5. In the analyses, we used three factors of trust: trust in strangers, trust in known others (mean of trust in family, friends, neighbors, and coworkers), and trust in institutions (mean of trust

[6]https://www.census.gov/quickfacts/fact/table/US/PST045216.

Factor	Category	% (N)
Age	18-24	10.6% (54)
	25-34	16.5% (84)
	35-44	17.5% (89)
	45-54	20.3% (103)
	55-64	17.9% (91)
	65 and over	17.1% (87)
Income	High (≥ $100K)	20.3% (103)
	Mid ($35K - $99,999)	34.8% (177)
	Low (< $35K)	44.9% (228)
Education	High school degree or less	24.4% (124)
	Some college but no degree	24.4% (124)
	Associate's degree	11.4% (58)
	Bachelor's degree	27.6% (140)
	Graduate degree	11.8% (60)
	Prefer not to say	0.4% (2)
Gender	Male	33.7% (171)
	Female	66.3% (337)
Race	White	41.7% (212)
	Black	33.5% (170)
	Asian	14.6% (74)
	Other	10.2% (52)
Employment	Full-time	38.0% (193)
	Part-time	13.4% (68)
	Unemployed	8.3% (42)
	Non-labor	40.4% (205)
Have Chronic Illness (Yes)		47.44% (241)
Have Regular Access to Vehicles (Yes)		84.25% (428)
Have Extra Rooms in Home (Yes)		49.61% (252)

Table 3: Demographic profile of the dataset (N = 508). Note that the percentage of each factor does not always sum to 100% because of rounding.

Demographic Factor	Represented % (N)	Underrepresented % (N)
Age	44.7% (227)	55.3% (281)
Education	39.4% (200)	60.6% (308)
Income	44.9% (228)	55.1% (280)

Table 4: Represented and Underrepresented groups divided by Age, Education, and Income. The percentage means the portion of the entire dataset (N=508).

Trust Construct	Trust Item	Mean (SD)
Strangers	Strangers	1.83 (0.83)
Known Others	Family	3.51 (0.74)
(Cronbach's $\alpha = 0.75$)	Neighbors	2.67 (0.83)
	Friends	3.24 (0.77)
	Coworkers	2.67 (0.78)
Institutions	Churches	2.83 (0.91)
(Cronbach's $\alpha = 0.87$)	Schools	2.71 (0.84)
	Media	2.19 (0.86)
	Police	2.71 (0.95)
	Legislature	2.14 (0.82)
	Authorities	2.39 (0.82)
	Courts	2.50 (0.87)
	Companies	2.34 (0.80)

Table 5: Participants' trust in different people, groups and organizations in their life. Scale: 4-point Likert scale, ranged from 1 (no trust at all) to 4 (a high amount of trust). Cronbach's α is the internal consistence reliability of the construct.

in churches, schools, media, police, legislature, authorities, courts, and companies).

Computer Self-efficacy & Perceived Ease of Use: Following similar research [38], we drew from existing computer self-efficacy [15] and perceived ease of use scales [70]. Determinants of computer self-efficacy included encouragement by others, others' use, and organizational support [15]. We chose to represent network support instead of organizational support due to the nature of our study, and also to reflect how individuals' access to social networks who used technology influenced their participation in a prior study [19]. Our survey questions reflected the factors encouragement by others and individual support and included questions such as "*I could use sharing economy applications if there was no one around to show me how*", and "*I know people who can show me how to use sharing economy applications*".

We referred to Venkatesh's Technology Acceptance Model 3 for a perceived ease of use scale [70]. We used questions such as "*Interacting with sharing economy applications is clear and understandable*," "*I think it is easy to get sharing economy applications to do what I want to do*," and "*Interacting with sharing-economy applications does not require mental effort*". Table 6 shows the mean results and internal reliability of the items used in each measure.

Other Control Variables: We introduced other demographic factors (gender, race, and employment status) as control variables in the regression model. We have four dummy variables for race: White, Black, Asian, and others; and four dummy variables for employment status: full-time employment, part-time employment, unemployed and looking for jobs, and non-labor. Non-labor includes retired, student, stay-at-home parent, unable to work, and out of work but not looking for jobs.

Given that existing popular sharing economy services included space and vehicle sharing, we included controls such as, "*Overall, how would you rate your neighborhood as a place to live?* (5-point

Computer Self-efficacy & Perceived Ease of Use	Mean (SD)
Self-Efficacy (Cronbach's $\alpha = 0.63$)	3.29 (1.00)
Ease of Use* (Cronbach's $\alpha = 0.83$)	3.18 (0.88)

Table 6: Participants' Computer Self-efficacy and Perceived Ease of Use. Scale: 5-point Likert scale, ranged from 1 (very low) to 5 (very high). *Note that 17 participants reported *Not Applicable* in Ease of Use and were not included in the average and Cronbach's α.

Likert-scale)," "*Do you have extra room(s) in your home?* (Yes/No)," "*Do you have regular access to a vehicle?* (Yes/No)" to get a sense of how respondents rated their neighborhoods in terms of quality, and whether they had access to extra rooms and vehicles. We also asked a question to gauge respondents' interests in health-related services—we asked whether respondents had an existing chronic illness to ensure that interest extended beyond respondents who had a chronic illness. The question was: "*If you have a chronic or ongoing illness or disease, how often do you visit your health care provider in relation to your chronic health condition?*" In the analyses, we used a single variable to indicate if a participant has chronic illness (Yes/No). Table 3 includes details of all control variables we used.

3.3 Analysis

To test the hypotheses, we used two models. We applied logistic mixed-effects regression to examine the relationship between independent variables and *Past Use of Sharing Economy Applications*. We applied linear mixed-effects regression to examine the relationship between independent variables and *Willingness to Pay for Future Sharing Economy Services*.

We first built a null model including the participant ID as a random factor. Then we fit a model adding application IDs (or service IDs), demographic variables, trust, and self-efficacy as fixed factors. We conducted likelihood ratio tests to evaluate how the alternative models are improved from the null models.

We also calculated marginal R^2 and conditional R^2 to assess how the model fits the dataset's variance. The marginal R^2 indicates the variance explained by the fixed factors and the conditional R^2 indicates the variance explained by both random factors and fixed factors.

We used Python and Excel to pre-process the raw dataset (e.g., collapsing variables) and R (with lme4 package [7]) to conduct the regression analyses and calculate related assessments (e.g., Cronbach's α [59] and the likelihood ratio test).

4 RESULTS

We used a likelihood ratio test to compare the two alternative models to their null models. The alternative models made better

Factor	Odds Ratio	95% CI	p
Age: underrepresented	.304	[.182, .510]	$< .001$
Income: underrepresented	.822	[.453, 1.492]	.520
Education: underrepresented	.600	[.340, 1.061]	.079
Trust in Strangers	1.294	[.928, 1.805]	.128
Trust in Institutions	2.079	[1.237. 3.495]	$< .01$
Trust in Known Others	.564	[.333, .954]	$< .05$
Computer Self-efficacy	1.442	[1.072, 1.940]	$< .05$
Ease of Use	2.054	[1.474, 2.861]	$< .001$

Table 7: The logistic mixed-effects regression model predicting participants' past use of sharing economy applications. Note that the table only includes factors regarding our hypotheses. CI: Confidence interval.

Factor	β	Std. Err.	p
Age: underrepresented	-.269	.083	$< .01$
Income: underrepresented	.076	.092	.411
Education: underrepresented	-.022	.095	.815
Trust in Strangers	.086	.053	.103
Trust in Institutions	.428	.082	$< .001$
Trust in Known Others	.075	.085	.382
Computer Self-efficacy	.314	.045	$< .001$
Ease of Use	.152	.052	$< .01$

Table 8: The linear mixed-effects regression model predicting participants' willingness to pay for sharing economy services. Note that the table only includes factors regarding our hypotheses.

predictions than the null models for both *Past Use of Sharing Economy Applications* ($\chi^2_{(23)} = 214, p < .0001$) and *Willingness to Pay for Future Services* ($\chi^2_{(27)} = 451, p < .0001$).

The alternative model predicting *Past Use of Sharing Applications* explains 67% of the variance (conditional $R^2 = .67$, marginal $R^2 = .31$), and the alternative model predicting *Willingness to Pay for Future Services* explains 62% of the variance (conditional $R^2 = .62$, marginal $R^2 = .27$) in participants' willingness to pay for future services.

Next, we examined whether multicollinearity exists in our dataset. Demographic variables such as education and income are often correlated and could bias the results of the analysis. Therefore the examination of multicollinearity was necessary to eliminate this potential bias. To test for multicollinearity, we calculated the variance inflation factors (VIFs) [42] and found that all VIFs were in the range of 1.0 to 3.0 for both the logistic mixed-effects model (past use of sharing economy applications) and linear mixed-effects model (willingness to pay for future sharing economy services). All of the VIFs were smaller than 10, a typical threshold of multicollinearity, which indicated that the correlation between the factors did not impact our models.

Table 3 provides a summary of respondents' demographic data. The majority of our respondents were female (66.3%), held less than a bachelor's degree (60.2%), were White (41.7%), and had a household income of less than $35,000 per year. Compared to the 2016 U.S. demographic[7], there was more balance among ethnicities, a higher percentage of women, and a higher percentage of those holding less than a bachelor's degree.

4.1 Hypotheses Testing

The regression models for predicting the two dependent variables are listed in Table 7 (*Past Use of Sharing Economy Applications*, logistic mixed-effects regression) and Table 8 (*Willingness to Pay for future Sharing Economy Services*, linear mixed-effects regression).

[7]According to the U.S. Census 2016, 50.8% of the population is female, 70.2% don't have a bachelor's degree, and percentage of 76.9% of the population is White. https://www.census.gov/quickfacts/fact/table/US/PST045216.

4.1.1 Demographics. *H1a-b* asserted that individuals who are older than 44 years of age were a) less likely to have used sharing economy services, though were b) more willing to pay for a broader range of sharing economy services in the future than people who are younger. Our models support *H1a* ($OR = .304, p < .001$) but disconfirm *H1b* ($\beta = -.269, p < .01$). People who are older than 44 are less likely to have used sharing economy applications and less willing to pay for future sharing economy services than people who are younger.

H1c-d asserted that individuals whose annual household incomes were less than $35K were less likely to c) have used sharing economy services, though were d) more willing to pay for future sharing economy services than people whose incomes were higher than $35K. However, our models did not support *H1c* ($OR = .822, p = .520$) nor *H1d* ($\beta = -.022, p = .815$). In other words, with other factors controlled, income-level does not show correlation to one's past use of sharing applications or willingness to pay for future sharing economy services.

H1e-f asserted that individuals without a college degree were less likely to have e) used sharing economy services, though were f) more willing to pay for future sharing economy applications than people who had a bachelor's degree. Our models do not support *H1e* ($OR = .600, p = .079$) nor *H1f* ($\beta = .076, p = .411$). With other factors controlled, having a bachelor's degree is not correlated to one's past use of sharing applications and willingness to pay for future sharing economy services.

4.1.2 Trust Factors. *Hypotheses 2a-b* asserted that people who have higher trust in strangers were more likely to a) have used sharing economy services and b) were more willing to pay for future sharing economy services than those who have lower trust in strangers. However, our results do not support *H2a* ($OR = 1.294, p = .128$) nor *H2b* ($\beta = .086, p = .103$).

Hypotheses 2c-d asserted that people who have higher trust in institutions were more likely to a) have used sharing economy services and b) were more willing to pay for future sharing economy services than people who haver lower trust in institutions. Both *H2c* and *H2d* are supported by our dataset. Individuals with trust in institutions were more likely to have used sharing economy applications ($OR = 2.079, p < .01$) and were more willing to pay for future sharing economy services ($\beta = .428, p < .001$).

Though not included in our original hypotheses, trust in known others is a significant predictor of one's past use of sharing economy applications, when other factors are controlled. People who have higher trust in known others are less likely to have used sharing economy applications ($OR = .564, p < .05$). However, trust in known others shows no significant correlation to one's willingness to pay for future sharing economy services when other factors are controlled ($\beta = .075, p = .382$).

4.1.3 Computer Self-efficacy and Perceived Ease of Use. *Hypotheses 3a-b* asserted that people who have lower computer self-efficacy were less likely to a) have used sharing economy applications and b) be less willing to pay for future sharing economy services than those who have higher computer self-efficacy. Both *H3a* ($OR = 1.442, p < .05$) and *H3b* ($\beta = .314, p < .001$) are supported. That means, people who have lower computer self-efficacy are less likely to have used sharing-economy applications and are less willing to pay for future sharing economy services.

Hypotheses 3c-d asserted that people who have lower perceived ease of use were less likely to c) have used sharing economy applications and be d) less willing to pay for future sharing economy services than those who have higher perceived of use. Both *H3c* ($OR = 2.054, p < .001$) and *H3d* ($\beta = .152, p < .01$) are supported by our data. In other words, people who have lower perceived ease of use are less likely to have used sharing-economy applications and are less willing to pay for future sharing economy services.

4.2 Comparing Represented and Underrepresented Users

To contextualize results, we compared underrepresented participants' levels of trust, computer self-efficacy, and ease of use to represented users'. This led to fifteen t-tests between represented and underrepresented respondents. Repeating t-tests on the same dataset fifteen times increases the chance of Type-I errors, and therefore, a correction process was necessary for the tests. We used the Benjamini-Hochberg (BH) correction, which is a general correction procedure. The BH correction is better at gaining the power of analyses than the widely used Bonferroni correction, which is overly conservative [11]. We used a false discovery rate of 25%, which is a default value of the BH correction. Note that the p-values reported below have been adjusted after the BH correction.

Among the fifteen t-tests between represented and underrepresented respondents, twelve were significant. Results showed significantly lower trust in strangers among underrepresented users by education ($M = 1.72, SD = .79$) and income ($M = 1.75, SD = .78$) than presented users' education ($M = 2.01$, $SD = .84$; $t(406) = -3.86$, $p < .001$) and income ($M = 1.91$, $SD = .86$; $t(500) = -2.22$, $p < .05$). Trust in known others showed the same pattern, with significantly lower values among underrepresented users by education ($M = 2.91$, $SD = .62$) and income ($M = 2.89$, $SD = .55$) than represented users' education ($M = 3.21$, $SD = .48$; $t(492) = -6.19$, $p < .001$) and income ($M = 3.13$, $SD = .60$; $t(497) = -4.60$, $p < .001$). Finally, trust in institutions was lower among underrepresented users by education ($M = 2.38$, $SD = .62$) and income ($M = 2.41$, $SD = .62$) than presented users' education ($M = 2.62$, $SD = .58$; $t(446) = -4.36$, $p < .001$) and income ($M = 2.53$, $SD = .61$; $t(483) = -2.29$, $p < .05$). However, age did not correlate with any of the three kinds of trust.

	Past Use	Willingness to Pay for Future Services
Age (45 and older)	Neg. Corr.	Neg. Corr.
Income (<$35K)	—	—
Education (<a college degree)	—	—
Trust in Strangers	—	—
Trust in Institutions	Pos. Corr.	Pos. Corr.
Trust in Known Others	Neg. Corr.	—
Computer Self-efficacy	Pos. Corr.	Pos. Corr.
Ease of Use	Pos. Corr.	Pos. Corr.

Table 9: Summary of Results. Neg. indicates a negative correlation; Pos. indicates a Positive correlation; — means that these factors were not significant

Results showed significantly lower computer self-efficacy among underrepresented users by age ($M = 3.12$, $SD = .96$), education ($M = 3.23$, $SD = .96$), and income ($M = 3.18$, $SD = .94$) than represented users' age ($M = 3.55$, $SD = .95$; $t(475) = -4.88$, $p < .001$), education ($M = 3.45$, $SD = .95$; $t(422) = -2.55$, $p < .05$), and income ($M = 3.43$, $SD = 1.00$; $t(478) = -2.96$, $p < .01$). Similarly, results showed significantly lower ease of use among underrepresented users by age ($M = 2.95$, $SD = .84$), education ($M = 3.10$, $SD = .84$), and income ($M = 3.09$, $SD = .85$) than represented users' age ($M = 3.45$, $SD = .84$; $t(474) = -6.51$, $p < .001$), education ($M = 3.29$, $SD = .84$; $t(410) = -2.31$, $p < .05$), and income ($M = 3.25$, $SD = .89$; $t(477) = -2.08$, $p < .05$). These differences suggest that self-efficacy and perceived ease of use may moderate sharing economy participation.

5 DISCUSSION

Our results examine the current state of participation in the sharing economy, with the goal of promoting social inclusion and greater access and equity, especially among underrepresented users. We include a list of our findings in Table 9. In summary, with other factors controlled for:

- The factors positively correlated with past use included: Trust in Institutions, Computer Self-efficacy, and Ease of Use;
- The factors negatively correlated with past use included: Age and Trust in Known Others;
- The factors positively correlated with willingness to pay for future services included: Trust in Institutions, Computer Self-Efficacy, and Ease of Use;
- The factor negatively correlated with willingness to pay for future services included: Age.

5.1 Trust in Technology Institutions

Despite its relative youth, the technology-enabled sharing economy has upended represented commerce in a variety of ways. Perhaps most significantly, the sharing economy connects consumers at a speed and scale that is unprecedented, relegating represented brick-and-mortar transactions to the background. Mature e-commerce services like eBay have had to implement a wide variety of policies and mechanisms to facilitate transactional trust between strangers, such as reputation systems and fraud protection programs [46, 50, 56]. In contrast, our results suggest that trust in strangers is not related to sharing economy use. Instead, trust in institutions is a significant predictor of use. This may be surprising given the high-profile and sometimes rocky relationship between companies like Uber and the media (e.g., [30]), but speaks to what may be a deep underlying faith people have in both technology and in corporations. Indeed, extensive prior work has demonstrated the importance of institution-based trust in online [55] and offline [57] marketplaces. In online contexts, much of this earlier research focused on trust in B2C online transactions between consumers and professional electronic vendors [26]. More recently, and consistent with our work, a study showed that "trust in Uber" has an influence on customer intention while "trust in drivers" is insignificant [45].

Dillahunt and Malone [20] found that "lack of trust in the sharing-economy platform" was a barrier to participation among what they called less advantaged populations, demographics who were similar to our underrepresented users. While Americans have little confidence in institutions such as places of worship, U.S. Congress, media, and schools [51], one explanation for underrepresented users' lack of trust is their greater lack of trust in institutions more generally. This distrust stems from a long history of unequal treatment for minority populations in domains such as health care, legal services and representation, and employment [14, 68]. This distrust may impede an underrepresented user's ability to participate in the sharing economy. Though not a focus of our work, widespread biases in transactions between strangers (e.g., observed biases against African American hosts on Airbnb [23]) may also negatively impact use. To promote greater sharing economy use among underrepresented users, companies might consider what steps they can take to promote institutional trust and prioritize the needs and concerns of these users. Consistent with prior work [19], we suggest that to build trust in similarly underrepresented users, companies should establish relationships with known community organizations with complementary goals. These efforts would help to certify and build their brands to create familiarity in these communities [19].

5.2 The Sharing Economy as a Gateway to Economic Opportunity

Concerns about the digital divide arose in the 1990s, as it became clear that computers would be central players in the future of work [48]. However, smartphone adoption is still inequitable, with low-income and less-educated people less likely to own a smartphone [3]. With this backdrop in mind, our results surface new opportunities as well as concerns. In contrast to prior studies [2, 4, 60, 61], we find that income and education do not appear to inhibit access to the sharing economy; that is, people with lower incomes and less education are as likely to use the sharing economy as their represented counterparts. The opportunity for new pathways to employment and income may be especially valuable for these underrepresented users. However, it may be that disparities are displaced rather than diminished. In particular, low computer self-efficacy and perceived ease of use inhibit participation. It may be that blue collar jobs that were once available to these demographics (e.g., driving a taxi, cleaning a house) are becoming even less accessible due to new kinds of technology-enabled barriers to participation.

There are a number of opportunities for addressing these concerns. First, network support is shown to increase perceived ease of use, and thus, computer self-efficacy in other contexts [15, 70]. Dillahunt et al. [19] propose kiosk-based systems that lower the barrier to entry to sharing economy services. Such systems could be placed in urban locations such as employment agencies and could educate underrepresented users about sharing economy applications. Our results also indicate that people are generally interested in learning new skills in the future; researchers might target skill-building and educational opportunities that align with these interests. This work also suggests a call for the companies running sharing economy services to widen their market-base by creating "advertisements as tutorials"—similar to how Apple introduced Siri and other iPhone features [49]—other methods of providing tutorials specifically to underrepresented users.

6 LIMITATIONS AND FUTURE WORK

While our results show that trust in institutions, computer self-efficacy, and perceived ease of use positively correlate to individuals' past use and willingness to pay for future sharing economy services, we discuss some attributes of our study that may limit our ability to generalize from our results and present opportunities for future work. For example, we recruited respondents living in the U.S. through Qualtrics. Understanding whether our results generalize to the broader population will require additional research.

Next, it is unclear how participants' geographic locations influenced their use or availability of sharing economy applications. Some existing applications' services are limited to specific areas [66]. People who do not live in areas where specific services, such as TaskRabbit, are available, would not have been able to use the services, even if they were willing to do so. We collected the states where the participants lived; however, we need more detailed geographic data, such as the city or ZIP code, to better clarify the relationships between users' geographic areas and availability of the applications.

In addition, we did not make a clear distinction between consumers and providers (i.e. workers) of sharing economy platforms. Future research should work to disentangle these variables and how they correlate to individuals' past use of and willingness to consume or provide for these applications.

Finally, our respondents included individuals who had heard of at least one of the sharing economy services and consisted of both represented and underrepresented users. To fully understand how the sharing economy could be more inclusive and accommodate non-users, we must analyze data from all non-users [29], which is an area that is open for future research. Further research could also explore the potential for sharing economy applications that address acquiring new knowledge and learning new skills. Our results suggest that our respondents were willing to pay for this future service.

7 CONCLUSION

The United Nations' SDGs aspire to eradicate global poverty, provide reliable transportation systems, and increase sustainable tourism for job opportunities by 2030. As employment and economic resources become increasingly contingent, ensuring equitable access to sharing economy activities, as well as equal rights while participating in the sharing economy, is a crucial goal.

This research examines how demographic factors, trust, computer self-efficacy, and perceived ease of use impacted past participation in and the willingness to pay for future services of the sharing economy. We find that trust in institutions, computer self-efficacy, and ease of use all positively correlated to past use and willingness to pay for future sharing economy services. Our findings do not confirm prior work that suggests that consumers of the sharing economy are more likely to have high incomes, more education, or higher trust in strangers, though the divergence may be explained by our focus on producers and consumers together. This work provides next steps for researchers, companies, and policymakers to promote greater sharing economy participation.

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