Safety and Health Perceptions of Location-based Augmented Reality Gaming App and Their Implications

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Abstract
This study seeks to understand the potential safety and health implications of location-based augmented reality gaming apps ("LAR apps") through studying people perception of Pokémon GO, a popular LAR gaming app. These perceptions can affect app usage behavior, app retention rate, and market share which can be critical to policymakers and app developers. An online survey is conducted to capture the impacts of Pokémon GO regarding: (i) perceived risk of using the app and opinion of prohibiting its usage while driving and cycling, (ii) frequency of app-related distracted driving and cycling, (iii) frequency of app-induced driving and potentially unsafe driving behavior, (iv) average daily steps before and after using the app, and (v) perceived physical and mental health benefits. Multivariate binary probit models and random parameters ordered probit models were estimated to capture users' and non-users' characteristics that affect these perceptions, attitude, and behavior. The results suggest that LAR gaming apps can potentially promote physical activity by encouraging people to walk more, increase social interactions such as app-related discussions, but also contribute to increased app-related distracted driving and cycling, app-induced driving, and unsafe driving behavior. The study findings and insights can provide valuable feedback to legislators and LAR gaming app developers for designing policies and app mechanisms that can address the safety concerns of using such apps, and provide physical and mental health benefits to its users.

Keywords: Safety perception, location-based augmented reality apps, distracted driving, distracted cycling, physical activity, social interaction

1. Introduction and Motivation

Advancements in information and communication technologies have led to exponential growth in smartphone ownership and usage over the last decade. By February 7, 2021, 85% of the United States (U.S.) adults and over 90% of *Millennials* (i.e., people who were born between 1981 and 1996 (Pew Research Center, 2019)) had smartphones (Pew Research Center, 2021). Smartphones have gradually become an integral part of everyday life and have profound impacts on users' decisions (e.g., what to buy and where to go) (Wang et al., 2016; Li et al., 2019). It is expected that people, especially future generations, will spend more time on smartphone and its related technologies (e.g., smartphone apps), become more comfortable with them, and be more susceptible to their influence (Owens et al., 2015; Comscore, 2017).

Smartphone proliferation provides great opportunities to policymakers for using smartphones as a low-cost ready-to-use platform to design apps that can influence user travel behavior such as departure time and mode choice (Guo and Peeta, 2017; Sunio and Schmöcker, 2017; Li et al., 2019; Guo and Peeta, 2020; Shen et al., 2020; Guo et al., 2021a). However, it also brought a new form of distraction to drivers and cyclists which can contribute to the growing number of distraction-related accidents, particularly among young and/or novice drivers or cyclists. Distracted driving or cycling is defined as engaging in competing non-driving or non-cycling related activities that requires visual, physical, auditory, cognitive, etc. (Young et al., 2007). According to NHTSA, around 9% of all fatal crashes and 14% of injury crashes in 2019 in the U.S. involved at least one distracted driver (NHTSA, 2020). A study by Institute on Traffic and Road Safety of the University of Valencia (INTRAS) showed that nearly 90% of all cyclist-related crashes in Spain between 2008 and 20213 involved at least one distracted cyclist (INTRAS, 2014). Young drivers (aged 17-22 years) are much more likely to send email or text messages while driving compared to drivers in other age groups and they touched their smartphones on average 1.71 times per minute while driving (Kita and Luria, 2018). Similarly, teen cyclists (aged 12-17 years) and young adult cyclists (aged 18-34 years) are more likely to use smartphones compared to older adults (Goldenbeld et al., 2012). Many policymakers, practitioners, and researchers have attempted to understand factors that affect smartphone usage while driving and cycling and design strategies to reduce smartphone-related driving and cycling accidents.

1.1 Smartphone-related driving and cycling distractions

Most of the studies related to smartphone-related driving and cycling distractions focused primarily on smartphone-related driving distractions among which most are limited to understanding distractions from making phone calls and texting until a few years ago (Ortiz et al., 2018). These studies found that using (smart)phones can significantly increase the physical, auditory, and cognitive workload of drivers and cyclists, and subsequently contribute to reductions in their ability to perceive and safely react to unexpected events (Jiang et al., 2019; Jannusch et al., 2021). It can also affect drivers' and cyclists' ability to focus on the road, maintain speed and lane positioning control, detect hazards, and detect and respond appropriately to traffic signals (Caird et al., 2014; Jiang et al., 2019). Hence, most studies concluded that drivers and cyclists who talk or text while driving or cycling are more likely to be involved in traffic accidents (Hassani et al., 2017; Lin and Huang, 2017; Tang et al., 2021). For example, Klauer et al. (2006) found that the collision risk associated with texting while driving is five times higher than driving under the influence of alcohol. Some studies even concluded that texting and talking are two of the most dangerous secondary activities within the car (Lansdow, 2012; Prat et al., 2017; Caird et al., 2018). Although many countries introduced stiff punishments towards (smart)phone usage while driving and cycling, they have limited effects on (smart)phone usage while driving and cycling and some people even intentionally hide their (smart)phone usage from being detected (Jannusch et al., 2021). Given the social interaction and information flow utility of smartphones, it can be more and more challenging to expect people to not interact with their smartphones while driving and cycling, particularly during the COVID-19 pandemic (Vollrath et al., 2016; Guo et al., 2021c). However, it is still challenging to understand the complex impacts of

smartphone usage on driving and cycling safety as missing information about drivers' smartphone activity type at the time of accidents in police reports (Jannusch et al., 2021), false testimony given by involved parties (Vollrath et al., 2016), and observation challenges related to identifying specific smartphone-related activities (whether they are texting or surfing online) (Gauld et al., 2016). Furthermore, cycling-related smartphone distractions may be underreporting as many of such accidents did not result in injuries or property damages, and police was not involved (Jiang et al., 2019; Tang et al., 2021).

To curtail (smart)phone usage while driving and cycling, information-based behavior intervention strategies, technology-based strategies, and legislative strategies are three most commonly used approaches. Information-based behavior intervention strategies involve developing public awareness programs that highlight the risk of (smart)phone-related distractions while driving and cycling. Technology-based strategies focus on developing hand free devices (e.g., cellphone holder and bone conduction headphones) and apps (e.g., LifeSaver and Mojo) to limit (smart)phone-related distractions. Legislative strategies involve prohibiting handhold device and the use of headphones or earphones on or in both ears while driving and cycling. Despite these efforts, many recent studies found that over half of the drivers and cyclists engage various types of smartphone related activities, particularly younger adults (Oviedo-Trespalacios et al., 2019; Young et al., 2020; Tang et al., 2021).

To sum up, previous studies have made enormous contributions towards understanding the safety impacts of texting and making phone calls while driving and cycling. However, only a few recent studies (e.g., Hassani et al., 2017; Jannusch et al., 2021) investigated beyond texting and making phone calls and studied behaviors that exist in smartphones but not in regular phones, such as using GPS, reading social media, searching/changing music, reading notifications, etc. They found that younger drivers are more likely to engage smartphone-only behaviors compared to texting and making phone calls. Furthermore, the emerging location-based augmented reality apps (hereafter referred to as "LAR apps") may create new safety and health challenges and opportunities for policymakers and practitioners.

1.2 Location-based augmented reality apps and their potential safety and health impacts

LAR apps have recently gained widespread attention. Such apps use augmented reality technologies to overlay interactive virtual objects with digital content (e.g., in-app benefits such as in-app items and contents) on top of real-world locations, and encourage people to interact with these virtual objects for tangible (e.g., information) and intangible benefits (e.g., enhanced user experience) based on their locations tracked via Global Positioning System (GPS), digital compass, accelerometers and other tracking mechanisms (Dirin and Laine, 2018). A recent effort by Guo et al. (2021b) proposed a framework for using LAR apps that allows transportation system operators (e.g., traffic control centers) to overlay incentivizing virtual objects in the real-world traffic network based on users' locations for influencing their route and mode choice decisions in both short- and long-term. Such apps can provide a low-cost solution to improve transportation system performance (e.g., reduced total system travel time) by reducing the need to invest in physical infrastructure.

Despite the popularity and potential benefits of LAR apps, little or no research has been carried out to investigate some key safety- and health-related issues of using such apps. Firstly, similar to engaging in phone-related activities such as making phone calls and texting (Stutts et al., 2001; Simons-Morton et al., 2005; Stavrinos et al., 2011; Guo et al., 2017; Lin and Huang, 2017; Stavrinos et al., 2018; NHTSA, 2020; Guo et al., 2021b), using LAR apps to locate and interact with virtual objects while driving and cycling can increase users' safety risk exposure due to *app-related distracted driving and cycling*. One recent study has shown that drivers who are distracted by visual-manual-cognitive tasks (e.g., using apps) are 4.5 times more likely to experience crashes compared to undistracted drivers (Higgins et al., 2017).

Secondly, LAR apps will most likely bring new safety hazards such as *app-induced driving* that do not exist in other types of phone-related activities. Such apps, especially when integrated with gamification

or social components, often encourage users to drive more frequently, longer, and to different locations for gaining in-app incentives through their interaction with virtual objects (Guo et al., 2021b). This app-induced driving can not only aggravate traffic congestions but also make users more susceptible to road accidents (*accident proneness*). As shown in literature, as people drive longer, the likelihood of them having accidents increases (e.g., McEvoy et al., 2006; Zhou et al., 2009; Sween et al., 2017; Tang et al., 2021). In addition, users may end up driving in unfamiliar areas while trying to locate virtual objects which can further heighten the risk of having accidents (Dingus et al., 2016).

Thirdly, a common practice used by app developers (e.g., Niantic) to improve driving safety is to limit or disable certain app features if the detected speed is over a certain threshold. This might be counterproductive as some users may perform unsafe driving maneuvers (e.g., abrupt braking) or intentionally drive slower than the traffic to interact with LAR apps which can be more hazardous to both app users and other road users.

Fourthly, few studies have focused on understanding users' safety perceptions of using LAR apps while driving and cycling and opinion of prohibiting its usage while driving and cycling, if these perceptions are correlated, and what sociodemographic (e.g., gender) and behavioral (e.g., if they drive or not) factors affect them. Such perceptions can be different from the perceptions of doing other types of phone-related activities while driving and cycling which have been addressed in previous studies. Furthermore, these perceptions impact the ability to attract new users, retain current users, and user compliance with legislative regulations to limit unsafe app usage. As shown in literature (Wogalter and Mayhorn, 2005; Nelson et al., 2009), many failed legislative efforts to limit cellphone usage while driving can be partly explained by drivers' low perceived risk of using cellphone while driving. Thus, without addressing the aforementioned safety-related issues, using LAR apps can potentially jeopardize the safety of all road users.

Fifthly, the integration of gamification and social component with LAR apps that reward walking, cycling, and user collaboration can potentially promote physical activities and social interactions. There is ample evidence that increasing physical activities and social interactions can provide physical and mental health benefits such as increasing lifespan and lowering risk for many chronic diseases (e.g., Type 2 diabetes) and mental illness (e.g., depression) (Miles, 2007; Krittanawong et al., 2017). However, few studies have focused on identifying factors associated with perceived physical health and social interaction increase because of using LAR apps.

Finally, risk perception is important related to LAR app development because it determines (i) the app usage behavior of its current users, (ii) whether its current users want to continue using the app, and (iii) whether potential users want to start using the app. The subsequent app usage behavior is related to the actual risk of the users. This has been observed in pedestrian crossing behavior (Rankavat and Tiwari, 2020), speed choice (Charlton and Starkey, 2016), and technology acceptance (Lee and Song, 2013; Guo et al., 2021d). Whether current users want to continue using the app and potential users want to start using the app can potentially determine the app retention rate and market share, respectively.

1.3 Pokémon GO, the most popular LAR gaming app

Pokémon GO, a free-to-play LAR gaming app, leverages AR to put fixed- (e.g., PokéStops) and dynamic-location (e.g., Pokémon) virtual objects overlaying in the real-world and rewards users for interacting with them within its interaction circle (around 20 meters) for in-app items (Figure 1). Its map is created based on OpenStreetMap and its fixed-location virtual objects are often representing landmarks in real-world, such as libraries, park entrances, and statues. Based on the detected user moving speed (via GPS and accelerometers), the app can promote walking and cycling by rewarding users with additional in-app items and other benefits, and discourage using the app while driving by disabling certain features when the detected speed is over a certain threshold (20 km per hour based the authors' personal experience). It has attracted massive number of users since its launch in 2016 and ranks top 10 grossing app on both Google Play and App Store. As of September 2019, Pokémon GO is ranked only behind Google Play Games as the

second most popular mobile gaming apps in the U.S. with 10.66 million monthly users in the U.S. (Statista 2020). It also maintained a relatively high 3-day retention rate, a commonly used app performance metric that measures the percentage of users who still use the app 3 days after the initial download, at 60% compared to the app industry average 15% in 2018 (Mobile App Daily, 2019). It can be considered as one of the most popular if not the most popular LAR app in the world.

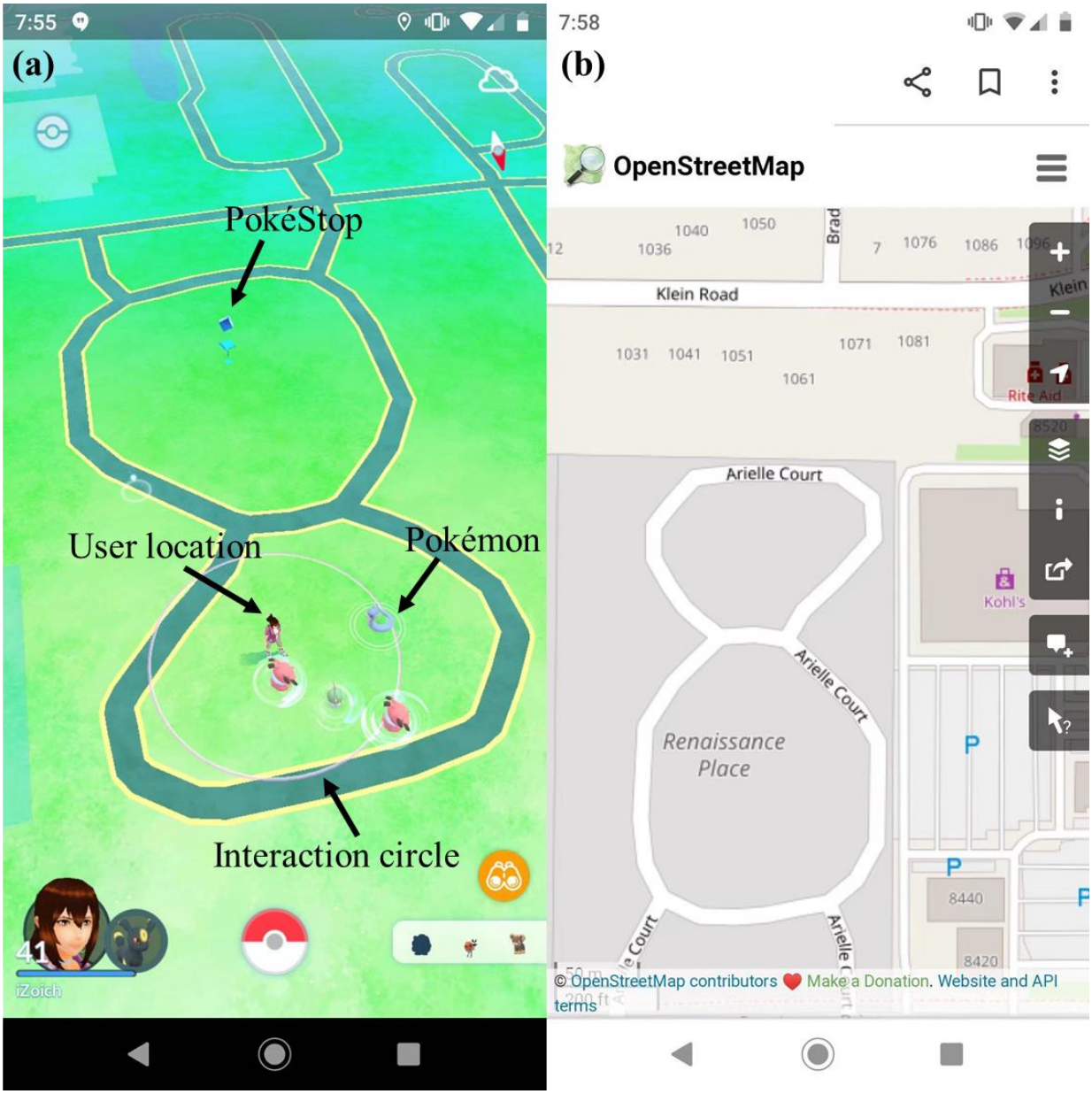


Figure 1. Pokémon GO interface (a) and corresponding OpenStreetMap (b)

Most of the existing studies related to Pokémon GO (Kogan et al., 2017; Nigg et al., 2017; Vella et al., 2017) have been focused on understanding its potential to promote physical activity, decrease sedentary behavior, and provide opportunities for social interactions using self-reported survey data. Some studies have addressed a few safety impacts of the app usage. For example, after analyzing Tweeter postings between July 10 and 19, 2016, Ayer et al. (2016) suggested that many drivers and pedestrians were distracted by Pokémon GO. LaMagna (2016), Serino et al. (2016), and Chong et al. (2018) advised caution

on using Pokémon GO while walking and driving. Barbieri et al. (2017) and Sawano et al. (2017) conducted app-related accident case studies to illustrate the increased risk of using Pokémon GO while walking and driving. Pourmand et al. (2017) reviewed 44 peer-reviewed publications related to videogame-related illness and injury along with 17 news reports related to Pokémon GO-related injuries, and predicted the immersive experience brought by the app can potentially lead to both physical trauma as well as psychological and behavioral disorders. Guo et al. (2021b) highlighted some of the potential safety implications of using such apps but additional studies are needed to understand factors that affect the safety and health-related issues associated with using Pokémon GO.

1.4 Study objectives

This study selects Pokémon GO, a popular LAR gaming app developed by Niantic, as a case study to understand the following safety and health implications of using LAR gaming apps through analyzing self-reported behavioral data from an online survey: (i) perceived risk of app usage while driving and cycling (hereafter referred to as "perceived app-related driving and cycling risk"), (ii) the opinion regarding LAR gaming app-use prohibition while driving and cycling, (iii) increase in app-related distracted driving and cycling using self-reported frequency of using the app while driving and cycling, (iv) increase in app-induced driving and potentially unsafe driving behavior (i.e., intentionally driving slower than the traffic) for using the app, (v) average daily steps before and after using the app, (vi) perceived physical (i.e., if using the app makes you physically healthier) and mental (i.e., if using the app increases social interactions) health benefits, and (vii) factors affecting these self-reported perceptions and behavior. Understanding these safety implications can help facilitate the design of app mechanisms to increase LAR gaming app attractiveness and promote physical activity increase without compromising user safety. The result insights can also aid legislators to formulate and enforce laws related to LAR gaming app usage more effectively.

The rest of the paper is organized as follows: the following two sections describe the survey and modeling methods used in this study, respectively. Then, descriptive statistics and statistical model results are analyzed to understand the correlation between various factor and the safety and health implications of using LAR gaming apps after that, followed by conclusions and discussion on policy implications.

2. Survey Design and Implementation

An 80-item anonymous online questionnaire was designed for this study. The survey consists of three unconditional sections for all participants and four conditional sections for some participants. The survey flow is presented in Figure 2.

The first unconditional section was composed of questions related to participants' sociodemographic characteristics such as gender, age, marital status, residential location, household structure, driving and cycling experience, and car ownership. The second unconditional section was designed to capture participants' user status (i.e., user or non-user) and familiarity with Pokémon GO. The third unconditional section asked participants to provide their response to four safety perception-related questions including perceived risk of using Pokémon GO while driving and cycling, and their opinions on whether using it while driving and cycling should be prohibited.

Conditional sections were designed for users, users who are drivers (i.e., have a valid U.S. driver license, and hereafter referred to as "user-drivers"), users who are cyclists (i.e., reported that they ride a bike, and hereafter referred to as "user-cyclists"), or participants who wear or carry a device that tracks daily walk/run steps and willing to share the information (hereafter referred to as "participants with an activity tracker"), respectively. Users were asked questions related to how frequently they discuss Pokémon GO with friends/family and strangers, and how frequently they used the app with them, and if they agree that using Pokémon GO can make them physically healthier and socialize more in the first conditional section.

In the second conditional section, user-drivers were asked to provide their app-related driving behavior such as frequency of using the app while driving, if their weekly driving distance increased because of using the app, and frequency of intentionally driving slower than the traffic to interact with virtual objects in the app.

In the third conditional section, user-cyclists were asked to provide their app-related cycling behavior such as frequency of using the app while cycling. All the questions in third unconditional section and first three conditional sections were measured on a 5-point Likert scale where 1 is “never”, “definitely not risky”, “definitely should not be prohibited”, or “definitely no”, and 5 is “almost always”, “definitely risky”, “definitely should be prohibited” or “definitely yes”.

The last conditional section was designed for participants with an activity tracker. These participants were asked to check the data from their activity tracker when they answered this section of survey. Non-users only needed to report their average daily walk/run steps for the week prior to the time of survey, while users needed to report their average daily walk/run steps for the week prior to using Pokémon GO and for the week prior to the time of survey which can be considered after using Pokémon GO. If such users used Pokémon GO for less than a week, they were asked to provide average daily walk/run steps two days prior to the survey. Apart from these relatively restricted questions, users were also given an opportunity to share their experiences related to Pokémon GO in an open-ended question which can potentially be used to explain some of the self-reported behavior and perceptions.

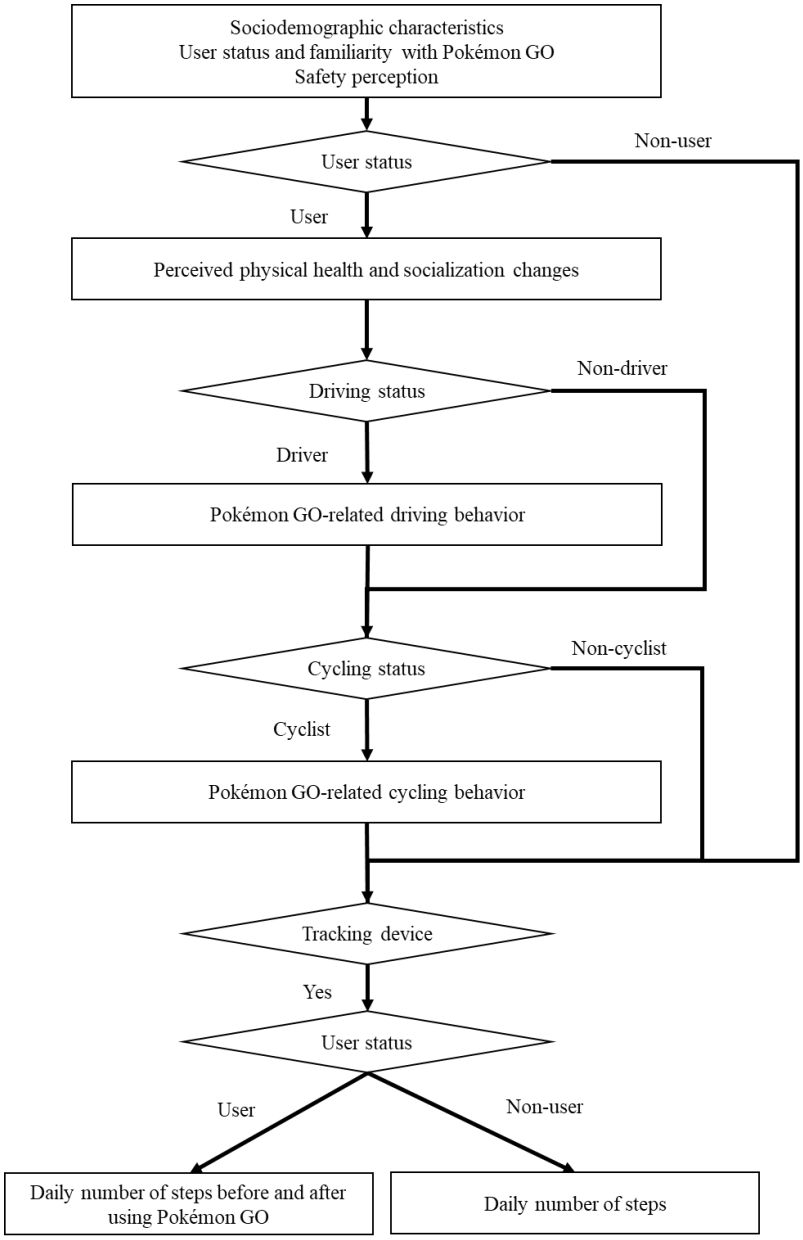


Figure 2. Survey flow

Participants were recruited through social networking services (e.g., Twitter) and online forums (e.g., Reddit) postings, flyer distributions, and email recruitment distributed by contacting employers and institutions. The data collection protocol was approved by Institutional Review Board at Purdue University. Participants could quit the survey at any time, and two attention check questions were included (e.g., please select the third answer for this question). Only completed surveys with correct attention check question answer were used in data analysis. 1166 completed surveys from participants (18 years old or older and living in the U.S.) from 41 states in the U.S. were recruited between September 2018 and January 2019. Based on participants' Pokémon GO user status, they are classified into two groups, including 566 users and 600 non-users. Most of the participants completed the survey within 15 minutes. Among the users, 466 of them are drivers, 192 of them are cyclists, and 144 of them are both drivers and cyclists.

3. Methodology

To understand factors that affect four safety perception (perceived app-related driving and cycling risk and opinion of prohibiting app usage while driving and cycling), two possible modeling methods were used, including ordered probit models with random parameters and bivariate ordered probit models with random parameters.

Six separate random parameters ordered probit models were estimated using the simulated maximum likelihood method with 300 Halton draws to understand factors affecting (i) increased app-related distracted driving and cycling among user-drivers and user-cyclists (i.e., self-reported frequency of using the app while driving and cycling), (ii) self-reported increase in app-induced driving and potentially unsafe driving behavior among user-drivers, and (iii) perceived physical health and social interactions changes because of using Pokémon GO among users. These models can capture heterogeneity among subgroups of app users and the ordered discrete nature of the dependent variables. The modeling method is presented in section 3.1.

Two random parameters bivariate ordered probit models were estimation: (i) one model with dependent variables as "perceived risk of using the app while driving" and "opinion of prohibiting it while driving", and (ii) the other model with dependent variables as "perceived risk of using the app while cycling" and "opinion of prohibiting it while cycling". The reasons of using random parameters bivariate ordered probit models are is can factor the potential cross-equation error correlation between people's perceived risk and opinion as well as account for potential heterogeneity. The results of the model estimation were compared with estimating these four dependent variables separately using random parameters ordered probit models. The modeling method is presented in section 3.2.

3.1 Random parameters ordered probit models

Using the likelihood of user i self-reported increase in app-induced driving as an example, it can be formulated as follows:

$$y_i^* = \beta X_i + \varepsilon_i \tag{1}$$

where y_i^* denotes the latent likelihood of self-reported increase in app-induced driving for each user coded as 0, 1, 2, 3 and 4 in Likert scale ranging from "definitely no" to "definitely yes", X_i is a vector of the contributing factors considered, β is the vector of estimable coefficients, and ε_i is a random error term assumed to be normally distributed across users. Observed ordinal data, y_i, for each observation can be written as:

$$y_i = \begin{cases} 0 & if\ y_i^* \le \mu_0\ \ (Definitely\ no) \\ 1 & if\ \mu_0 < y_i^* \le \mu_1\ \ (Somewhat\ no) \\ 2 & if\ \mu_1 < y_i^* \le \mu_2\ \ (Neutral) \\ 3 & if\ \mu_2 < y_i^* \le \mu_3\ \ (Somewhat\ yes\ ) \\ 4 & if\ y_i^* > \mu_3\ (Definitely\ yes) \end{cases} \tag{2}$$

where $\mu_0 = 0$, and μ_n (n = 1, 2, 3) are thresholds that are constant ($\mu_1 < \mu_2 < \mu_3$) and estimated along with the β. Then, the predicted the likelihood of user i self-reported increase in app-induced driving for given X_i can be written as the following:

$$\begin{aligned} P(y_i = 0) &= \Phi(-\beta X_i) \\ P(y_i = 1) &= \Phi(\mu_1 - \beta X_i) - \Phi(-\beta X_i) \\ P(y_i = 2) &= \Phi(\mu_2 - \beta X_i) - \Phi(\mu_1 - \beta X_i) \\ P(y_i = 3) &= \Phi(\mu_3 - \beta X_i) - \Phi(\mu_2 - \beta X_i) \\ P(y_i = 4) &= 1 - \Phi(\mu_3 - \beta X_i) \end{aligned} \tag{3}$$

where $\Phi(\cdot)$ is the cumulative normal distribution. Thresholds, μ_n, show the range of the normal distribution associated with the specific values of the response variables.

To understand the effect of changes in the explanatory variables on the self-reported increase in app-induced driving, marginal effects are estimated. It is important to estimate marginal effects for ordered probit models because it can show the effects of vector of independent variables X_i on the intermediate categories. Otherwise, if only the parameter estimates are available, these effects are ambiguous. The marginal effects of factor X_i on the self-reported increase in app-induced driving can be calculated as follows:

$$\begin{aligned}
\frac{\partial P(y_i = 0)}{\partial X_i} &= -\phi(-\beta X_i)\beta' \\
\frac{\partial P(y_i = 1)}{\partial X_i} &= [\phi(\mu_0 - \beta X_i) - \phi(\mu_1 - \beta X_i)]\beta' \\
\frac{\partial P(y_i = 2)}{\partial X_i} &= [\phi(\mu_1 - \beta X_i) - \phi(\mu_2 - \beta X_i)]\beta' \\
\frac{\partial P(y_i = 3)}{\partial X_i} &= [\phi(\mu_2 - \beta X_i) - \phi(\mu_3 - \beta X_i)]\beta' \\
\frac{\partial P(y_i = 4)}{\partial X_i} &= -\phi(\mu_3 - \beta X_i)\beta'
\end{aligned} \tag{4}$$

where $\phi(\cdot)$ is the standard normal density function and β' represents the effect of changes in the explanatory variables on the self-reported increase in app-induced driving.

Previous studies in transportation and related domains have utilized random parameters models to capture the unobserved heterogeneity in the data (Anastasopoulos, 2009; Guo et al., 2021b). The limitation of using fixed parameters when these parameters vary across observations, include but not limited to inconsistent, inefficient, and biased parameter estimates. The addition of an error term correlating with the unobserved factors, ε_i, can translate individual heterogeneity into the parameter heterogeneity as follows:

$$\beta_i = \beta + \varphi_i \tag{5}$$

where φ_i is a randomly distributed term. To simulate maximum likelihood estimates for random parameters order probit models, 300 Halton draws are used.

3.2 Random parameters bivariate ordered probit models

Similarly, using the likelihood of user i perceived risk of using the app while driving and opinion of prohibiting the app usage while driving as an example, it can be formulated as follows:

$$\begin{aligned}
y^*_{i,1} &= \beta_1 X_{i,1} + \varepsilon_{i,1} \\
y^*_{i,2} &= \beta_2 X_{i,2} + \varepsilon_{i,2}
\end{aligned} \tag{6}$$

All the notations in Eq. 6 are similar to Eq. 1 and

The cross-equation correlated error terms can be written as (Russo et al., 2014):

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}] \tag{7}$$

where ρ is the cross-equation correlation coefficient of the error terms. Hence, the joint probability for $y_{i,1} = j$ and $y_{i,2} = k$ can be written as with $\emptyset$ as the standard normal cumulative distribution function:

$$P(y_{i,1}=j, y_{i,1}=k|X_{i,1}, X_{i,2}) = \begin{pmatrix} \emptyset_2[(\mu_j - \beta_1' X_{i,1}), (\theta_k - \beta_2' X_{i,2}), \rho] \\ -\emptyset_2[(\mu_{j-1} - \beta_1' X_{i,1}), (\theta_k - \beta_2' X_{i,2}), \rho] \end{pmatrix} - \begin{pmatrix} \emptyset_2[(\mu_j - \beta_1' X_{i,1}), (\theta_{k-1} - \beta_2' X_{i,2}), \rho] \\ -\emptyset_2[(\mu_{j-1} - \beta_1' X_{i,1}), (\theta_k - \beta_2' X_{i,2}), \rho \end{pmatrix} \quad (8)$$

Calculation of the marginal effects for random parameters bivariate ordered probit models and the incorporation of random parameters is similar to Eq. 4 and Eq. 5, respectively.

3.3 Potential differences between users and non-users

As shown in Table 2, users and non-users have very different perspectives and opinions towards app usage while driving and cycling. It is possible that different factors affect users' and non-users' perspectives and opinions differently. Using the two combined likelihood ratio tests (Washington et al., 2010),

$$X^2 = -2[LL(\beta_A) - LL(\beta_U) - LL(\beta_{NU})] \quad (9)$$

where $LL(\beta_A)$ is the log-likelihood of the model at convergence with data of both users and non-users, $LL(\beta_U)$ is the log-likelihood at convergence of the model estimation with users, and $LL(\beta_{NU})$ is the log-likelihood at convergence of the model estimation with non-users. The second set of tests is as follows:

$$X^2 = -2[LL(\beta_{U,NU}) - LL(\beta_{NU})] \quad (10)$$

where $LL(\beta_{U,NU})$ is the log-likelihood of the model using the converged parameters from model for non-users for users' data, $LL(\beta_{NU})$ and is the log-likelihood at convergence using non-users' data. Chi-squared tests were used with the degrees of freedom equal to the summation of the number of parameters in the overall model.

All model estimations were performed using NLOGIT 6. The selection of the final model is based on likelihood ratio tests (Washington et al., 2010), goodness-of-fit measures (McFadden pseudo-R2, Akaike Information Criterion (AIC), and corrected Akaike Information Criterion (AICc)), and prediction accuracy.

4. Descriptive Statistics

4.1 Participants' sociodemographic and behavioral characteristics

Users' and non-users' sociodemographic and behavioral characteristics are summarized in Table 1. It is important to note that most of the participants in this study were relatively young, single, with higher education and higher income. Considering the survey delivery method, its voluntary nature, and how they were compensated, it is possible that most people who were interested in completing the survey, using or not using Pokémon GO, are more likely belong to these demographics. The data collected may not represent the safety perception of the general population.

TABLE 1 Sociodemographic and behavioral characteristics of participants

	Users	Non-users
Number of participants	566	600
Gender (percentage)		
Male	54.2	51.8
Female	45.8	48.2
Age		
Post-Millennials (born after 1996)	19.1	17.1
Millennials (born between 1981 and 1996)	65.0	66.2
Generations older than Millennials (born before 1981)	15.9	18.7
Average age (standard deviation)	28.5 (9.5)	29.0 (9.6)
Marital status (percentage)		
Married	31.4	31.8
Single	65.0	62.5
Other	3.6	5.67
Education (percentage)		
Without college degree	26.1	20.2
College degree	37.8	35.5
Post graduate degree	36.1	44.3
Employment status (percentage)		
Employed full or half time	49.3	42.1
Student	41.5	54.0
Others	9.2	3.9
Household income (percentage)		
Under $25,000	38.5	41.0
$25,000 ~ $50,000	20.3	21.7
Over $50,000	41.2	37.3
Residential location's level of urbanization (percentage)		
Urban	34.3	36.3
Suburban	54.2	51.5
Rural	12.5	12.2
Drivers (percentage)	78.8	80.5
Driving experience (among drivers)		
Novice drivers (2 years or less)	13.0	15.3
2 to 5 years	17.9	24.2
More than 5 years	69.1	60.5
Annual mileage (among drivers)		
Less than 9,000 miles	57.6	65.7
9,000 to 14,999 miles	27.2	24.4
15,000 miles or more	15.2	9.9
Cyclists (percentage)	33.9	50.7
Average number of automobiles per household	2.96	2.76
Average number of persons per household	2.69	2.55
Familiarity with Pokémon GO (percentage)		
Extremely familiar	61.7	6.8
Very familiar	28.5	18.3
Moderately familiar	8.1	38.3
Not very familiar	1.7	24.9
Not familiar at all	0	11.7

4.2 Participants' safety perception related to Pokémon GO

Descriptive statistics of participants' perceived app-related driving and cycling risk and opinions of prohibiting its usage while driving and cycling are presented in Table 2. It shows that most participants perceived app-related cycling risk to be lower compared to app-related driving risk, and more of them considered using the app while cycling should not be prohibited unlike their opinion of using it while driving.

In terms of users' and non-users' perceived risk and opinions, users perceived app-related driving and cycling risk to be lower compared to non-users, and their opinions of using the app while driving and cycling are more likely to lean towards not prohibiting its usage while driving and cycling. Furthermore, two independent sample chi-square tests were conducted to evaluate if their perception and opinion were similar. The test results show that users and non-users have statistically significant differences ($\chi^2 > 9.49$, significant at 0.05 level) in terms of their perceived risk of using the app while driving ($\chi^2 = 13.17$), opinion of prohibiting it while driving ($\chi^2 = 52.34$), perceived risk of using the app while cycling ($\chi^2 = 118.34$), and opinion of prohibiting it while cycling ($\chi^2 = 137.707$).

Table 2 Risk perception of using the app while driving and cycling and opinion of prohibiting the app usage while driving and cycling

	Users	**Non-users**
Number of participants	566	600
Perceived risk of using the app while driving: number (percentage)		
Definitely dangerous	406 (71.7)	472 (78.7)
Probably dangerous	126 (22.3)	103 (17.2)
Neutral	22 (3.9)	16 (2.6)
Probably *not* dangerous	11 (1.9)	4 (0.7)
Definitely *not* dangerous	1 (0.2)	5 (0.8)
Opinion of prohibiting the app usage while driving: number (percentage)		
Definitely should be prohibited	264 (46.6)	392 (65.3)
Probably should be prohibited	152 (26.9)	132 (22.0)
Neutral	82 (14.5)	49 (8.2)
Probably should *not* be prohibited	40 (7.1)	19 (3.2)
Definitely should *not* be prohibited	28 (4.9)	8 (1.3)
Perceived risk of using the app while cycling: number (percentage)		
Definitely dangerous	166 (29.3)	321 (53.5)
Probably dangerous	197 (34.8)	162 (35.3)
Neutral	100 (17.7)	38 (6.3)
Probably *not* dangerous	81 (14.3)	23 (3.9)
Definitely *not* dangerous	22 (3.9)	6 (1.0)
Opinion of prohibiting the app usage while cycling: number (percentage)		
Definitely should be prohibited	84 (14.8)	195 (32.5)
Probably should be prohibited	102 (18.0)	162 (27.0)
Neutral	114 (20.2)	121 (20.1)
Probably should *not* be prohibited	124 (21.9)	94 (15.7)
Definitely should *not* be prohibited	142 (25.1)	28 (4.7)

4.3 User-drivers' driving-related behavior

The descriptive statistics of driver-related behavior are presented in Figure 3 and the descriptive statistics of factors that may affect such behavior are presented in Table 3.

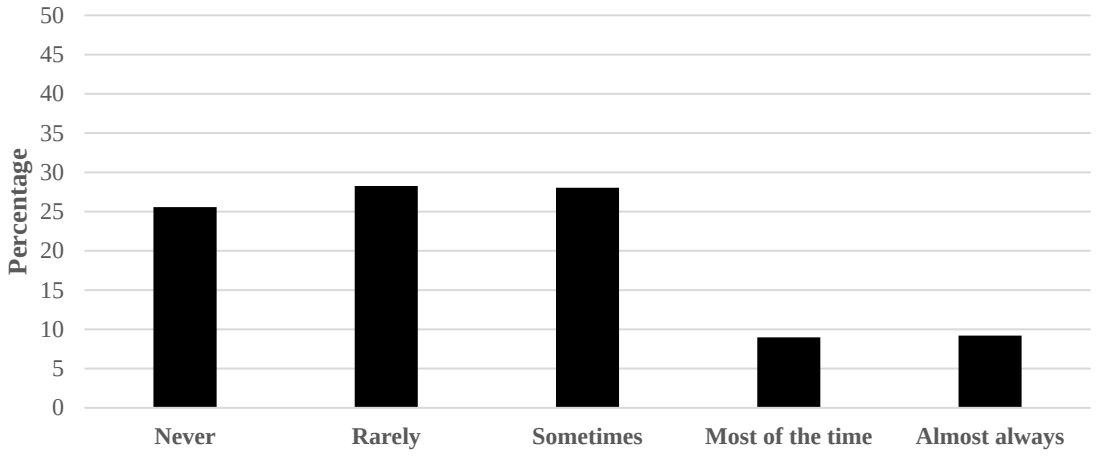


Figure 3a

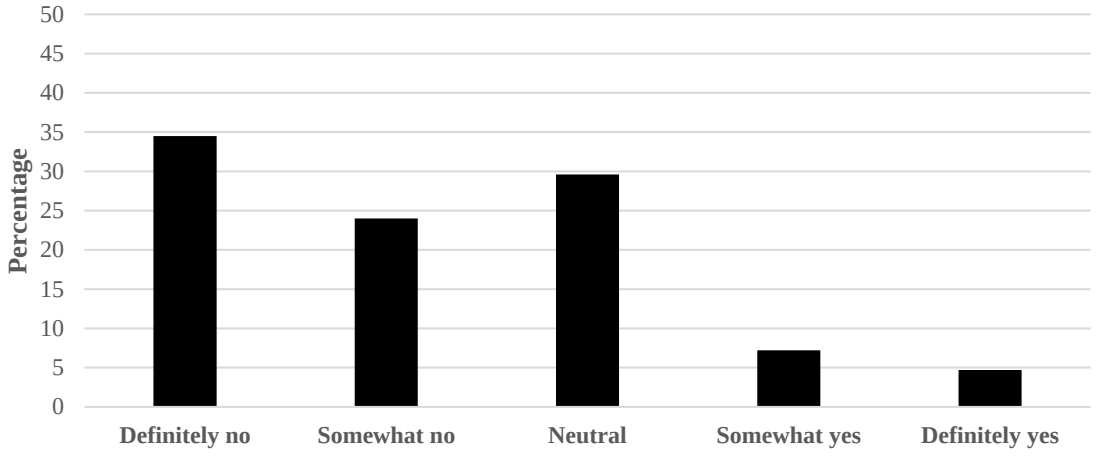


Figure 3b

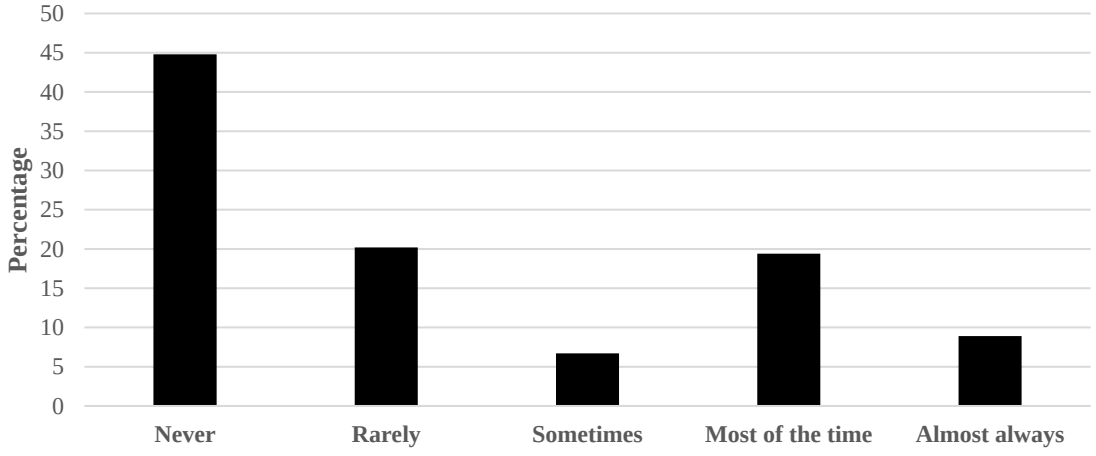


Figure 3c

Figure 3. Self-reported app usage frequency while driving (a), increase in distracted driving (b) and frequency of intentionally driving slower than the traffic (c).

TABLE 3 Descriptive statistics of independent variables that are statistically significantly correlated with increase in driving-related risk exposure (*N*=466)

	Percentage
App perception and usage	
App familiarity	
"Somewhat familiar", "not very familiar" or "not familiar at all"	40.6
"Extremely familiar" or "very familiar"	59.4
Likelihood of continuing using the app for the next three months	
"Neutral", "unlikely" or "very unlikely"	24.5
"Extremely likely" or "likely"	75.5
In-app spending	
$10 or less	70.8
More than $10	29.2
Passenger app usage frequency while driving	
"Sometimes", "rarely" or "never"	71.2
"Almost always" or "most of the time"	28.8
Risk perception of using the app while driving	
"Somewhat risky", "neutral", "somewhat not risky", or "definitely not risky"	33.5
"Definitely risky"	66.5
Sociodemographic characteristics	
Age	
Post-millennials	19.3
Millennials or older generations	80.7
Annual driving distance	
Less than 9,000 miles	59.5
9,000 miles or more	40.5

4.4 User-cyclists' cycling-related behavior

Descriptive statistics of app usage frequency while cycling among user-cyclists are presented in Figure 4. Over a quarter of cyclists reported that they "most of the time" or "almost always" use the app while cycling. Such behavior can potentially lead to safety hazards as these users may be more likely to demonstrated unsafe behaviors (e.g., not slowing down to look both ways before crossing) and be involved in a bicycle crash compared to those who does not use the app while cycling (Goldenbeld et al., 2012; Terzano, 2013). Descriptive statistics of possible related factors are presented in Table 4.

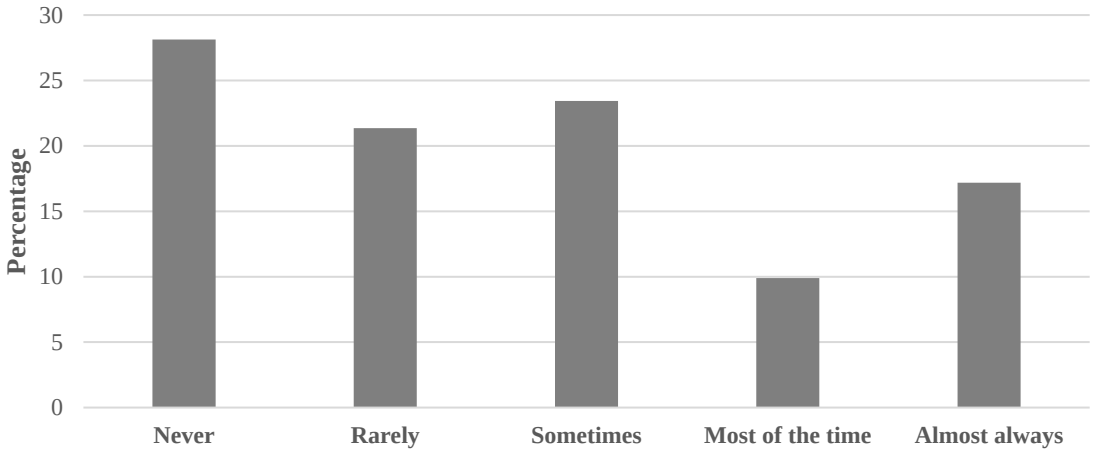


Figure 4. Self-reported app usage frequency while cycling

TABLE 4 Descriptive statistics of independent variables that have statistically significantly correlation with self-reported app usage frequency while cycling (*N*=192)

	Percentage
App perception and usage	
App familiarity	
"Somewhat familiar", "not very familiar" or "not familiar at all"	10.9
"Extremely familiar" or "very familiar"	89.1
Risk perception of using the app while cycling	
"Somewhat risky", "neutral", "somewhat not risky", or "definitely not risky"	70.2
"Definitely risky"	20.8
Sociodemographic characteristics	
Gender	
Male	62.5
Female	37.5
Living area	
Urban	32.3
Suburban or rural	67.7

4.5 Perceived health benefits

To understand factors that affect users' perceived physical health benefits and the amount of social interaction changes because of using Pokémon GO, questions "do you agree that playing Pokémon GO can increase your physical health" and "do you agree that using Pokémon GO can increase your social interactions" were asked, respectively. Table 5 presents descriptive statistics of these two variables and possible independent variables.

TABLE 5 Descriptive statistics of health-related dependent variables and independent variables that are statistically significantly correlated with them (*N*=566)

	Percentage
Dependent variables	
Do you think using Pokémon GO can make you healthier physically	
Definitely no	3.4
Somewhat no	12.0
Neutral	25.3
Somewhat yes	34.8
Definitely yes	24.5
Do you think using Pokémon GO can increase your social interactions	
Definitely no	13.6
Somewhat no	19.8
Neutral	30.7
Somewhat yes	28.6
Definitely yes	7.3
Independent variables	
How frequently do you walk around just to use Pokémon GO in a week on average	
"0-1", "2-3", or "4-5"	83.6
"6-7" or "more than 7"	16.4
How many hours do you exercise in a week on average	
Under six hours a week	63.3
Seven hours or more a week	36.7
How often do you use Pokémon GO with friends and/or family members	
"Sometime", "rarely" or "never"	69.8
"Almost always" or "most of the time"	30.2
How often do you discussion Pokémon GO-related topics with friends and/or family members when not using Pokémon GO	
"Sometime", "rarely" or "never"	76.7
"Almost always" or "most of the time"	23.3
How often do you carpool with other people to use Pokémon GO	
"Rarely" or "never"	76.9
"Almost always", "most of the time", or "sometimes"	23.1
How often do you use Pokémon GO with strangers	
"Rarely" or "never"	84.6
"Almost always", "most of the time" or "sometimes"	15.4

4.6 Changes in daily activity level

Among 1166 participants, 496 participants with an activity tracker (240 users and 256 non-users) were included to study the impacts of Pokémon GO on users' daily steps. Non-users reported an average of 7825 daily walk/run steps (standard deviation 5096), while users reported an average of 6788 daily walk/run steps (standard deviation 3419) for the week prior to they started date for using Pokémon GO (hereafter referred to as "before using Pokémon GO") and 9634 daily walk/run steps (standard deviation 3961) for the week prior to the time of survey (hereafter referred to as "after using Pokémon GO") representing an over 40% increase on average.

Figure 5 illustrates daily walk/run steps change among users before and after using Pokémon GO. Over 70% of users reported increase in number of daily steps on average after using Pokémon GO, but six participants (2.8%) reported the opposite. These six participants were given the options to share the reasons of their reduced physical activities. A commonly cited reason is the proximity of PokéStops to their home

or work location which incentive them to use the app at home or work during free time and reduced their desire to do other outdoor activities.

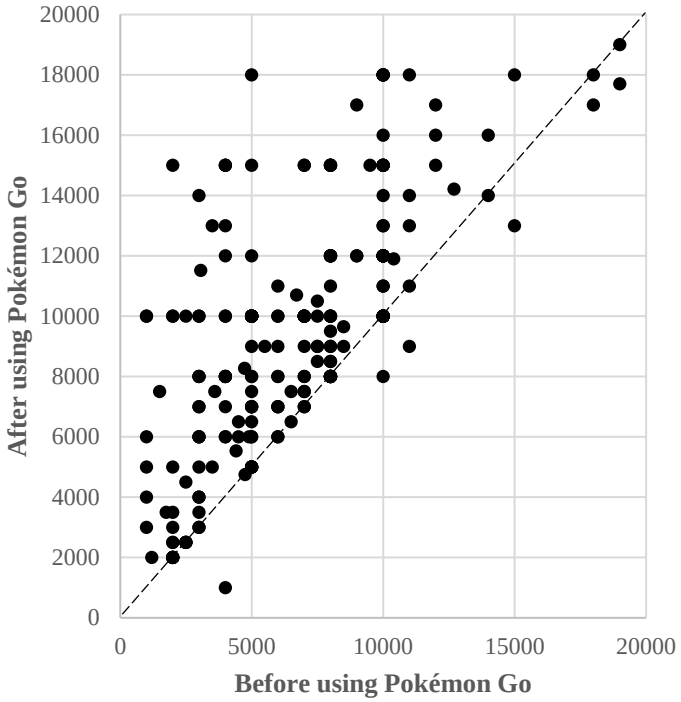


Figure 5. Self-reported steps/day before and after using Pokémon GO

5. Results

5.1 Model estimation for safety perceptions

For safety perceptions related to using the app while driving and cycling, initially, (i) four independent ordered probit models were estimated using all data with all variables at a 95% confidence level. (ii) Next, eight independent ordered probit models were estimated by separating user and non-user data and two combined likelihood ratio tests discussed in section 3.3 were conducted. The test results show that it was better to separate users and non-users in model estimation. (iii) After that, four bivariate ordered probit models were estimated with two models for users and non-users, respectively. The bivariate ordered probit models showed strong correlation in these outcomes. Furthermore, capturing these correlations can lead to more efficient parameter estimates with reduced standard errors and improvement in goodness-of-fit. (iv) Finally, four random parameters bivariate ordered probit models were estimated which can address both unobserved heterogeneity and cross-equation error correlation. The final models show greater prediction accuracy compared to other models.

Normal, uniform, triangular, Weibull, and lognormal distributions for random parameters were explored. The normal distribution was found to provide the best statistical fit, which is consistent with several previous studies (Anastasopoulos, 2009; Guo et al., 2018; Guo et al., 2021c). All random parameters were found to be normally distributed. As all independent variables are indicators variables, their marginal effects illustrate the estimated probability changes for each ordered outcome when it changes from zero to one, while other variables are set to be equal to their estimated means (Washington et al., 2010). The final model estimation results are shown in Tables 6-9. The correlation parameters suggest that the unobserved factors tend to jointly increase (or decrease)

In Tables 6 and 7, numbers 1 to 4 for perceived risk of using the app while driving represent using the app while driving is "definitely not risky or somewhat not risky", "neutral", "somewhat risky", and "definitely risk", respectively. For opinion of using the app while driving, numbers 1 to 4 represent using the app while driving should "definitely not be prohibited or somewhat not be prohibited", "neutral", "somewhat be prohibited", and "definitely be prohibited", respectively.

In Tables 8 and 9, numbers 1 to 5 for perceived risk of using the app while cycling represent using the app while cycling is "definitely not risky", "somewhat not risky", "neutral", "somewhat risky", and "definitely risk", respectively. For opinion of using the app while cycling, numbers 1 to 5 represent using the app while cycling should "definitely should not be prohibited", "somewhat should not be prohibited", "neutral", "somewhat should be prohibited", and "definitely should be prohibited", respectively.

As shown in Tables 6-9, male and female participants have very different safety perspectives towards using Pokémon GO while driving and cycling. In terms of the perceived risk, male users are less likely to consider using Pokémon GO while driving is "definitely risky" and most of the male users are less likely to consider using Pokémon GO while cycling is "somewhat risky" or "definitely risky" compared to their female counterparts. As "male indicator" has random parameters in Table 8, it suggests that some male users (about 12%) are more likely to consider using Pokémon GO while cycling is "somewhat risky" or "definitely risky" compared to female users. In terms of their opinions related to Pokémon GO, male users are more likely to using Pokémon GO while cycling should "definitely *not* be prohibited" or "somewhat *not* be prohibited", while male non-users are less likely to consider using Pokémon GO while driving should "definitely be prohibited" and less likely to consider using Pokémon GO while cycling should "definitely be prohibited" or "somewhat be prohibited". As "male indicator" has random parameters in Table 6, it suggests that some male users (about 30%) are more likely to consider using Pokémon GO while driving is "somewhat risky" or "definitely risky" compared to female users.

Participants in different age groups also have very different safety perspectives towards using Pokémon GO while driving and cycling, particularly between post-millennials and older generations. For users, post-millennials are less likely to consider using Pokémon GO while driving is "definitely risky" and are more likely to consider using Pokémon GO while cycling should "definitely *not* be prohibited" or "somewhat *not* be prohibited". "Post-millennial" indicator has a random parameter in Table 8. It means although most post-millennial users (about 80%) prefer definitely or somewhat *not* to prohibit using Pokémon GO while cycling, some of them are more likely to consider using Pokémon GO while cycling should "definitely be prohibited" or "somewhat be prohibited" compared to older generations. For non-users, most post-millennial non-users are less likely to consider that using Pokémon GO while driving is "definitely risky" compared to their older counterparts, while a small portion of them (around 20%) considered the opposite (random parameters). Furthermore, most post-millennial non-users are more likely to against the idea that using Pokémon GO while cycling is "definitely risky" and it should "definitely be prohibited" compared to older generations.

Participants' residential location area type is an important factor affecting their safety perspectives. Users living in urban areas are more likely to consider using Pokémon GO while driving should "definitely be prohibited" or "somewhat be prohibited", and using Pokémon GO while cycling is "somewhat risky" or "definitely risky", while are less likely to consider should "definitely *not* be prohibited" or "somewhat *not* be prohibited" compared to users who live in suburban or rural areas. For non-users, those who live in rural areas are more likely to consider sing Pokémon GO while driving should "definitely *not* be prohibited", and those who live in urban area are more likely to consider using Pokémon GO while cycling is "somewhat risky" or "definitely risky" and should "definitely be prohibited" or "somewhat be prohibited" compared to their respective counterparts.

TABLE 6 Perceived risk of using the app while driving and the opinion of prohibiting it while driving among users (*N*=566)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects			
		Above zero	Below zero	1	2	3	4
Perceived risk of using the app while driving							
Constant	1.57	—	—				
Male indicator (1, if participant is male; 0, otherwise)	-0.25*	—	—	0.01	0.02	0.06	-0.09
Post-millennials indicator (1, if participant is a post-millennial; 0, otherwise)	-0.32*	—	—	0.01	0.02	0.07	-0.10
Driver indicator (1, if participant is a driver; 0, otherwise)	-0.22*	—	—	0.01	0.02	0.05	-0.08
Threshold 1	0.48						
Threshold 2	1.47						
Opinion of prohibiting it while driving							
Constant	1.53*	—	—				
Male indicator (1, if participant is a female; 0, otherwise)	-0.10 (0.19*)	29.9	70.1	0.02	0.01	0.01	-0.04
Driver indicator (1, if participant is a driver; 0, otherwise)	-0.42*	—	—	0.07	0.05	0.04	-0.17
Urban indicator (1, if participant lives in urban area; 0, otherwise)	0.18*	—	—	-0.03	-0.02	-0.01	0.07
Threshold 1	0.56						
Threshold 2	1.28						
Correlation parameter	0.26*						
Final log-likelihood	-697.59						
ρ^2	0.24						

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

TABLE 7 Perceived risk of using the app while driving and the opinion of prohibiting it while driving among non-users (*N*=600)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects			
		Above zero	Below zero	1	2	3	4
Perceived risk of using the app while driving							
Constant	1.26	—	—				
Single indicator (1, if participant is single; 0, otherwise)	-0.23*	—	—	0.01	0.01	0.05	-0.07
Post-millennials indicator (1, if participant was born after 1996; 0, otherwise)	-0.14 (0.17*)	20.5	79.5	0.01	0.01	0.03	-0.04
Threshold 1	0.45						
Threshold 2	1.40						
Opinion of prohibiting it while driving							
Constant	1.95	—	—				
Male indicator (1, if participant is female; 0, otherwise)	-0.32*	—	—	0.03	0.03	0.05	-0.11
Rural indicator (1, if participant lives in urban area; 0, otherwise)	-0.21*	—	—	0.02	0.02	0.03	-0.08
Married indicator (1, if participant was married; 0, otherwise)	0.08*	—	—	-0.01	-0.01	-0.01	0.03
Threshold 1							
Threshold 2							
Correlation parameter	0.21*						
Final log-likelihood	-565.73						
ρ^2	0.29						

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.
* Denotes the parameter is significant at 0.05 level.

TABLE 8 Perceived risk of using the app while cycling and the opinion of prohibiting it while cycling among users (*N*=566)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Perceived risk of using the app while cycling								
Constant	1.88*	—	—					
Biker indicator (1, if participant is a biker; 0, otherwise)	-0.36*	—	—	0.03	0.07	0.04	-0.02	-0.12
Male indicator (1, if participant is male; 0, otherwise)	-0.13 (0.11*)	11.9	88.1	0.01	0.02	0.01	-0.05	-0.04
Urban indicator (1, if participant lives in urban area; 0, otherwise)	0.25*	—	—	-0.02	-0.04	-0.03	0.01	0.09
Threshold 1	0.89							
Threshold 2	1.44							
Threshold 3	2.37							
Opinion of prohibiting it while cycling								
Constant	0.89*	—	—					
Biker indicator (1, if participant is a biker; 0, otherwise)	-0.47*	—	—	0.15	0.03	-0.02	-0.07	-0.10
Male indicator (1, if participant is a male; 0, otherwise)	-0.16*	—	—	0.05	0.01	-0.01	-0.02	-0.04
Post-millennials indicator (1, if participant was born after 1996; 0, otherwise)	-0.12* (0.15*)	21.2	78.8	0.04	0.01	-0.01	-0.02	-0.03
Urban indicator (1, if participant lives in urban area; 0, otherwise)	0.27*	—	—	-0.08	-0.02	0.01	0.04	0.07
Threshold 1	0.62							
Threshold 2	1.16							
Threshold 3	1.79							
Correlation parameter	0.15							
Final log-likelihood	-789.19							
ρ^2	0.23							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

TABLE 9 Perceived risk of using the app while cycling and the opinion of prohibiting it while cycling among non-users (*N*=600)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Perceived risk of using the app while cycling								
Constant	2.42	—	—					
Post-millennials indicator (1, if participant was born after 1996; 0, otherwise)	-0.33*	—	—	0.01	0.02	0.03	0.07	-0.13
Male indicator (1, if participant is a male; 0, otherwise)	-0.25*	—	—	0.01	0.02	0.02	0.05	-0.10
Married indicator (1, if participant was married; 0, otherwise)	0.09 (0.20*)	67.4	32.6	-0.01	-0.01	-0.01	-0.02	0.04
Threshold 1	0.67							
Threshold 2	1.12							
Threshold 3	2.27							
Opinion of prohibiting it while cycling								
Constant	1.87	—	—					
Post-millennials indicator (1, if participant was born after 1996; 0, otherwise)	-0.28*	—	—	0.03	0.05	0.03	-0.01	-0.10
Male indicator (1, if participant is a male; 0, otherwise)	-0.21*	—	—	0.02	0.04	0.02	-0.01	-0.08
Urban indicator (1, if participant lives in urban area; 0, otherwise)	0.18*	—	—	-0.02	-0.03	-0.02	0.01	0.07
Threshold 1	0.87							
Threshold 2	1.47							
Threshold 3	2.18							
Correlation parameter	0.14							
Final log-likelihood	-874.62							
ρ^2	0.27							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

In terms of participants' marital status, non-users who are single are less likely to consider using Pokémon GO while driving is "definitely risky", while married non-users are more likely to consider that using Pokémon GO while driving should "definitely be prohibited" and most of them (around 67%) are more likely to consider that using Pokémon GO while cycling is "definitely risky" compared to their respective counterparts. At the same time, over 30% of married non-users are less likely to consider that using Pokémon GO while cycling is "definitely risky" compared to single or divorced/separated ones.

Whether a participant drive (bike) only affect their safety perception towards using the app while driving (cycling) among users. Users who drive are less likely to consider using Pokémon GO while driving is "definitely risky" and using Pokémon GO while driving should "definitely be prohibited". Users who bike are more likely to consider that using Pokémon GO while cycling is "definitely not risky", "definitely not risky", or "neutral" and should "definitely *not* be prohibited" or "somewhat *not* be prohibited".

5.2 Model estimation for driving-related behavior

To understand factors that affect self-reported increase in app-related distracted driving (i.e., app usage frequency while driving), self-reported increase in app-induced driving and potentially unsafe driving behavior (i.e., intentionally driving slower than the traffic) for using the app, random parameters ordered probit models were estimated for user-drivers (N=466). These behaviors are related to user-drivers' risk exposure. Independent variables that are statistically significantly correlated with either of the three dependent variables (p<0.05) are presented in Table 3. The model estimation results are presented in Tables 10-12. All random parameters were found to be normally distributed.

As shown in Tables 10-12, user-drivers who consider that using the app while driving is "definitely" risky are less likely to report frequent app-related distracted driving and frequent intentionally drive slower, and most of them are less likely to agree that their app-induced driving increases. However, a small portion of such user-drivers were more likely to report app-induced driving increase (about 7%) despite acknowledging its risk as this indicator variable has random parameters (Table 11).

User-drivers who have high app familiarity ("very familiar" or "extremely familiar" with the app) are more likely to report higher frequency of app-related distracted driving and engaging unsafe driving behavior, and most of them are more likely to report increased app-induced driving. Some of these user-drivers (36%) are less likely to report increased app-induced driving despite of their high app familiarity.

The model estimation results show that user-drivers whose passenger(s) "almost always" or "most of the time" use the app while driving are also more likely to report high frequency of app-related distracted driving, increase in app-induced driving, and high frequency of engaging unsafe driving behavior.

User-drivers who have high likelihood of continuing app usage in near future ("extremely likely" or "likely" to use the app for the next three month), and most user-drivers who spend more money than average user (spends "more than $10" with 3-month after using the app as most of the users spend less than $10 at the time of the survey (YouGov, 2016)) are more likely to report high frequency of app-related distracted driving, increase in app-induced driving, and high frequency of engaging in potentially unsafe driving behavior.

Among variables related to users' sociodemographic characteristics, the results show that user-drivers who are graduate or undergraduate students are less likely to report high app usage frequency while driving or increased app-induced driving.

User-drivers who drive relatively less (less than 9,000 miles per year) are also more likely to report high frequency of app-related distracted driving, increase in app-induced driving, and higher frequency of engaging potentially unsafe driving behavior.

TABLE 10 Random parameters ordered probit models for app usage frequency while driving (1 being "never" and 5 being "almost always") (*N*=446)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	0.58	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.44*	—	—	-0.13	-0.05	0.09	0.05	0.04
Likely continue user indicator (1, if user is "extremely likely" or "likely" to use it for the next three months; 0, otherwise)	0.37*	—	—	-0.11	-0.03	0.08	0.04	0.03
App spending indicator (1, if user spends "more than $10" on the app within 3-month after using the app; 0, otherwise)	0.42*(0.46*)	81.9	18.1	-0.11	-0.06	0.08	0.05	0.04
Passenger indicator (1, if user's passenger(s) "almost always" or "most of the time" use the app while driving; 0, otherwise)	0.80*	—	—	-0.26	-0.03	0.18	0.07	0.05
Risk perception of using the app while driving								
Driving-related app usage risk indicator (1, if user considers using the app while driving is "definitely risky"; 0, otherwise)	-1.01*	—	—	0.23	0.16	-0.14	-0.11	-0.13
Sociodemographic characteristics								
Student indicator (1, if user-driver is an undergraduate or graduate student; 0, otherwise)	-0.31*	—	—	0.09	0.03	-0.07	-0.03	-0.02
Short driving distance indicator (1, if user-driver drives less than 9,000 miles annually; 0, otherwise)	0.36*	—	—	-0.09	-0.03	0.07	0.03	0.02
Threshold 1	1.01							
Threshold 2	2.08							
Threshold 3	2.62							
ρ^2	0.27							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

TABLE 11 Random parameters ordered probit models for self-reported increase in app-induced driving (1 being "definitely no", and 5 being "definitely yes") (N=446)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	-0.24	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.27* (0.71*)	64.8	35.2	-0.10	0.01	0.02	0.06	0.01
Likely continue user indicator (1, if user is "extremely likely" or "likely" to use it for the next three months; 0, otherwise)	0.51*	—	—	-0.20	0.04	0.03	0.11	0.02
App spending indicator (1, if user spends "more than $10" on the app within 3-month after using the app; 0, otherwise)	0.40* (0.86*)	67.8	32.2	-0.15	0.01	0.02	0.10	0.03
Passenger indicator (1, if user's passenger(s) "almost always" or "most of the time" use the app while driving; 0, otherwise)	0.63*	—	—	-0.25	0.05	0.04	0.13	0.03
Risk perception of using the app while driving								
Driving-related app usage risk indicator (1, if user considers using the app while driving is "definitely risky"; 0, otherwise)	-0.50* (0.13*)	6.5	93.5	0.19	-0.01	-0.03	-0.13	-0.04
Sociodemographic characteristics								
Student indicator (1, if user-driver is an undergraduate or graduate student; 0, otherwise)	-0.27*	—	—	0.11	-0.02	-0.02	-0.06	-0.01
Short driving distance indicator (1, if user drives less than 9,000 miles annually; 0, otherwise)	0.45*	—	—	-0.17	-0.01	0.02	0.12	0.04
Threshold 1	0.71							
Threshold 2	1.02							
Threshold 3	2.16							
ρ^2	0.29							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

TABLE 12 Random parameters ordered probit models for self-reported frequency of potentially unsafe driving behavior (1 being "never", and 5 being "almost always") (N=446)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	0.07	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.43*	—	—	-0.15	-0.01	0.11	0.03	0.02
Likely continue user indicator (1, if user is "extremely likely" or "likely" to use it for the next three months; 0, otherwise)	0.33*	—	—	-0.12	-0.01	0.09	0.02	0.01
App spending indicator (1, if user spends "more than $10" on the app within 3-month after using the app; 0, otherwise)	0.48* (0.48*)	84.1	15.9	-0.16	-0.03	0.12	0.04	0.02
Passenger indicator (1, if user's passenger(s) "almost always" or "most of the time" use the app while driving; 0, otherwise)	0.75*	—	—	-0.28	0.02	0.19	0.05	0.02
Risk perception of using the app while driving								
Driving-related app usage risk indicator (1, if user considers using the app while driving is "definitely risky"; 0, otherwise)	-0.65*	—	—	0.21	0.05	-0.16	-0.06	-0.03
Sociodemographic characteristics								
Short driving distance indicator (1, if user drives less than 9,000 miles annually; 0, otherwise)	0.45*	—	—	-0.14	-0.04	0.11	0.04	0.02
Threshold 1	0.74							
Threshold 2	1.02							
Threshold 3	2.23							
ρ^2	0.27							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

5.3 Self-reported app usage frequency while cycling

To understand factors that affect self-reported increase in distracted cycling (i.e., app usage frequency while cycling), random parameters ordered probit models were estimated for user-cyclists (N=192). Independent variables that have statistically significantly correlation with app usage frequency while cycling (p<0.05). The model estimation results are presented in Table 13.

The model estimation results show that user-cyclists who consider using the app while cycling is less risky ("definitely not risky" or "somewhat not risky") are more likely to report high frequency of app-related distracted cycling. This is similar to user-drivers reporting higher frequency of app usage while driving if such users perceive it as low risk (Table 10).

User-cyclists who have high app familiarity, like user-drivers with the same characteristics, are also more likely to report higher frequency of app-related distracted cycling.

Both male and urban indicators are random parameters which capture unobserved heterogeneity among male user-cyclists and user-cyclists who live in urban area in terms of their frequency of app-related distracted cycling. Majority of male cyclists (about 90%) are likely to report higher frequency of app-related distracted cycling compared to female cyclists.

5.4 Perceived physical health and the amount of social interactions changes

To understand factors that affect users' perceived physical health benefits (i.e., "do you agree that playing Pokémon GO can increase your physical health") and the amount of social interaction changes because of using Pokémon GO (i.e., "do you agree that using Pokémon GO can increase your social interactions"), random parameters ordered probit models were estimated. Tables 14 and 15 present the model estimation results related to perceived physical health and the amount of social interactions changes

In terms of perceived physical health changes because of using Pokémon GO, the model estimation results show that users who are more familiar or engaged with the app are more likely to perceive that using the app can promote improvement in their physical health (Table 14).

Users who frequently walk around just to use the app (more than six times a week on average) are more likely to agree that using the app can improve their physical health likely due to their increased walking frequency which they consider as physical health improvement. Heterogeneities exist among physically active users (exercised at least six hours a week) as majority of them (78.8%) considered using the app can improve physical health, while the rest did not.

Model estimation results show that users who frequently use Pokémon GO with family members, friends or strangers, or frequently carpool with other users to collaborate in the app are more likely to consider it can promote their increased social interactions (Table 15). The results also show that users who frequently discuss Pokémon GO with family members and friends when they are not using the app are more likely to consider it increased their social interactions.

Slightly over half of users who are single considered that using the app can increase their social interactions while the rest did not. This is possible due to the heterogeneity existed among these users in terms of how they used the app. Additional studies are needed to address how social component in LAR apps affect users who are single.

TABLE 13 Random parameters ordered probit models for app usage frequency while cycling (1 being "never" and 5 being "almost always") (N=192)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	-0.71	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.71*	—	—	-0.27	-0.01	0.11	0.08	0.08
Risk perception of using the app while driving								
Cycling-related app usage not risky indicator (1, if user considers using the app while cycling is "definitely not risky" or "somewhat not risky"; 0, otherwise)	1.04*	—	—	-0.34	-0.05	0.08	0.12	0.20
Sociodemographic characteristics								
Male indicator (1, if user is male; 0, otherwise)	0.56* (0.43*)	90.3	9.7	-0.21	-0.01	0.09	0.06	0.07
Urban indicator (1, if user lives in urban area; 0, otherwise)	-0.12* (0.69*)	43.1	56.9	0.04	0.01	-0.02	-0.01	-0.02
Threshold 1	0.36							
Threshold 2	1.30							
Threshold 3	1.82							
ρ^2	0.28							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

TABLE 14 Random parameters ordered probit models for physical health improvement (1 being "definitely no" and 5 being "definitely yes") (*N*=566)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	1.52	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.29*	—	—	-0.02	-0.05	-0.05	0.03	0.08
App spending indicator (1, if user spends "more than $10" on the app within 3-month after using the app; 0, otherwise)	0.33*	—	—	-0.02	-0.05	-0.06	0.02	0.10
Walk around and play indicator (1, if user walks around just to use Pokémon GO at least 6 times a week on average; 0, otherwise)	0.57*	—	—	-0.02	-0.07	-0.10	0.01	0.19
Sociodemographic characteristics								
Active indicator (1, if user exercise at least seven hours per week; 0, otherwise)	0.24* (0.30*)	78.8	21.2	-0.01	-0.04	-0.04	0.02	0.08
Threshold 1	0.85							
Threshold 2	1.69							
Threshold 3	2.69							
ρ^2	0.26							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

TABLE 15 Random parameters ordered probit models for social interaction increase (1 being "definitely no" and 5 being "definitely yes") (*N*=566)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	0.82	—	—					
App perception and usage								
High frequency of using the app with friends and family (1, if user "almost always" or "most of the time" using Pokémon GO with friends/family); 0 otherwise)	0.21*	—	—	-0.03	-0.04	-0.01	0.06	0.02
High frequency of using the app with strangers (1, if user "almost always", "most of the time" or "sometime" using Pokémon GO with strangers); 0 otherwise)	1.02*	—	—	-0.11	-0.16	-0.12	0.24	0.15
High frequency of discussing the app with friends and family (1, if user "almost always", "most of the time" or "sometimes" using Pokémon GO with friends/family); 0 otherwise)	0.41*	—	—	-0.06	-0.07	-0.02	0.12	0.04
Carpool indicator (1, if user "almost always", "most of the time" or "sometimes" carpool to collaborate in Pokémon GO; 0, otherwise)	0.68*	—	—	-0.09	-0.11	-0.05	0.18	0.07
Sociodemographic characteristics								
Single indicator (1, if user is single; 0, otherwise)	0.01 (0.18*)	52.2	47.8	-0.01	-0.01	-0.01	0.01	0.01
Threshold 1	0.75							
Threshold 2	1.69							
Threshold 3	3.10							
ρ^2	0.31							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

6. Safety and Health Implications

6.1 Safety implications: safety perceptions

There are four possible safety implications related to people's safety perceptions of LAR gaming app usage. First, difference between safety perceptions of users and non-users (Table 2) may be attributed to two underlying factors: (i) users' experiences with the app may provide a more informed perception/opinion, or (ii) users may be overconfidence in their ability to interact the app while driving and cycling that can lead to bias in their perception/opinion. Such differences can also be partly explained by the cognitive dissonance theory (Harmon-Jones and Mills, 1999) that people tend to seek consistency between their perception and behavior. One of them must change when there is an inconsistency to eliminate the dissonance, and in most cases, perception will change to accommodate the behavior. In this case, if a user uses the app while driving or cycling, he or she may then try to justify their action by stating or considering such behavior as less risky. Similar observations were also found in Nelson et al. (2009) and Atchley et al. (2011) in which many drivers would engage in texting and tried to justify their texting behavior by suggesting such behavior is less risky.

Second, males are more likely to play down the risk of using the app while driving and cycling and are less likely to support prohibiting app usage while driving and cycling compared to females. This is consistent with previous findings that females are more likely to support legislations against reading and sending texts/emails while driving or cycling compared to males (Struckman-Johnson et al., 2015; Rudisill and Zhu, 2017; Pope et al., 2019) due to personality factors (Costa et al., 2001) or gender-based socialization (Schwebel and Barton, 2005).

Third, younger generations are more likely to perceive app-related cycling risk is lower compared to relatively older generations, and less likely to support prohibiting app usage while cycling. Such results are consistent with previous studies (Ichikawa and Nakahara, 2008; Chataway et al., 2014; Useche et al., 2018) that younger generations perceived using cellphone while cycling as less risky. This may be partially attributed to their underestimation of the risk of serious consequences while driving and cycling, overestimation of their driving and cycling skills, and limited ability to recognize driving-related and cycling-related safety hazards.

Fourth, people's safety perceptions of the app are restricted by the area they live in ("urban indicator" and "rural indicator") and their point of view ("driver indicator" and "biker indicator"). People who believe that the driving/cycling environment is complex (living in urban environment) are more likely to see the risk of distracted driving and cycling caused by the app and more incline to prohibit the usage of the app. At the same time, user-drivers and user-bikers who may benefit from using the app while driving or cycling may consider prohibiting the app usage while driving and cycling as too extreme despite that many of them understand the risk of app-related distracted driving and cycling.

6.2 Safety implications: risky driving behavior

Six possible safety implications can be identified related to risky driving behavior. First, information strategies that focus on highlighting the risk of distracted driving has its limited related to app usage while driving ("driving-related app usage risk indicator" in Table 11). The model estimation results show that despite methods focusing on improving user-driver risk awareness by providing warning messages such as "do not play Pokémon GO while driving" in the app can reduce the likelihood of increased distracted driving and potentially dangerous driving behavior, it may not prevent the app-induced driving which is unique to LAR apps. This suggests that certain app mechanisms and other types of strategies should be in place alone with the existing mechanisms such as warning messages to further discourage app-induced driving.

Second, some users may always try to figure out the app mechanisms (familiarity) and maximize their benefits from the app ("familiar indicator") by performing risky driving behavior. Their high familiarity with the app may suggest that they have better knowledge of app mechanisms (e.g., know where they can interact with virtual objects and at what speed they should drive to enable most app features) and

try to leverage their knowledge to gain more in-app benefits. At the same time, some users may choose to ride a bike or walking more to these virtual object locations instead of driving as they may perceive riding a bike or walking can provide additional in-app benefits.

Third, social influence plays a critical role in drivers' risky driving behavior ("passenger indicator"). For example, these user-drivers may observe passengers using the app to collect in-app benefits while they are driving and perceive that using the app in the car is a good way to collect in-app benefits or pass time. Such results are similar to others studies which show subjective norms (e.g., others think I should talk on the mobile phone or texting while driving), injunctive norm (e.g., talking on the mobile phone or texting while driving is acceptable behavior), observing peers or parents talking on the mobile phone or texting while driving, and other types of social influence play an important role in influencing people's intention to making phone calls or texting while driving (Riquelme et al., 2010; Carter et al., 2014). Considering that passengers and drivers may also engage in app-related conversations while both of them are using the app, this can bring another form of distraction which can further increase the risk of user-drivers and their passengers.

Fourth, app retention rate ("likely continue user indicator") and in-app spending () can be considered as metrics to identify likely retained users and active users, respectively. 90-day user retention rate (percentage of users returning to the app at least once within 90 days) is often used to measure the success of an app by comparing it to market average in practice (Birnbaum et al., 2015). Activities related to in-app purchases (e.g., total money spent and number of transactions compared to user average) have been used as one of many indicators to identify active users in prior studies (Hadiji et al., 2014; Runge et al., 2014; Lee and Shin, 2016). Such model estimation results suggest that likely retained user-drivers and most active user-drivers are more likely to actively seeking ways to enhance their app usage experience and collect more in-app benefits as they may feel more invested or engaged in the app compared to those who spent less. At the same time, such high app engagement may have safety implications such as high frequency of app-related distracted driving, increase in app-induced driving, and high frequency of engaging in potentially unsafe driving behavior. However, some of user-drivers who spend more money than their peers are more likely to report lower frequency of app-related distracted driving (19%), no increase in app-induced driving (32%), and lower frequency of engaging potentially unsafe driving behavior (16%). These findings may be attributed to heterogeneities in user-driver motivations of in-app spending. It is possible that some of these user-drivers may not be active users but spend money to accelerate app progress or bypass app mechanisms for improving their app experience rather than using the app more frequency or spending more efforts. It is important to note that in-app purchase is only one of many indictors (e.g., times spent and frequency of logging in) used to identify active users.

Fifth, the existing imbalanced distribution of virtual object density may be beneficial to some users as many universities often have clusters of virtual objects such as Pokémon and PokéStops ("student indicator"). Such users do not need to drive long distance to interact with virtual objects as most of these objects can be easily access in their everyday life.

Sixth, the app-induced driving for user-drivers who drives less than 9,000 miles annually ("short driving distance indicator") is higher than their counterparts. It is likely that these user-drivers are not exhausted from their possibly long-distance daily travel and have more time and/or energy to drive after work/school.

6.3 Safety implications: distracted cycling

Three possible safety implications can be identified related to distracted cycling. First, information strategies that focus on highlighting the risk of distracted cycling play an important role in reducing distracted cycling ("cycling-related app usage not risky indicator" in Table 10).

Second, gender differences are observed in terms of distracted cycling. This is similar to previous studies related to cellphone usage while cycling (Chataway et al., 2014; Ethan et al., 2016; Truong et al., 2016). Truong et al. (2016) suggested a possible explanation for such gender differences is that female cyclists who often keep their cellphones in a handbag cannot easily access their cellphones while cycling compared to male cyclists who often keep their cellphones in the pocket.

Third, over half of cyclists (around 60%) who live in urban area are less likely to report higher frequency of app-related distracted cycling. This may be attributed to that most users-cyclists consider using the app while cycling in a more complex urban cycling environment (e.g., higher traffic on shared roads) which make them use the app while cycling less frequently. However, around 40% of such user-cyclists are more likely to use the app while cycling. This is possibly due to relatively high virtual objects density in urban areas that encourage user-cyclists to use the app more frequently while cycling despite the potential complex cycling environment.

6.4 Health implications: perceived physical health and mental health

Familiar and engaged users (i.e., spend more in-app purchase than average users) are more likely to report more favorable perception of the app in terms of app's benefits to physical health. Some users who are ready physically active may consider Pokémon GO-related physical activities as light exercise (Nigg et al., 2017), which may not contribute much to their overall physical health as they have already exercised a lot (averaging more than one hour per day).

Social component in Pokémon GO for encouraging and rewarding collaborations can offer social interactions opportunities for its users to connect with family members and friends, and meet new people. As shown in some of the stories shared by participants in the open-ended question, Pokémon GO has become a convenient conversion starter with family members and friends regardless of if they are users or not, and some participants said that the app help them to spend more time with their children and they became more open to share non-Pokémon GO stories with each other giving them a good bonding experience.

6.5 Health implications: increased physical activity level

Considering that nearly 75% of users are very likely to use Pokémon GO for the next three months, Pokémon GO could potentially have a measurable impact on these users' increase in life expectancy due to well-established health benefits of increased physical activity on reducing heart disease, stroke, Type 2 diabetes, depression, and some cancers, etc. (e.g., Sparling et al., 2000) if these users can maintain the same activity level.

Based on several government agency recommendations and some studies (Tudor-Locke and Bassett, 2004; CDC, 2014; ODPHP, 2016), 8,000 steps per day is considered as the activity guideline for staying healthy, but only 21% of the U.S. adults meet this guideline (Althoff et al., 2016). About 70% users reached the activity guideline after using Pokémon GO, compared to about 43% of them reached it before using Pokémon GO and 50.0% non-users reached it. It is also important to note that a larger percentage of participants reached physical activity guideline compared to the national average regardless of their Pokémon GO user status. This is likely because participants with an activity tracker are more health conscious and enthusiastic on average (Dennison et al., 2013), and Pokémon GO provides them a channel to have light-exercise while enjoying it at the same time. These factors may also contribute to user perceived overall physical activity increases after using Pokémon GO.

Additional tests were performed to examine whether certain subpopulations among users experienced a larger increase in daily steps compared to other subpopulations. Gender, age, marital status, driver or non-driver, automobile ownership, physical activity level before playing Pokémon GO and involvement in Pokémon GO were the criteria used to specify different subgroups. The main observation identified is that users, who are female (46.4% increase), millennials or younger (44.3% increase), single (44.0% increase), drivers (45.4% increase), have more than two cars (46.9% increase), have higher engagement level (spending at least $10 on in-game purchase) (51.2% increase), or had physical activity level below the activity guideline (75.8% increase), experienced a larger increase in daily steps after using Pokémon GO compared to their counterparts. It is important to note that such subgroup comparison does not suggest the independency among these groups, and additional studies are needed to provide a better understanding in terms of factors contributing to physical activity increase associated with Pokémon GO usage.

7. Discussions and Conclusions

As smartphones and apps are more and more integrated into people's daily lives, many recent efforts have been made to use location-based AR gaming apps for changing travel behavior, gaming, education, tourism, etc. These apps can provide digital content to users by overlaying interactive virtual objects with information on users' real-world locations through smartphones based on their locations. Users are often encouraged to frequently interact with virtual objects for in-app benefits by changing their real-world locations. These unique features differentiate LAR gaming apps from other apps and have the potential to change users' behavior. However, using such apps can have safety implications when users are using the app to locate and interact with virtual objects while driving or cycling as they are physically and cognitively distracted from their primary tasks (driving or cycling). In addition, some users may increase their driving distance to collect more in-app benefits and/or engage in unsafe driving maneuvers such as intentionally driving slower than the traffic to bypass speed-limitation based regulatory app mechanisms. These potential safety hazards are relatively unique to LAR gaming apps and may not exist in many other cellphone/smartphone-related activities such as making phone call and texting which are the primary focuses of most previous studies. Furthermore, gamification and social component that often exist in LAR apps also can potentially have health implications such as improving physical health and increasing social interactions. To provide a better understanding of LAR gaming apps' safety and health implications, this study uses Pokémon GO, a LAR gaming app, as a case study to understand the safety perception and self-report app usage behavior of LAR gaming apps while driving and cycling, including frequency of app-related distracted driving and cycling, self-reported increase in app-induced driving and potentially unsafe driving behavior, perceived physical health and social interactions changes, and factors that attribute to these behavior and perception.

The results show that most people understand the risk of using LAR gaming apps while driving and agree such app usage should be prohibited while driving. However, many users reported increase in app-induced driving despite acknowledging its risk based on model estimation results. It is also important to note that many user-drivers still reported app-related distracted driving and dangerous driving maneuvers despite acknowledging its risk. These results show that improving user risk awareness of using the app while driving can reduce likelihood of app-related distracted driving and dangerous driving maneuvers, but additional app mechanisms are still needed to further reduce increased app-induced driving. Possible app mechanisms can include (i) using the concept of diminishing returns (Thornton and Francia, 2014) by reducing the in-app benefits received as the total number interactions with virtual objects increase within a given period to reduce the attractive of making redundant trips and increasing driving distance by making such trips less rewarding; (ii) utilizing multiple communication systems (e.g., identifying if the smartphone is connected with vehicle's Bluetooth) to detect whether users are driving rather than relying only on moving speed to detect it. This can potentially make actions such as intentionally driving slower than the traffic for interacting with virtual objects less feasible; and (iii) promoting the usage of LAR apps in a relatively safer environment such as using it on a bus or ridesharing services by providing additional in-app incentives for using these modes instead of limiting or prohibiting most of app features if the detected moving speed is over a threshold. These mechanisms can potentially reduce app-related distractions and likelihood of making unsafe maneuvers without compromising the apps' attractiveness. Additional studies are needed to further evaluate the effectiveness of the proposed mechanisms.

Most people considered that using Pokémon GO are less risky while cycling compared to the perceived risk of using it while driving and reported higher frequency of app-related distracted cycling compared to frequency of app-related distracted driving. These results may raise concerns related to potential high exposure to app-related cycling risk. As many recent studies (Byington and Schwebel, 2013; Ethan et al., 2015; Tate et al. 2015) have shown, distracted cycling can lead to reduced attention to traffic, increased injury risk and likelihood of performing risky behavior. To address the potential app-related distracted cycling, efforts can be made to (i) promote safety awareness of using the app while cycling such as pushing in-app safety awareness messages and launch public awareness programs; (ii) provide technology-based and app mechanism-based solutions such as promoting the usage of bicycle electronic device holders (Mwakalonge et al., 2014) or cellphone armbands and offering hand-free options to collect

in-app benefits automatically while cycling; and (iii) introduce legislations to prohibit or limit using hand-held devices while cycling. As many states have prohibit using hand-held devices while driving, the safety awareness related to using hand-held devices while cycling is low and relevant legislations are relatively sparse.

In terms of potential health impacts of using LAR gaming apps, the results illustrate their mechanism for rewarding physical movement and integrated social component for collaboration can potentially motivate users to go outside and exercise or walk more, especially for users who are under the recommended daily physical activity level, and foster interactions with friends, family members, and other users whom they may not have opportunities to interact with.

7.2 Limitations and future research directions

This study is not without its limitations which can be addressed in future research. First, the voluntary nature and the topic of the survey, and its online delivery method can potentially bias our sample towards people who have internet access and who may already have interest in LAR apps or Pokémon GO. Many of these participants belonged to younger generations, students, with relatively high education, or relatively high income. There may be selectivity bias problems because of this. Thus, the study results may not be representative of the general population, particularly for safety perspectives of non-users. Additional studies are needed to capture the safety and health implications of the apps on the general population.

Second, the analysis was conducted using self-reported behavioral data which has its limitations and may lead to biased results (Langenbucher and Merrill, 2011). Possible limitations include memory biases (e.g., transience) and social desirability bias (i.e., reporting experiences that are considered to be socially acceptable or preferred). Future studies have been planned by the authors to install physical and app activity trackers on a group of participants' smartphones to record more accurate app-related activities instead of relying on self-reported data.

Third, the study sights were drawn from one LAR gaming app, Pokémon GO. Future study can potentially include other LAR apps designed for non-gaming purpose (e.g., shopping LAR apps) to provide additional insights on the safety and health implications of LAR apps.

Fourth, Pokémon GO has gone through several mechanism updates to promote more social interactions after we conducted the survey. These efforts may influence people's willingness to carpool and socialize as reported by Guo et al. (2021b). During the initial period of COVID-19 pandemic, people's travel behavior has changes drastically during that period (Guo et al., 2021c) and Pokémon GO has made some further changes to improve its usage during the pandemic. Additional studies are needed to understand the potential safety and health implications of LAR apps during the pandemic.

Fifth, although this study is one of the first to comprehensively address the various aspects of the safety and health implications of LAR gaming apps, some of the questions related to the safety and health aspects of such apps remain to be answered. For example, Pokémon GO users may be subjected to possible assault and robbery risks when meeting strangers or playing alone during nighttime. Some of them may drive to new or unfamiliar locations which may increase the safety risks. As shown in previous studies, people driving in an unfamiliar environment are more likely to involve in accidents compared to driving in a familiar environment (Wilks et al., 1999; Ansari et al., 2000; Wu, 2015). Furthermore, additional studies are needed to understand the implications of distracted walking while using Pokémon GO and similar LAR gaming apps.

Sixth, this study was conducted in the U.S. and additional studies are needed to understand its safety and health implications in other countries, particularly in the developing countries. It is possible that users in some developing countries are more likely to use the app while driving and cycling as these countries may lack regulations or enforcement related to app usage. At the same time, in some countries like China or U.K. with higher traffic camera density, people may be less likely to use such apps.

Seventh, additional models can be considered such as random parameters ordered probit models with heterogeneities in means and variances, correlated random parameters with heterogeneity in means, and multivariate Bayesian hierarchical Gaussian copula models to better capture the unobserved heterogeneities in future data analysis (Li et al., 2021; Wang et al., 2021; Zhang et al., 2021).

Eighth, "definitely not dangerous" and "probably not dangerous" for "perceived risk of using the app while driving" due to their relatedly small percentages. There may be possible aggregation bias leading to the possibility of losing information.

The study findings and insights can aid transportation planners and app designers to design LAR app-related policy and app mechanisms while factoring the potential safety- and health-related implications associated with using such apps. An extension of this study can be to compare user-driver performance (e.g., response time) while they are engaging LAR apps to their performance while doing other phone-related activities in a realistic or simulated driving environment. This can potentially address the limitations of stated preference survey and self-reported behavioral data used in this study. This study can also be extended to other LAR apps to validate the findings of this study. Another research direction can be studying the long-term impacts of LAR apps on users' physical activity level and social interactions by observing a group of LAR app users.

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