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User Acceptance Factors of Usage-Based Insurance

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Abstract. Intelligent Transportation Systems (ITS) are utilized in car insurance policies known as Usage-Based Insurance (UBI), where driving data is collected using a telematics device to determine driving behavior. This enables offering personalized car insurance fees based on driving performance. Current research focuses on advantages, disadvantages, and privacy aspects of UBI, paying less attention to its user acceptance. In this work, we propose a UBI acceptance model based on an adaptation of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and test it with 585 participants by means of structural equation modeling. We find that social influence and hedonic motivation are the most important predictors of the intention to use UBI, and perceived privacy influences it indirectly. Furthermore, we refine the model with new connections, improving model fit.

Keywords. Usage-Based insurance, technology acceptance, telematics insurance

1. Introduction

Intelligent Transportation Systems (ITS) include applications such as automatic tolling, cooperative driving, and traffic control [1], as well as innovations based on vehicle and driver behavior information [2]. One of these innovations is Usage-Based Insurance (UBI), also known as telematics insurance, pay as you drive (PAYD), or pay how you drive (PHYD). Whereas in the traditional car insurance models payments are calculated based on data such as age, gender, driving history, or marriage status [3], insurance payments in UBI are based on driving styles, which in turn are determined based on data such as speed, acceleration, braking, or time and distance driven. These data are collected using a telematics device: a dongle (a plug-and-play device), a black box (a professionally installed device), a smartphone app, or a built-in embedded system. After analyzing driving data, the insurer provides feedback to help drivers to improve their skills. If drivers get a good score during their contract, they get a discount on their next insurance payment. Figure 1 illustrates participants and processes of UBI in a simplified manner.

Previous research on UBI considered various aspects of its adoption and usage. Derikx et al. [4] investigate the role of monetary incentives in UBI adoption using a survey in a hypothetical scenario. Soleymanian et al. [3] analyze costs and benefits of a UBI

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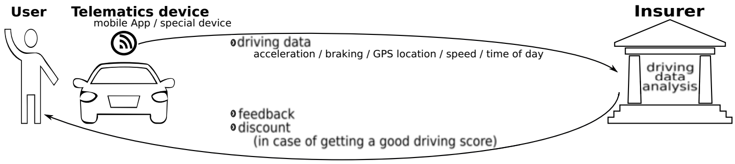

Figure 1. Parties and processes of UBI (simplified).

program based on real-world usage data (but without contact with the users). Quintero et al. [5] conduct a qualitative study on usability and user acceptance of UBI. Although in 2020, the UBI market size exceeded USD 30 billion, and it is expected to grow by over 20% until 2027 [6], UBI acceptance has not been studied in depth from the consumers' perspective. Although Tian et al. [7] and Mayer [8] extended the Technology Acceptance Model (TAM [9]) and Unified Theory of Acceptance and Use of Technology (UTAUT [10]) to UBI, these models are focused on organizations, rather than individuals. In addition, these models miss some important constructs (see Section 2). Therefore, we propose an acceptance model based on UTAUT2 [11], which focuses specifically on consumers. We consider the following research questions: (1) What are possible user acceptance factors of UBI? (2) What is the best fitting acceptance model based on the identified acceptance factors? The contributions of this work are as follows:

a. We develop a theoretical model of user acceptance of UBI and validate it with 585 participants it using structural equation modeling (SEM) and regression analysis
b. We show that *social influence* and *hedonic motivation* are the most important predictors of the intention to use UBI. Also, we identify the importance of *perceived privacy* as a factor that influences *behavioral intention* to use UBI indirectly
c. We find that UBI users are more concerned with the trustworthiness of the insurer, than that of UBI technology itself

2. Related Work and Theoretical Background

TAM, UTAUT and UTAUT2 have been extended to various areas, some of them being similar to the UBI. Thus, Adell [12] researches acceptance of driver support systems, highlighting the importance of *social influence* and *behavioral intention* to use. She finds that *effort expectancy* plays a minor role in influencing intentions to use such systems. In contrast, Madigan et al. [13] find in the context of Automated Road Transport Systems (ARTS) that *effort expectancy*, *performance expectancy* and *social influence* are important predictors of *behavioral intention*. Koul and Eydgahi [14] confirm the relevance of *perceived usefulness* and *perceived ease of use* in the intention to use a driverless car, whereas the influence of driving experience and age is negative. The Car Technology Acceptance Model (CTAM) by Osswald et al. [15] introduces *anxiety* and *perceived safety* as additional constructs. We include *perceived safety*, but not *anxiety* in our models, as it was not statistically significant in UTAUT [10].

Mayer [8] extends UTAUT to UBI, finding *economic incentives* and *effect on driving pleasure* as important factors, whereas *perceived privacy* plays a minor role. Tian et al. [7] found that the role of *perceived enjoyment* and *trust* are relevant to the decision

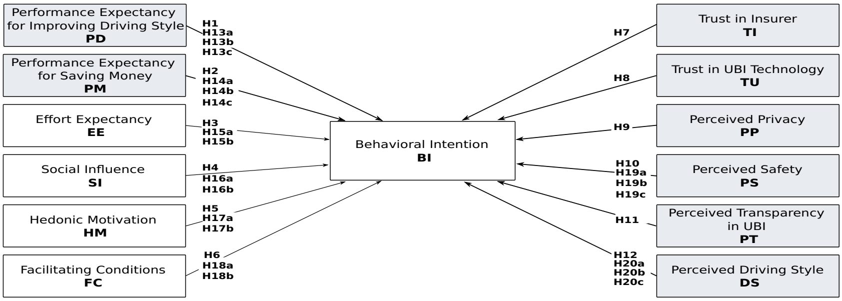

Figure 2. Research model for user acceptance of UBI. Original UTAUT2 constructs are presented in lighter rectangles and lines.

to use telematics insurance. Quintero et al. [5] research usability and acceptance of UBI, identifying negative consequences of using UBI (e.g., provoke dangerous driving, reduce the enjoyment of driving, and privacy concerns), as well as factors which influence the intention to use UBI such as *perceived country driving style* and *individual driving style*.

Adapting the UTAUT2 model. Figure 2 depicts our research model, presenting the original UTAUT2 in lighter rectangles and lines. We removed from UTAUT2 the constructs *price value*, *habit*, and *use behavior*. Venkatesh et al. [11] included the *price value* construct as a tradeoff between the perceived benefits of the system and the monetary costs for using it. In UBI, the monetary costs (e.g., telematics device, installation costs, and internet connection costs for sharing driving data in programs that use an embedded system or a black box) are most often borne by the insurers. The customers only have to pay the costs of the smartphone and the Internet access in UBI programs that use a smartphone app as a telematics device. Considering that smartphones play an important role in modern life, the costs related to smartphone usage are not additional ones specific to using UBI. For these reasons, we decided to remove the *price value* from our model. Regarding *habit* and *use behaviour*, these factors are not applicable for participants who have never used such systems. Thus, we had to remove them from our model, as we envisioned that recruiting enough participants that have hands-on experience with UBI will be difficult. This intuition was later confirmed in the recruitment process (see Section 3). Below we define the constructs *behavioral intention*, *performance expectancy*, *effort expectancy*, *social influence*, *hedonic motivation*, and *facilitating conditions* from UTAUT2 in the UBI context (adapted from [11]). We also formulate the hypotheses according to the original UTAUT2, which are described in Table 1.

Behavioral intention (BI) is defined as the degree to which a person has formulated a conscious intention to be or not to be covered by UBI (adapted from [16, p. 214]). *Performance Expectancy* is split into performance expectancy for improving driving style (PD) and for saving money (PM) based on the specific benefits provided in UBI to customers. We define PD as the degree to which users improve their driving skills with UBI and PM as the degree to which users save money in insuring their car with UBI. *Effort Expectancy (EE)* is defined as the degree of ease associated with the use of UBI technology. *Social influence (SI)* is defined as the degree to which people perceive that close relations (e.g., family and friends) believe they should be covered by a UBI program. *Hedonic Motivation (HM)* is defined as the fun or pleasure derived from using UBI. Finally, *Facilitating conditions (FC)* are defined as the degree to which users believe that they have necessary resources and support to use UBI. In UBI, the resources (e.g., telematics device and product information) and support (e.g., customer support) are provided by the insurer. In the case of users without experience using UBI, they might reflect these resources and support from their current insurer.

Additional acceptance factors and moderating effects. We include *trust in the insurer (TI)* in our model, defining it as the users' perception that the UBI insurer has beneficial attributes towards them (adapted from [17]): *Benevolence* is the perception that UBI insurer is acting in users' best interest. *Competence* refers to the perception that UBI insurer has the ability to provide UBI technology and *Integrity* is defined as the perception that UBI insurer is honest and keeps promises to users.

Furthermore, since UBI programs are based on various technologies (e.g., telemetry, data analysis, artificial intelligence), we include *trust in UBI technology (TU)*, defining it as the users' perception that UBI technology has the attributes necessary to perform as expected (adapted from [18]): *Functionality* is the perception that UBI technology has the capability, functionality, or features to process driving data and to provide feedback on driving performance to users. *Reliability* refers to the perception that UBI technology works properly processing driving data and providing feedback on driving performance and *Helpfulness* is defined as the perception that the insurer and UBI technology provide adequate and responsive support for users in using UBI.

Drivers share their data with the insurer to determine their driving score. Although some studies find that people are willing to adopt UBI despite privacy issues [4,3], other studies find that some people have concerns that their data could be used for customer profiling or marketing, which might influence the intention to be covered by a UBI program [8,5]. Thus, we include *Perceived Privacy (PP)* in our model, defining it as the degree to which users believe that the collection, access, processing, and disclosure of their driving data by the UBI insurer is consistent with their expectations (adapted from [19]).

Quintero et al. [5] find that some users would like to have more transparency in UBI on score calculation, data sharing and data storage. Lack of transparency might influence adoption of UBI programs. Thus, we define *Perceived Transparency in UBI (PT)* as the degree to which users perceive that the rationale behind their obtained driving score is clear in UBI. Quintero et al. [5] also identify that drivers would be more willing to join UBI when they perceive their driving style as "good". Thus, we add *Perceived Driving Style (DS)* to our model, defining it as the degree to which drivers believe that they drive carefully and cautiously, obeying traffic rules (adapted from [8, p. 121]). Osswald et al. [15] find that *perceived safety (PS)* influences the intention to use IT in the car driving context. We add PS to our model, defining it as the degree to which users believe that using UBI will not negatively affect their well-being (adapted from [15]).

Regarding moderators, some studies examine the relationship between drivers' age or gender and risky driving. Young drivers are more engaged in risk-taking behavior [20, 21], and males were reported to have a higher number of traffic violations, accidents and errors than females [22,21]. Younger drivers have more willingness to adopt UBI and improve their driving score faster than older drivers [3]. Females were identified to have the highest improvement in their driving score using UBI. Additionally, some drivers believe that getting a good driving score is difficult in a country where others drive aggressively [5]. Thus, we propose *perceived country driving style (CDS)* as a possible moderator in our model, defining CDS as the perception of how carefully others drive and follow traffic rules. Hypotheses related to moderators are described in Table 1.

3. Method

We developed an online survey[2] to validate which factors influence acceptance of UBI. In this section, we present the measurement scales, followed by the survey structure, recruitment process, sample characteristics and details about data analysis.

Measurement scales. All constructs were measured on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree", except the *Privacy Concern* scale which ranges from "not at all concerned" to "extremely concerned". We removed two items from original scales. In EE, we removed the original Item 2 ("It is easy for me to become skillful at using mobile Internet") because "becoming skillful" does not fit the car insurance context. In PM, we removed the original Item 2 ("Using mobile Internet increases my chances of achieving things that are important to me"), considering that in UBI the chance of saving money does not depend on using UBI, but on the driving style.

Survey structure. We consider three kinds of UBI users: Current Users (CU) are covered by a UBI program. Former Users (FU) had used a UBI program in the past but are no longer covered by it. Potential Users (PU) are individuals over 18 years old with driving licenses who have never been covered by a UBI program.

We performed 2 iterations with 7 researchers to identify possible study design concerns, such as formulation of hypotheses and the wording of the items. After including their feedback, we conducted a pilot study with 12 participants (4 CU, 4 FU, 4 PU) to test completion time and the survey flow. The survey was organized in five parts: In the first part, we presented a 55-second video to provide participants with an explanation about the UBI systems. We then asked 3 quiz questions to check the understanding of UBI, providing feedback to participants on their responses. The second part asked participants about their current car insurance, how long they have been covered by this insurance, and the reasons for choosing it. The third part presented the UBI scenario depending on each user group (PU, CU or FU). This scenario provides context to participants, so that they are all in a similar position before starting the questionnaire. For PU, we presented a hypothetical situation in which they have the option to be covered by a UBI program under their current insurer. For CU and FU, we suggested replying to the questionnaire based on their current and former experiences using UBI, respectively. The fourth part contains 63 questions about the scales to test our model, with 3 additional attention check questions. In the scales for BI, PM, PD, EE, HM, TI, TU, PS, PP, and PT, we used the conditional "would" for PU to allow them to answer based on the proposed hypothetical scenario described above. Finally, participants were asked about driving experience (i.e., annual distance traveled) and privacy concerns towards sharing information with companies, as well as demographics such as age, country of residence, education level, occupation, and English level.

Recruitment. The survey was approved by the data protection office of our university. We recruited CU, FU, and PU through Prolific (an online platform for research studies), selecting participants from countries with the highest number of participants available in the platform who meet the selection criteria (have a driving license and a car insurance). Looking for more CU and FU, we also recruited participants through a student mailing list of our university and Call for Participants (a network for research studies). The study was conducted in March and April 2021.

[2]The survey questionnaire and other materials are available at:https://doi.org/10.5281/zenodo.5708834.

In Prolific, participants from Germany, Ireland, United Kingdom, and the United States were first screened asking about their experience with UBI. The screening survey took approximately 3 minutes to complete. We excluded participants whose responses were incorrect for two or more of the three attention check questions. From 807 participants, 791 met the selection criteria. We identified 25 CU, 74 FU, and 692 PU. We invited 25 CU, 74 FU, and 400 PU to take part in the study, of which 22 CU, 67 FU, and 398 PU responded. The survey took approximately 20 minutes to complete. We received a total of 487 valid survey responses. A valid survey response is defined as a participant's response with two out of three correct answers in the attention checks. Participants were compensated with .30 GBP for the screening survey and 2 GBP for the main survey.

In Call for Participants, we received 59 completed surveys out of 75. We identified 11 CU, 24 FU, and 24 PU, but only 7 CU, 3 FU, 21 PU responses were valid. Regarding the email list of our university, we received 75 completed surveys out of 167 responses (7 CU, 2 FU, and 66 PU). Unfortunately, only 3 CU and 64 PU responses were valid. Participants recruited via these two channels were invited to voluntarily enter into a raffle to win one of fifteen 10 Amazon gift cards.

In total, we received 585 valid surveys (29 CU, 64 FU, and 492 PU). The survey was hosted on a LimeSurvey server at our university.

Sample characteristics. Our data set includes 585 observations: 328 participants identified as female, 253 as male, 2 as non-binary, and 2 did not disclose their gender. Of our participants, 492 have no experience with UBI while 93 have experience with it; 64 have used it in the past and 29 are currently enrolled in a UBI program. Participants ranged in age from 19 to 77 years ($m=39, \sigma=14$). In terms of English skills, most participants reported having a native speaker level (453), followed by proficient (109), intermediate (18), and basic (5). Regarding education, 44% had a bachelor degree, 20% had a master degree, 17% had no completed academic or professional education, 14% had completed vocational training, 3% had a PhD degree, and 2% did not disclose their educational level. Most participants were from United Kingdom (77%), followed by Germany (13%), United Stated (5%), Ireland (2%), and other European countries (3%). Regarding privacy concerns, most of our participants are moderately concerned about sharing their information with companies ($m=3.35, \sigma=1.12$).

Data analysis. We used the software Stata version 14 [23], assuming a significance level of 0.05. Each theoretical construct depicted in Figure 2 should include only one factor. To check this, we ran factor analyses with Varimax rotation [24] with every construct, and found that each construct was well-described by only one factor. Factor loadings and Cronbach's alpha values are satisfactory [24,25].

We ran a Structural Equation Modeling (SEM) to test the theoretical model [26]. Because the data set is rather small compared to the complex model [26, p. 14] we decided to check for moderator effects by linear regressions. We used the SEM builder, a graphical tool of Stata, to build the model. The observed variables were included to create the latent variables and all connections were added according to our theoretical model. We evaluated the *Root mean squared error of approximation* (RMSEA) and the *probability that the RMSEA value is less than* 0.05 (pclose). RMSEA is defined as "an absolute fit index scaled as a badness-of-fit statistic where a value of zero indicates the best result." [26, p. 273] and pclose is the probability that the value of RMSEA is less than 0.05 [27, p. 199]. Values of $RMSEA < 0.05$ and $pclose > 0.05$ indicate a good fit of the model [27, p. 152]. To improve the model, *modification indices* (mindices) *for* *path coefficients and covariances that were constrained or omitted in the fitted model* were used [27, p.160]. When the pclose and RMSEA indicate a poor fit of the model, we ran mindices to get recommendations about new connections between constructs which helped us to improve the model. In Section 4, we provide more details about the data analysis and results using the methodology described above.

4. Results

422 of the participants reported driving between 5.000 and 19.999 km per year, 100 drove less than 5.000 km per year, 43 drove more than 20.000 km per year, and 20 did not know their mileage. 144 reported having less than 1 year of experience with car insurance, 333 have between 1 and 5 years, 101 have more than 5 years of experience, and 7 do not know. Regarding UBI coverage, most of the participants have not had any experience with it (492), 64 have used it in the past, and 29 are currently enrolled in a UBI program. Because previous works were conducted only with participants without experience with UBI, we intended to include people with experience using it to extend previous findings. Working with the limited participant sample, we were able to recruit 93 participants with such experience. The reasons given by FU about why they are no longer covered by UBI programs were: did not get a desirable discount (13), got a better offer from another insurer (40), had technical problems with the telematics device (6), considered the driving rating unfair (6), did not improve the driving style (6), and that UBI usage distracted too much during driving (4).

To validate our acceptance model, we started with the theoretical model described in Section 2, running a SEM analysis. We performed 22 iterations to refine the model, including the recommendations from mindices. Following these suggestions, we removed the insignificant latent variables: EE, FC, TU, PT, and DS and removed the direct path between PP and BI. We also included covariances between some constructs, which can be interpreted as correlations between the latent variables. The Goodness of Fit statistics ($pclose = 0.953$, $RMSEA = 0.042$) indicates that the model improved and has a good fit.

Six hypotheses were supported by the analysis: Respondents with higher performance expectancy for improving their driving style and for saving money have a higher behavioral intention ($H1$ and $H2$). Respondents that say that their family and/or friends think that they should use UBI have a higher behavioral intention ($H4$). A higher hedonic motivation ($H5$), trust in insurer ($H7$) and perceived safety ($H10$) also lead higher intention to use UBI. Hypotheses $H3$, $H6$, $H8$, $H9$, $H11$, and $H12$ were not supported. According to the standardized coefficient, HM (.35) and SI (.26) were the best predictors for BI. This suggests that the opinion from others about UBI and the enjoyment of using UBI play the most important role in the intention to be covered by a UBI program. Although PP did not predict BI, it has a correlation with all other factors. That means there is an indirect connection between PP and BI through PD, PM, SI, HM, TI, and PS. The highest correlation could be found between perceived privacy and trust in insurer (.5) and performance expectancy for improving the driving style (.38).

We ran linear regressions to test hypotheses $H13(a)(b)(c)$, $H14(a)(b)(c)$, $H15(a)(b)$, $H16(a)(b)$, $H17(a)(b)$, $H18(a)(b)$, $H19(a)(b)(c)$, and $H20(a)(b)(c)$ because, as Kline [26] suggests, the data set is too small to run the whole model with the assumed moderators. Thus, taking age, gender, and perceived country driving style (CDS) of participants as moderator variables, we calculated 20 linear regressions. We found that the variables age, gender and perceived country driving style do not significantly moderate the effects between the latent variables (PD, PM, SI, HM, and PS) and the BI.

Table 1. Hypotheses from the UBI acceptance model with the results from the first and final analysis after improving the model. Hypotheses supported are presented in bold, which are considered in the refinement process to get the values shown in *after the improvements* column. β | B represent standardized (β) and unstandardized (B) coefficients $***$ Statistically significant at 0.001 level; $**$ at 0.01 level; $*$ at 0.05 level.

	Hypothesis	*First analysis*	*After the improvements*
H1	**PD is positively related to BI**	0.22 | 0.20$***$	0.17 | 0.19$***$
H2	**PM is positively related to BI**	0.22 | 0.18$***$	0.13 | 0.15$***$
H3	EE is positively related to BI	−0.02 | −0.02	
H4	**SI is positively related to BI**	0.33 | 0.32$***$	0.26 | 0.31$***$
H5	**HM is positively related to BI**	0.45 | 0.37$***$	0.35 | 0.37$***$
H6	FC is positively related to BI	−0.03 | −0.05	
H7	**TI is positively related to BI**	0.16 | 0.17$*$	0.12 | 0.17$*$
H8	TU is positively related to BI	−0.04 | −0.05	
H9	PP is positively related to BI	0.08 | 0.07	
H10	**PS is positively related to BI**	−0.16 | −0.22$***$	0.08 | 0.11$**$
H11	PT in UBI is positively related to BI	−0.06 | −0.08	
H12	DS is positively related to BI	0.08 | 0.14	
H13	The effect of PD on BI is moderated by: (a) age, (b) gender, and (c) CDS	(a) 0.004 (b) 0.052 (c) −0.011	
H14	The effect of PM on BI is moderated by: (a) age (b) gender (c) CDS	(a) 0.006 $*$*but age is* 0.004 (b) 0.049 (c) 0.039	
H15	The effect of EE on BI is moderated by: (a) age (b) gender	(a) 0.005 (b) 0.051	
H16	The effect of SI on BI is moderated by: (a) age (b) gender	(a) 0.0001 (b) −0.104	
H17	The effect of HM on BI is moderated by: (a) age (b) gender	(a) −0.002 (b) 0.060	
H18	The effect of FC on BI is moderated: by: (a) age (b) gender	(a) 0.001 (b) 0.078	
H19	The effect of PS on BI is moderated by: (a) age (b) gender (c) CDS	(a) 0.001 (b) −0.101 (c) −0.016	
H20	The effect of DS on BI is moderated by: (a) age (b) gender (c) CDS	(a) 0.004 (b) −0.031 (c) −0.030	

5. Discussion

We collected and analyzed the responses from different user groups, such as potential, current, and former users. We decided to build a general model which addresses the concerns of all groups, extending the findings of previous works, which only focused on potential users [4,8,7]. We assume that different levels of experience related to UBI can influence the users perception of factors considered in our model. For example, although we removed Habit from our model, current and former users have used UBI for a period, building some habits of using it, which could cause bias in their responses. We managed this concern by analyzing all possible connections between factors and identifying potential factors' relationships. Thus, in contrast to Mayer [8], who found that PP plays a minor role in predicting BI, we found that although PP does not predict BI, it influences other factors such as PM, PD, HM, SI, TI, and PS, which predict BI. Therefore, our findings suggest that PP plays an important role in the intention to use UBI, and thus, insurers should pay attention to this factor to increase UBI adoption. Another example is the inclusion of FC in our model. Although only current and former users have first-hand experience with UBI, we consider that potential users can leverage FC, i.e., information provided by UBI insurers, to extrapolate their experience with traditional insurance models and build a clear picture of UBI even before joining such an insurance model.

The enjoyment of using UBI (HM in our model) is identified as the most influential factor on BI which is aligned to the findings of Mayer [8] and Tian et al. [7]. These enjoyment features of UBI are connected to the interaction with cars and with other devices, where usability plays an important role. Usability is also related to SI and PS, two other predictors of BI in our model. Although Mayer [8] does not find SI as a predictor of BI, Tian et al. [7] report it as a good predictor of BI for people under 40 years old. Thus, the experience of others (e.g., relatives, friends, etc.) with UBI using the telematics device, obtaining a discount, improving driving style, among others, influence the decision of people to adopt it. This suggests that referral programs could be an effective way to increase UBI adoption. Regarding PS, usability is an important aspect to take into account for interface design to prevent distracting drivers during trips and provide non-intrusive feedback in real-time, thus avoiding accidents. Therefore, insurers should pay attention to HM and PS to avoid rejection of UBI due to low usability [5], as well as to SI to avoid negative influence or bad references from others which could decrease its adoption.

Aligned to the findings by Mayer [8] and Tian et al. [7], *trust in an insurer (TI)* is identified as a predictor of BI. We also included in our theoretical model *trust in UBI technology*, but it was not identified as a predictor of BI. That suggests that users focus trust in the UBI context on the insurer, paying less attention to the technology applied and the required infrastructure to implement such programs. Thus, insurers could increase the UBI adoption by enhancing TI, e.g., by providing timely customer support, or by making sure that the calculated driving scores are transparent [5].

While Derikx et al. [4] find that saving money provides higher motivation to adopt UBI, our results also show that monetary benefits (PM) play a greater role than driving style improvement (PD) in the intention to use UBI, and that driving style (DS) does not predict BI. Insurers could leverage this finding, by providing cost estimation tools, as suggested by Quintero et al. [5]. It is possible that good drivers with experience may be less inclined to adopt UBI, because they already pay low fees in traditional models. Thus, if insurers want to increase adoption among this category of users, they have to consider incentives tailored for this group. For example, progressive discounts, which could further reduce the insurance premium for drivers who have consistently gotten the maximum score over a prolonged period of time.

Limitations. Our findings are limited by the small number of current and former users, despite active recruitment efforts. Although the countries where we ran our survey offer UBI programs [6], majority of our participants are potential users and come from the United Kingdom. Furthermore, we do not measure the real use of UBI, but the perceptions of different factors and the intention to use such systems.

6. Conclusion

We adapted and extended the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) based on the benefits offered to users in UBI: improving driving style and saving money. We added six constructs: *trust in insurer*, *trust in UBI technology*, *perceived privacy*, *perceived safety*, *perceived transparency in UBI*, and *perceived driving style*, as well as *perceived country driving style* as moderator. We evaluated our model based on the responses of 585 participants to an online survey. We conclude that *performance expectancy for improving driving style*, *performance expectancy for saving money*, *social influence*, *hedonic motivation*, *trust in insurer*, and *perceived safety* are predictors of the intention to use UBI, with *social influence* and *hedonic motivation* being the most relevant. Moreover, *perceived privacy* influences intention to use UBI indirectly and *per-ceived driving style* does not play any role in its adoption. Finally, the newfound connec-tions between predictors might indicate that further research is required to explore new factors relevant to the intention to use UBI. Further studies should explore the adoption of UBI for different populations, geographies, and UBI users.

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