Users' Privacy Concerns and Attitudes towards Usage-based Insurance: An Empirical Approach

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Abstract: Usage-based Insurance (UBI) is a car insurance model in which the insurance payment calculations are based on driving data such as speed, acceleration, braking, location, etc. Driving data are collected and analysed by the insurer to provide feedback on driving performance, help drivers improve their skills, and possibly apply a discount on their next renewal. So far, UBI research has been focused more on its architecture, benefits, or acceptance, while the users' perception of such forms of insurance and their privacy concerns received less attention. To fill this gap, we conducted an online survey with 281 participants and analysed their responses using qualitative and quantitative methods. We found that data collection and sharing are the main privacy concerns. Furthermore, we identified potential discounts as the most important feature in favor of adopting UBI, while data collection and unfair ratings are the main reasons to avoid or quit UBI.

1 INTRODUCTION

Traditional insurance models are based on subsidized systems, where customers who do not claim insurance benefits subsidize others who file such claims. Thus, it is common to find car insurance programs in which the fees paid by a driver who does not report any accident do not differ much from others who usually require the assistance of the insurer. The fees in these programs are calculated based on historical data averaged across customers grouped by criteria such as age, gender, or marriage status (Soleymanian et al., 2019). UBI programs represent a trend, in which the fee is based on a customer's personalized driving style. UBI is also known as *Telematics Insurance*, *Pay As You Drive (PAYD)*, or *Pay How You Drive (PHYD)*. As Figure 1 depicts, driving data are collected through a telematics device, such as a dongle, a black box, a smartphone app, or an embedded system, and analysed by the insurer. The user then gets feedback on driving performance and a possible discount on the renewal payment in case of getting a good driving score.

Soleymanian et al. (2019) found that the main benefits of UBI are the incentives to improve one's driving style through feedback, and the potential discount on their insurance fees. On the other hand, the main disadvantages are the privacy concerns (Arvidsson et al., 2011; Derikx et al., 2016; Soleymanian et al., 2019) and discrimination (most programs are designed for novice drivers or young people).

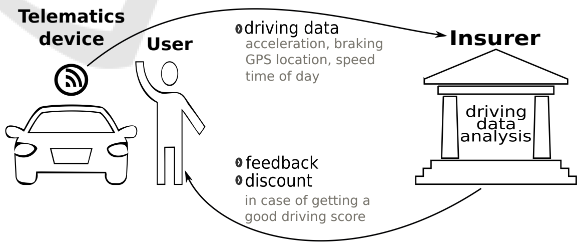

Figure 1: General Usage-Based Insurance model.

Although there is research about the technical aspects of UBI (Troncoso et al., 2010; Iqbal and Lim, 2006; Händel et al., 2013), its benefits (Soleymanian et al., 2019; Derikx et al., 2016; Litman, 2007), its user acceptance (Mayer, 2012; Tian et al., 2020), and usability issues (Quintero et al., 2020), less attention has been given to the users' perception of data collection and sharing, financial benefits, driving feedback, and driving style. We conducted this online survey

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to know more about these topics, and identify privacy concerns related to UBI. The following research questions (RQ) are addressed in this paper:

- RQ-1. What are the privacy concerns identified by users with UBI?
- RQ-2. What are the most important features of UBI that influence a person's decision for or against UBI?

The contributions of this study are as follows: (1) we determine that participants are aware of and concerned about the sharing and storage of their driving data, (2) we identify the *discount on the next renewal in case of getting a good driving score* as the most important factor in favor of UBI and *collection of my driving data (GPS location, acceleration, etc.)* and *driving rating is unfair* as the most important factors against deciding to use UBI. (3) Based on our findings, we draw recommendations that can help insurers increase the adoption of UBI. (4) We provide the source code and data to facilitate the replication of our analysis.

2 BACKGROUND AND TERMINOLOGY

Based on prior exploratory research (Derikx et al., 2016; Quintero et al., 2020), we identified several key factors as potential candidates for influencing UBI perception. In what follows, we define and describe each factor, and formulate hypotheses about the relationships between these factors.

Intention to Use UBI (IU) is the degree to which a person has formulated a conscious intention to be or not to be covered by UBI (adapted from (Warshaw and Davis, 1985, p. 214)).

Privacy Concerns (PC) follow a scale devised by Dinev and Hart (2006), and relate to opportunistic behavior with respect to the personal information shared with companies by the respondent in particular.

My Perceived Driving Style (MS) is the degree to which drivers believe that they drive carefully and cautiously, obeying traffic rules (adapted from (Mayer, 2012)).

Others' Perceived Driving Style (OS) is the perception of how carefully others drive and follow traffic rules Quintero et al. (2020).

Discount in UBI (DI) is how much money a driver can save by participating in UBI.

Driving Feedback (DF) relates to how often feedback is given to drivers based on their driving performance.

We then formulate the following hypotheses based on the aforementioned factors:

H1. People with low privacy concerns ($PC_{\downarrow}$) are more willing to be covered by UBI (IU) than others with high privacy concerns ($PC_{\uparrow}$).

H2. Magnitude of discount (DI) plays a greater role than the driving style feedback (DF) in UBI perception by users with high privacy concerns ($PC_{\uparrow}$).

H3. People with high privacy concerns ($PC_{\uparrow}$) prefer to avoid using smartphones as a telematics device.

H4. People with high privacy concerns ($PC_{\uparrow}$) prefer to avoid sharing telemetry with entities other than their insurer.

3 METHOD

In July 2021, we conducted an online survey with UBI users to determine their: (1) privacy concerns with UBI; (2) the most important UBI features that influence a person's decision for or against UBI; (3) preferences for sharing and storage of driving data. The selection criteria for our study were (1) to have a driving license, (2) to have experience being covered by a car insurance program. Our study got approval from the data protection officer of our university. The survey was conducted in English.

3.1 Recruitment

To recruit participants and manage the study we decided to use Prolific, an online platform for research studies, and hosted the survey on a LimeSurvey server in our university. Participants were screened asking about their experience with car insurance and specifically with UBI, as well as when they got their first driving license. Based on the number of UBI programs in the market and the participants in Prolific who met the selection criteria, only participants from Germany, Ireland, United Kingdom, and the United States were considered in this study. The screening survey took approximately 3 minutes to complete. 791 participants out of 807 met the criteria of having a driving license and car insurance. In UBI, we defined Current users (c) as people covered by a UBI program. Former users (f) are people who had been covered by UBI and for some reason are no longer covered by it. Potential users (p) are people with a driving license who never enrolled in a UBI program. In this paper, we noted current, former, and potential users with the subscripts c, f, p respectively. Thus, we identified 30 current, 77 former, and 684 potential users of UBI. We invited 30_c, 77_f, and 250_p to take part in our study, from which 15_c, 41_f, and 225_p participated. The survey took approximately 10 minutes to complete. We got a total of 281 completed surveys. Participants were rewarded with 0.30 GBP for the pre-screen survey and 1 GBP for the final survey.

3.2 Survey Structure

We developed the online survey questions based on existing literature and brainstorming sessions. We conducted a pilot with 5 researchers to identify concerns related to wording, and the connection between the research and survey questions. After including their feedback, we conducted another pilot with 6 participants (2_c, 2_f, 2_p) to test completion time and the survey flow. The final version of the survey has a 55s explanatory video and contains 68 questions, of which 3 are used for checking the understanding of UBI concepts from the video.

In what follows, we summarize the questionnaire, while the full text and other materials are available at zenodo.org/record/6114141:

Part 1: Explanatory video, including 3 quiz questions to validate the understanding of UBI concepts.

Part 2: Questions of UBI coverage, name of insurer and UBI program, and how long participants have been covered by this insurance. For former users, we asked about the reasons to quit.

Part 3: Questions related to privacy concerns (PC) and driving style (MS, OS).

Part 4: UBI scenario depending on each user group ($_c$, $_f$, $_p$). We provided a scenario for each kind of participant to contextualize them about using UBI before starting the questionnaire. For p users we presented a hypothetical situation in which their insurer is offering a UBI program and they have the option to be covered by UBI. For c and f users we suggested replying to the survey based on their current and former experience using UBI, respectively.

Part 5: Intention to use (IU) and preferences on UBI. We formulated questions related to which information participants are willing to share for evaluating their driving score, which telematics device they would prefer to use, with whom they prefer to share their driving data, and their preferred frequency and communication channel to get driving feedback. For c and f users we asked about the discount on their insurance programs.

Part 6: Demographics, such as age, gender, country of residence, education level, occupation, and driving experience (annual distance traveled).

3.3 Data Analysis

After collecting the survey data, we conducted a qualitative and quantitative analysis. We used an inductive thematic analysis (Braun and Clarke, 2006) going from codes to themes to analyse the comments provided by users in the open-ended questions. For quantitative analysis we used Pandas and SciPy, which are open-source data science tools. The statistical techniques we applied are covered in detail in Section 4.2.

4 RESULTS

160 participants identified as female, 119 as male, and 2 as diverse. The most represented age category was between 29 and 33 years old. Participants ranged in age from 21 to 77 years old. Regarding education, 118 had a bachelor degree, 74 had completed a postgraduate degree, 85 had completed professional or vocational education, and 4 preferred not to disclose. Most participants were potential users (225_p, 41_f, 15_c) of UBI. The geographic distribution is as follows: United Kingdom (255), followed by United Stated (17), Germany (7), and Ireland (2).

4.1 Qualitative Analysis

Considering that some parts of our survey gave participants the option to offer additional comments about their responses, we performed thematic analysis (Braun and Clarke, 2006) to reveal common themes among the 78 collected entries of unstructured text. Two researchers did so by coding the comments independently, then comparing notes and refining the codebook until consensus was reached. The results of thematic analysis are shown in Table 1. In what follows, we share the highlights, indicating which participant group referred to this idea.

Distracting feedback can cause a decline in user satisfaction: "It was annoying that they kept sending me driving alerts, I felt like I was being tracked and watched too much" ($P36_f$). In addition, it can lead to accidents caused by distracted driving: "On some local roads that are technically limited to 30, virtually every motorist drives at 40. When you're using UBI you have to stick to 30, and this causes a lot of irritation to the drivers stuck behind you, and as a driver it caused me a great deal of stress at times" ($P36_f$).

Model deficiency relates to statements about issues in scoring algorithms, because they are incomplete and cannot model the complex driving conditions that occur sometimes. For example, $P22_f$ stated they got a lower score for driving in the dark, even though it was

Table 1: Summary of thematic analysis. The references indicate how many participants mentioned a theme, they are coded by participant type: potential, current and former are marked as P, C, and F respectively.

Theme	Subtheme	References			Code
		P	C	F	
Barriers	Distracting feedback	4		1	Users feel uncomfortable using UBI
	UBI not convenient for users	4		3	Financially ineffective
	Model deficiency	2			Inaccurate data
		1	1		Danger awareness
		5	2	4	Scoring process is incomplete or unfair
		2			UBI tailored for young, inexperienced drivers
Decision making	Decision making	3			Difficult to decide
		5			Privacy concerns
Adoption	Increasing UBI adoption	1		1	Car sharing
		2			Ownership
		2			Self-sufficiency
		2			Data portability
		2			Critical mass

winter, and there are only a few hours of daylight during the season. P34$_f$ summarized that as "conditions on the road are not taken into account". In the words of P42$_f$ "those systems are not designed for real world driving ... only the hypothetical driving that is taught in lessons that doesn't exist in real life".

Danger awareness describes situations in which drivers are forced to make exceptions and act in ways that would be considered dangerous otherwise: "sometimes it is necessary to overtake and one has to speed up fast to do so and it [the system] can't take this into account. Also I have had to brake quickly to avoid an animal/unexpected unindicated moving across me and got marked down" (P2$_c$). "If I have to brake because a dog runs out in front of me I shouldn't have that go against me" (P63$_p$). We henceforth group this issue, along with model deficiency, under the term "big picture" problem.

Financially ineffective is how some participants see UBI, because in their experience it never delivered the promise of a lower premium. On the contrary, "[it is] absolutely useless and made my insurance more expensive by default" (P42$_f$), or "I have never encountered anyone who has had their premium reduced" (P22$_f$). This skepticism could be rooted in the belief that insurance companies only seek increased profits: "insurance companies are in the business of making money, not making driving safer" (P190$_p$).

Inaccurate data leads to erroneous scoring. Some of our participants encountered loss of a GPS signal or had their telematics devices stop working for a while: "I doubt its accuracy at times. We were told that sometimes the link goes [down] and it can disrupt the reading" (P63$_f$).

Car sharing and *ownership* references were also mentioned when pointing out limitations of UBI. When a car is shared by multiple people, it is not always possible to attribute a score to a specific person: "If you share a car with another person, how does UBI know who to rate or do they just average it out. A lot of people do share after all" (P82$_p$). This can also occur in families where the car is owned by a parent, but driven by a child: "needs to be a system divorced from driver ownership" (P249$_p$).

Critical mass must be achieved for UBI to be effective, according to some of our participants. The rationale is related to context, like in the case of *danger awareness*: "Data does not relate your driving to that of others and how it impacts you. If all cars are covered then UBI may be more conclusive" (P229$_p$).

It can be *difficult to decide* whether to join UBI: "Having never tried it or having had any experience of it, I don't know which I would prefer" (P114$_p$).

Data portability is another potential acceptance barrier, as tech-savvy users like P184$_p$ want to avoid vendor lock-in: "portability of that data across multiple UBI suppliers could also be an issue".

Privacy concerns where explicitly named by some participants, for example: "feels very big brother to me, so not a fan" (P112$_p$), or "do not know if my data will be shared or mis-used, very off putting" (P88$_p$).

Young drivers are seen as the group to benefit most by some participants, because UBI can help them improve their driving skills: "this is for the younger person starting out on their driving life" (P143$_p$).

Self-sufficiency can reduce the potential for privacy abuse, e.g.,: "a unit that can work to generate scores without communicating" (P254$_p$).

4.2 Quantitative Analysis

To test the hypotheses and answer the research questions, we applied statistical analysis. We first cleaned the data set by discarding responses from participants that did not provide consent, did not have a driving license at the time of participation, or have never been covered by car insurance. We then computed the correlations between the following factors: privacy concerns (PC), intention to use (IU), one's driving style (MS), the driving style of others (OS), the discount in UBI (DI), the frequency with which one receives feedback about their driving (DF), and preferences related to collecting (CD) and sharing (SD) driving data. Spearman and Pearson correlation was used for ordinal and continuous factors respectively.

We set the significance level to $p <= 0.05$ and use the following thresholds to define the correlations as *weak* $<= 0.35$, *moderate* $<= 0.67$, *high* $<= 0.89$, *very high* $<= 0.99$, or *perfect* 1 (Taylor, 1990). Note that correlations can be positive or negative, thus a correlation of -0.67 is "negative moderate".

4.2.1 Hypotheses Testing

Prior to running our questionnaire, we formulated several hypotheses about the participants' attitudes towards UBI. In what follows, we list these hypotheses and explain how they were tested. Note that due to space constraints, we do not include the detailed calculations of how the latent variables below were computed. However, all of the calculations are available in the supplementary materials (see Section 3.2).

We considered several latent variables, which we computed via 5-point Likert-scale questions. The variables are: *Intention to use* (marked as IU, measured through 3 questions), *Privacy concern* (PC, 5 questions), *preferences of sharing driving data* (SD, 6 questions), *preference of telematics device for collecting driving data* (CD, 1 question).

We then conducted an exploratory factor analysis to determine how many factors are needed to represent each latent variable. Thus, we used the Kaiser-Meyer-Olkin (KMO) test with a threshold of $KMO >= 0.6$ (Kaiser and Rice, 1974).

Next, we computed the Pearson or Spearman correlation for continuous and ordinal variables respectively. Note that we treat a latent variable as continuous if it can be represented by a single factor that was computed as the mean of ordinal variables.

We now present the results for each hypothesis.

H1: Following the methodology above, we find that the Pearson correlation between PC and IU is $corr = -0.129, p = 0.046$. This indicates a weak negative relationship, which suggests that participants with low privacy concerns are more willing to be covered by UBI. Therefore, our findings **support H1**.

H2: We considered the *Discount*, *Driving feedback*, and *Privacy concerns* only for current and former users, because only they have experience getting discounts and driving feedback in UBI programs. Given that these are ordinal variables, we calculated the Spearman correlation between PC and DI ($corr = 0.317, p = 0.044$), and PC and DF ($corr = 0.141, p = 0.379$). We found a weak positive correlation between PC and DI, while the correlation between PC and DF is not significant. That means, people with high PC expect to get a high discount in their UBI program. Therefore, **H2 is supported**.

H3: We analyzed the users' preference to collect their driving data using a *black box*, *dongle*, *embedded system*, or *smartphone app* as telematics device, as well as the option to *not collect* any driving data at all. Following our methodology, we calculated the Spearman correlation, resulting in the coefficients between variables depicted in Table 2

Table 2: Preference of collecting driving data using telematics device. *Corr* is the correlation between privacy concerns (PC) and the preference of collecting driving data using a particular telematics device. Note that entries in gray are not statistically significant.

Data collection preference	corr	p
Do not collect data	0.283	1.407e-06
Embedded system	0.022	0.713
Dongle	-0.025	0.682
Black box	-0.030	0.611
Smartphone app	-0.164	0.006

We found a weak positive correlation between PC and the preference to avoid data collection, as well as a weak negative correlation between PC and the usage of a smartphone app as a telematics device. Therefore, **H3 is supported**. Note that our results do not show whether other types of telematics devices are preferred, as other correlations were not significant. Moreover, the data shows clearly that avoiding data collection is preferred, if the option is available.

H4: We considered the users' preference to share their driving data with *academia*, a *government agency*, a *marketing agency*, *their insurer*, *other insurer*, and *traffic authorities*. We computed the Pearson correlation between PC and the preference to share driving data with the entities above, getting the coefficients depicted in Table 3.

Table 3: Preference of sharing driving data. *Corr* is the correlation between privacy concerns and the preference of sharing driving data with a given entity.

Entity to share data with	corr	p
Road traffic authorities	-0.197	0.001
My insurer	-0.248	2.819e-05
Academic researchers	-0.253	1.934e-05
Marketing companies	-0.299	3.593e-07
Government agencies	-0.305	2.116e-07
Other insurers	-0.311	1.132e-07

We found a weak negative correlation between PC and the willingness to share driving data with all entities above. Note that the strength of the correlation varies, e.g., participants with high privacy concerns are less reluctant to share data with road traffic authorities, and more so when it comes to sharing with other insurers or government agencies. For that reason, **H4 is not supported**, because in retrospect it is clear that the hypothesis was too optimistic. The results show that participants with high privacy concerns would rather not share data with anyone, even their insurer.

4.2.2 Analysis of Research Questions

In this section we present our analysis for each research question.

RQ-1: We considered the *PC* and questions related to the preference of storage and sharing of driving data, as well as the preference of telematics device type. We calculated the Pearson correlation between PC and each storage option for driving data, the results are shown in Table 4.

Table 4: Preference of driving data storage. *Corr* is the correlation between privacy concerns and the preference of storing driving data in a specific device or place. Entries in gray are not statistically significant.

Data storage preference	corr	p
Dev. installed by me	-0.026	0.663
Dev. installed by certified staff	-0.092	0.122
Insurer	-0.155	0.009
Other insurer	-0.176	0.003
My phone	-0.217	0.0002

The negative correlation shows that participants with high PC are reluctant to accept the collection of driving data regardless of storage method.

We also found that the Pearson correlation between PC and the option to participate in UBI without storing driving data is $corr = 0.215, p = 0.0003$, thus confirming the previous finding.

We also asked our participants about their preference to share driving data (e.g., speed, location, mileage, dashcam footage, etc., see materials referenced in Section 3.2 for a complete list). We found that participants are more open to sharing their speed, mileage, and braking behavior. Participants with high privacy concerns are not willing to share their location and dashcam recordings. More participants with high privacy concerns prefer not to share their driving data (14.95%) than those with low (1.42%) and neutral (3.56%) privacy concerns.

In addition, we computed the Pearson correlation between PC and the preference of sharing driving data with various entities. We found a weak negative correlation between PC and all previously mentioned entities (see Section 4.2.1), which suggests that participants with low privacy concerns are more willing to share their driving data.

We also asked our participants about their preference to use UBI with a black box, dongle, embedded system, or a smartphone app. We found that more participants with high privacy concerns like to get the benefits of UBI without any data collection.

If data collection is mandatory, participants with low and neutral privacy concerns would prefer to use a smartphone app as telematics device.

We conclude that participants identified as privacy concerns the sharing and storage of their driving data, especially when it comes to their position and dashcam recordings.

RQ-2: We asked participants about the most important features of UBI in favor and against UBI. Based on previous research and forums of UBI, we collected features of UBI, elaborating two lists, one with the arguments in favor (e.g., potential discount, driving feedback, etc.), and another with arguments against UBI (e.g., unfair ratings, age constraints, privacy concerns, etc.).

We found that a *discount on the next renewal in case of getting a good driving score* is the most important factor that influences a person's decision **in favor** of UBI. On the other hand, *collection of my driving data (GPS location, acceleration, etc.)* and *driving rating is unfair* are the most important factors **against** deciding to use UBI.

Other Findings: In addition, we found a weak positive correlation between PC and DI ($corr = 0.334, p = 0.012$), which suggests that participants with high privacy concerns expect a high discount. For driving feedback, we found that most participants do not want to get any feedback. However, if it were mandatory, they would like to receive it through email or a smartphone app.

We found a weak positive correlation between the MS-IU ($corr = 0.181, p = 0.002$), which suggests that people who consider themselves good drivers are willing to use UBI. We also found that only 8 participants out of 281 consider themselves bad drivers.

We found that participants aged between 29 and 38 have the highest privacy concerns. Also, participants under 33 are more willing to be covered by UBI. Participants with a Master or Bachelor's degree have the highest privacy concerns in our sample. In terms of occupations - employees, workers, and civil servants have the highest privacy concerns.

We did not find significant correlations between the intention to use and the participants' gender, the mileage driven, the discount in UBI, the residence country of our participants, or OS.

5 DISCUSSION

Our findings indicate that participants with high PC prefer not to use smartphone apps as telematics devices. This could be because participants are informed about potential vulnerabilities and tracking issues associated with smartphones, therefore they do not regard them as secure or private. However, this question remains to be explored in future research.

The correlation between privacy concerns and the expectation of a higher discount could be caused by the fact that privacy conscious users want a fair compensation for the data they share. In contrast, users with low privacy awareness may not fully realize the value of what they give up, hence they accept less favorable terms and have lower expectations.

Overall, our participants referred to the sharing and collection of data as the main factors that make them hesitate to join to UBI. The results show that participants would be more open towards UBI if they could take advantage of it without data collection and sharing. It is thus possible, that a self-sufficient system that relies on the resources of the car itself, and does not involve third parties, could have a higher acceptance. To the best of our knowledge, no such solutions are available to customers at the moment. Some researchers proposed systems that collect and share aggregated data (Händel et al., 2013; Iqbal and Lim, 2006; Troncoso et al., 2010), however they are susceptible to the "big picture" problem discussed in Section 4.1. Therefore, the design of an accurate and auditable self-sufficient solution remains an open question. We hypothesize that this can be achieved by re-purposing self-driving car technology. According to the requirements defined by the Society of Automotive Engineers (SAE) in (SAE J3016, 2018), a level-2 autonomous vehicle must be able to control steering, braking and acceleration independently (i.e., without receiving instructions from a remote server). Therefore, it must be aware of the environment, which includes other cars, road markings, weather and road conditions, etc. A re-purposed system could leverage the same technology, but with the goal of *evaluating the driving style* like an examination officer would, rather than with the goal of driving the car. Such an "examiner AI" could not only alleviate privacy concerns, but also address the "big picture" problem.

This would be of a great benefit, because our results show that a common limitation perceived by participants is the inability of UBI to understand the big picture of the road conditions, thus leading to inaccurate scores. Moreover, some users consider the scores to be unfair, this can happen if they deviate from the rules to prevent an accident. Such maneuvers are penalized by the algorithm, because it is unaware of what other agents (e.g, drivers, vehicles, pedestrians, animals) were doing in the given circumstances. Some of our participants express skepticism regarding UBI, stating that it will be inefficient unless a critical mass is achieved: either all vehicles must participate in such insurance, or the algorithms must be sophisticated enough to consider all relevant external factors. Since this is not feasible at the moment, a solution would be to make the algorithms more tolerant to such *outlier behaviour*. For example, they could penalize drivers only if they consistently deviate from the rules. Another possibility would be to provide an option to dispute scores. However, this feature must be implemented by taking into account the *burden of proof*. A driver may not always have a video recording to prove their innocence (e.g., in some countries such cameras may be illegal), so it would be unfair to penalize them if they failed to provide evidence during the dispute. We believe that insurers are in a better position to collect such evidence (e.g., by contacting traffic safety authorities, retrieving public camera footage, etc.), and thus the *presumption of innocence* principle must be guaranteed.

The feedback collected from our participants indicates that insurers are yet to make a compelling argument about why their service is unique and worth the investment. This could make some potential users hesitate to sign up, because UBI requires too much commitment up-front (e.g., acquiring new hardware, possibly modifying something in the car, etc.), without the certainty that good driving will lead to a discount. This is especially relevant when potential users learn from others through word of mouth that they have never met anyone who actually got a discount. Therefore, we posit that there could be an entry barrier that insurance companies have to bring down, e.g., by offering the hardware for free or by leveraging the hardware that modern cars are equipped with from the factory, or by improving transparency and making it easy to make accurate estimations of the discount amount. Such transparent estimation tools could assist potential users in making informed decisions.

Disagreement with the calculated driving scores is a major concern raised by the participants. Although none of them has explicitly stated they want more transparency in this calculation, we believe that the lack of such information could make users less likely to perceive the scoring results as objective. Our data show that most participants consider themselves good drivers, so they could attribute errors to the algorithm rather than to their own behaviour, thus reducing the level of satisfaction with the service. Therefore insurers might remediate this by increasing the transparency of all processes, including data collection, data sharing and driving score calculation.

Data portability is another concern mentioned by the participants. While Art. 20 of the General Data Protection Regulation (GDPR) guarantees the right to obtain one's data in a "structured, commonly used and machine-readable format and [..] to transmit those data to another controller without hindrance", customers in some parts of the world do not necessarily enjoy the same level of protection. It is therefore possible that adoption of UBI could be lower in regions where such protections are not available.

Regarding the most important feature in favor of UBI, the brochures of some UBI companies highlight *improving driving style* and *paying based on one's own driving style* as key advantages. However, our participants prioritized the discount on the next renewal, which can indicate that some users are focused on saving money, rather than on improving their driving style. This raises a question: *what is the users' rationale for joining UBI?* If the motivation is saving money, as participants remarked, this is included in the traditional car insurance, where drivers pay based on their historical claims. That means, even though in traditional car insurance novice drivers have a high insurance premium, they could pay less in the next years if they report no incidents to the insurer. Thus, good drivers can pay less even in traditional insurance, hence UBI should attract users with arguments other than reduced premiums. It is also possible that one's cultural background determines the extent to which the calculated discount influences adoption, however our sample is not diverse enough geographically to verify this hypothesis.

Regarding telematics devices, participants who do not have high privacy concerns prefer to use a smartphone app as a telematics device if data collection is unavoidable. This is despite usability issues that Quintero et al. (2020) identified earlier, e.g., high battery consumption or inaccurate GPS location. This suggests that users find smartphones appealing due to some benefits that outweigh these issues. For example, it could be due to (1) familiarity - they understand the user interface and there is no need to learn anything new, (2) privacy - they can turn it off when they want (e.g., when driving to certain addresses), (3) convenience - the smartphone is already used for maps and navigating, (4) cost savings - there is no need to purchase additional hardware, nor spend time setting it up, (5) perceived trust - users are used to storing sensitive data on their smartphones (e.g., photographs, correspondence), therefore they could also entrust them with their driving data. However, the usage of smartphones can lead to security issues that non-expert users are unaware of. Specifically, if a device runs outdated software (e.g., no updates are released by the manufacturer), then it could be an easier target for attackers. Considering that only a small portion of smartphones are running the latest software (Quintero et al., 2020), insurers should carefully consider the implications of using smartphones as telematics devices. This is especially important because driving data logs can be remotely manipulated on a compromised smartphone, which could lead to a higher rate of disputes. Moreover, malicious customers could manipulate the logs themselves (e.g., delete data for the period when they drove aggressively) in order to improve their score.

5.1 Recommendations

Based on the qualitative analysis of the feedback from our participants (see Sec. 4.1), we recommend insurers to work on improvements related to:

Car Sharing. If several family members use the same car, or if drivers change during a road trip, UBI should *provide a way to indicate who is currently driving the vehicle*. The data from our participants shows that such use cases are currently not handled well by their insurers. Note that the user experience must take into consideration the different types of telematics devices. While it is possible to link several smartphones to a car, or add a "user profiles" feature to a program that runs on a single smartphone, this is not an option when an embedded device is used for logging data, unless each person can somehow "check in" before they start driving.

Self-contained Systems that can evaluate the driving style without sharing data with third parties or sending it over a network would be a major step forward in addressing users' privacy concerns. Such systems would also address the "big picture" issue, because they provide fair scores even if not all vehicles on the road participate in UBI. This also applies to cases when no other vehicles are involved, e.g., a sudden braking maneuver to avoid a collision with an animal that crosses a street in a remote location. In such circumstances there is no nearby infrastructure that could provide recordings of the incident, nor are there other cars that could have caught it on their dashcam.

A "discard trip" feature could be an alternative stopgap measure until self-contained systems are available. A driver could remove a trip from their history if it involved an incident like the previously described maneuver to avoid an animal on the road. Insurance providers should also consider how this functionality could be abused by drivers who use it to hide their violations. This can be addressed in different ways, e.g., to limit the number of trips that can be discarded per month, or to incur a progressively larger penalty for each discarded trip, such that the accumulated penalty would exceed the penalty of an incident one attempts to conceal.

Participants' Culture should be taken into account at the moment of implementing UBI in a specific country. Our findings indicate that most participants are focused on saving money, which could be influenced by the cost of living in the country of residence, which might also influence acceptance of UBI.

Transparency. Providing users information about the different stages in UBI (e.g., data collection, storage, processing, etc.) could increase the transparency of driving data handling and score calculation (Quintero et al., 2020). Following the participants' preference about driving feedback, the insurers could provide this information by Email or smartphone app. UBI should provide clear information about how driving data are transformed into one's driving score.

5.2 Limitations

Our sample has a limited geographical distribution, as 91% of the participants come from the UK and 6% are from the USA, whereas the rest of the world adds up to less than 3%. We are therefore unable to observe variations in attitudes towards UBI that might be rooted in culture, or the way in which transport infrastructure is managed in specific countries. Considering that road design influences driving behaviour and leads to significant differences between countries in terms of traffic safety and the severity of accidents (Buehler and Pucher, 2017), we have reasons to believe that similar effects could apply to UBI and are worthy of examining in future work.

In addition, we had few participants experienced in UBI, most of them being potential users, rather than current or former ones. This is because the relative novelty of UBI makes it difficult to recruit participants with past experience.

6 RELATED WORKS

Aspects of UBI, such as acceptance, privacy, transparency and disadvantages have been discussed by researchers. In what follows, we summarize the findings of related literature.

After comparing several distance-based insurance programs, Litman (2007) concludes that these programs can be more beneficial for drivers and society than for insurers. He argues that drivers could get a lower premium by reducing the distance traveled, thus benefiting society (e.g., less pollution, fewer accidents, etc.).

However, others did not find significant effects on the mileage driven after using UBI for six months (Soleymanian et al., 2019). They also found that drivers improved their driving style during the observed period, but it is not clear whether this is a long-lasting effect.

Quintero et al. (2020) analyzed discussions in online communities of current and former users of UBI, and interviewed potential users. They found that drivers may identify their mistakes based on feedback, and thus drive more cautiously, hence reduce the frequency of accidents. In addition, insurers may have a more accurate risk estimation by analysing collected driving data.

The disadvantages of UBI discussed in literature are usually related to privacy concerns, discrimination, dangerous driving, lack of transparency (e.g., data usage, unclear evaluation criteria), and the investment costs for the insurer (Arvidsson et al., 2011; Derikx et al., 2016; Soleymanian et al., 2019; Quintero et al., 2020). For example, drivers could provoke dangerous situations while attempting to guess how the scoring works, due to lack of algorithmic transparency (Quintero et al., 2020). Discrimination can occur because most UBI programs to date target young drivers or people with little driving experience. Privacy concerns in UBI are related to the collection of drivers' location via GPS (Soleymanian et al., 2019; Quintero et al., 2020). Although some UBI programs do not use location to determine the driving score, several authors argued that privacy could be compromised by inferring locations through combinations of factors like: distance traveled, speed and time of driving, speed limits, start location or previous destinations (Dewri et al., 2013; Gao et al., 2014; Wahlström et al., 2016; Bellatti et al., 2017).

Some academic solutions have been designed to mitigate these privacy concerns, though at the time of this writing they are not yet implemented in practice. In particular, they attempt to solve the problem by performing all the calculations locally, and only sending aggregated data to the insurer (Händel et al., 2013; Iqbal and Lim, 2006; Troncoso et al., 2010).

Others examined the problem of UBI acceptance. Mayer finds that privacy concerns do not play a role, whereas the expected discount and hedonic motivation on driving are important acceptance factors (Mayer, 2012). Derikx et al. (2016) find that small financial rewards could motivate customers to share their driving data. Tian et al. (2020) conclude that perceived enjoyment and trust play an important role for some age groups.

7 CONCLUSIONS

We conducted an online survey with current, former, and potential users of UBI, analysing their responses through a qualitative and quantitative analysis.

The results indicate that privacy concerns arise if driving data are stored and shared. Given the choice, our participants would rather use self-sufficient UBI implementations that perform all the analysis locally and avoid sending data to the insurer or other parties.

We find that participants prioritize saving money over improving their driving style, when it comes to one's perception of UBI utility. It should be noted that no participants reported any actual savings they have made via UBI, nor do they know anyone who has. The issue is exacerbated by the lack of transparency of the scoring algorithms, which made some participants conclude that UBI is only meant to benefit insurers. Therefore, we consider that improving transparency should be a top priority, otherwise a growing share of users might be disappointed, thus reducing adoption.

Based on the results, we propose several recommendations for insurers, aimed at increasing UBI acceptance (see Section 5.1).

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