Prediction of attitudes towards human-centred cognitive vehicles aware of their users' routines and preferences

Ankit R. Patel[1], Flora Ferreira[2], Sergio Monteiro[3], Ana Carolina Silva[4], Wolfram Erlhagen[5] and Estela Bicho[6]

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Abstract— **Advances in the automotive industry are changing the relationship between cars and drivers. Advanced driver assistant systems, such as navigation systems, advanced cruise control, collision avoidance systems, and other safety systems, are now common and assist the driver in controlling the car. Smart key fobs have made getting in and starting the car almost effortless: the fob can be left in the pocket and the doors will unlock when a driver/user approaches the car and simply touches the door handle. This is a level of personalization and convenience that is almost standard today. The research presented here brings a new perspective on personalization and driver assistance systems. An online survey was conducted, which aimed to gather public opinion on the usefulness of endowing future (semi-)autonomous cars with social and cognitive behavior, such as the ability to learn drivers' routines and preferences in order to make decisions and perform actions in preparation for the next trip and to manage comfort within the cockpit without being commanded to do so. After filtering, the study included 657 respondents from 93 nations. The results demonstrate a favorable opinion towards such human-centered cognitive vehicles and could be helpful for designers in the automotive industry and other related stakeholders in the development of future cognitive vehicles.**

Index Terms— **Cognitive vehicles, Human-vehicle interaction, Personalization, Users' routines, Users' preferences**

I. Introduction

Advanced driver assistant systems (ADAS) have become more potent in recent years due to increasing computational power and various data-driven technologies. When the system has purely technology-driven dependency, there is no human touch and the power of reasoning is absent. Therefore, there is the risk that purely technology-driven developments will not fulfil the expectations of the end-user. In this connection, the need for research and development of personalized human-centered assistive systems is even more evident today. Importantly, if user expectations are not fully met by the assistive systems, there may be a decrease in trust between the two agents. Hence, a personalized human-vehicle interaction (HVI), which has the ability to make interactions more intuitive [1], [2] by means of cognitive capabilities (i.e., it learns user routines and preferences) is inevitable. A smart world also encompasses smart transportation systems, which comprises also smart/cognitive vehicles aware of their users' routines and preferences. Consequently, introducing cognitive abilities as a part of vehicle interaction ensures smooth and safe driving, and in doing so we can enhance the quality of life of vehicle occupants.

Human-centered assistive systems play a key role amid the current strong competition that is seeking to provide new ADAS features [3]–[5]. Indeed, users are more likely to have higher expectations from assistive systems, as they provide different features like alert systems [6], human motion recognition [7], human recognition [8], and assurance of safety on the road [9]. There are two main reason for this. First, digitization allows seamless connections between users and vehicles, and as a result, the relationship between a vehicle and its driver becomes stronger, more reliable, and personal. Second, users expect the experiences that they have with a vehicle to be as good as those they have with other smart devices.

One of the key concepts of ADAS is to provide interaction in a more personalized manner. Initially, this increases the trust between a driver and the vehicle, and it helps drivers to execute the decision-making process in any task they undertake. Of course, this could be achieved by making more accurate user-centric models and developing personalized interactions [10]. In recent years, all stakeholders have been interested in knowing user routines and preferences, as these will be helpful in introducing new assistive features in the coming years. By leveraging user routines [11], [12], it is possible to detect anomalies [13] and monitor the performance of the driver [14] and his/her behavior [15]. In normal daily life, we are not changing our preferences drastically, includes before starting of a trip, or even en route, and at the end of journey. This could lead to repetitive tasks (i.e., by means of learning) being performed within a vehicle.

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[1]Ankit R. Patel is a Ph.D. scholar with the Department of Industrial Electronics, ALGORITMI Research Center, University of Minho, Guimaraes, Portugal (Corresponding author: majorankit@gmail.com)

[2]Flora Ferreira is a Post-doctoral fellow with the Department of Mathematics, University of Minho, Guimaraes, Portugal (flora.ferreira@gmail.com)

[3]Sergio Monteiro is a Assistant Professor with the Department of Industrial Electronics, ALGORITMI Research Center, University of Minho, Guimaraes, Portugal (sergio@dei.uminho.pt)

[4]Ana Carolina Silva is a Software Developer Engineer, Bosch Car Multimédia Portugal, Braga, Portugal (anacarolina.silva2@pt.bosch.com)

[5]Wolfram Erlhagen is a Associate Professor with the Department of Mathematics, University of Minho, Guimaraes, Portugal (wolfram.erlhagen@math.uminho.pt)

[6]Estela Bicho is a Professor with the Department of Industrial Electronics, ALGORITMI Research Center, University of Minho, Guimaraes, Portugal (estela.bicho@dei.uminho.pt)

Clearly, preferences play a prominent role in the design of ADAS [16].

Prior works have shown that vehicles' cognitive capabilities have gained more attention from vehicle manufacturers and car users [17]–[19]. However, none provided clear investigation-based evidence to support this assertion. As far as is known, this is the first investigation of this subject area. Therefore, the results may be used as a reference for the development of future cognitive vehicles (CVs).

The remainder of this paper is organized as follows. The key objectives of the study are presented in Section II. Section III presents the method employed to conduct the survey and how data analysis was carried out. Detailed analysis of results is provided in Section IV, while Section V discusses the results and limitations of this paper. Finally, conclusions and future scope are given in Section VI.

II. Study objectives

The objective of this research was to gather public opinion on the expectation of endowing future (semi-)autonomous cars with social and cognitive behavior, such as the ability to learn drivers' routines and preferences in order to make decisions and perform actions in preparation for the (next) journey and to manage comfort within the cockpit without explicitly being commanded to do so.

Major demographic characteristics such as age group, gender, education, and occupation, and car driving experience information were used to ground the analysis of the responses and draw statistically significant results. The survey was intended to address some questions regarding drivers' acceptance of cognitive vehicles, with respect to the following use-cases:

Use case 1: Learning routines of different drivers with timestamps, and more specifically, where a driver intends to go next, when she/he intends to depart, when she/he expects to arrive at the destination, and how long she/he intends to stay at that destination.

Use Case 2: Anticipation of comfort inside the cockpit. Every driver has different seat positioning and mirror adjustment settings and a preferred temperature inside the cockpit that could be learned by a cognitive vehicle. The prediction of when the driver intends to depart (using Case 1) and the learned preferences could be used to create comfort inside the cockpit anticipatorily, thus saving time.

Use Case 3: Vehicle usage optimization after learning the routines of its different drivers (using Case 1). For example, the vehicle could propose the car's availability, when it is parked at a specific location, to another user/family member for a certain period of time.

Use Case 4: Vehicles' ability to avoid users making mistakes, such as forgetting objects when entering or exiting. As different users take different objects in and out of the vehicle at different times and destinations, the vehicle could learn these dynamics and alert the driver if they are about to forget an object.

III. Methods

A. Survey

A survey containing 27 questions (Table I and Fig. 1) was developed using the online tool QuestionPro (`www.eu.questionpro.com`) to explore solutions to the research question. From 5 August to 20 December 2020, participants were invited to complete this online survey via a link shared on various social media platforms, including Facebook, LinkedIn, and Twitter. University mailing lists were also used to reach out to academic and research-business-oriented communities.

Relevant information about CVs was provided to the respondents, along with consent and data assessment agreement. The survey consisted of the following essential parts:

1) First, an introduction with questions regarding socio-demographic profile. The survey also asked the respondents about their travel mode choices and trip information and their willingness to share their travel modes with family or non-family members.
2) There was a group of questions about their car driving experience and license-related information. This is important because a person with more driving experience can better understand the various driving-related functions alongside HVI and ADAS.
3) A group of questions (Q20-Q27) about specific expectations, which were developed using the five-point (1 = strongly disagree, 5 = strongly agree) Likert-scale with two parameters (first, useless to useful, and second, undesirable to desirable). As the manufacturing industry is looking for consumer-centric products, they inevitably need to satisfy the wishes and expectations of the customer through the vehicles' cognitive capabilities. These questions focus on providing viable solutions for CVs considering two key factors: user routines, and user preferences.

B. Data analysis

Data was analyzed with descriptive statistics, including frequencies and percentages. Bivariate analysis was conducted by performing Chi-square tests for independence to explore the relationship between the respondent's opinion on questions Q20-Q27 and the level of knowledge of HVI and ADAS. Kendall's Tau-c (tau_c) correlation coefficient was calculated to assess the strength of the relationship. The significance level was set at 0.05. The Statistical Package for Social Science (SPSS) software (version 26.0 for windows) was used for statistical analysis.

IV. Results

A. General data on respondents

In total, 657 valid responses (from 977 in total) were considered for technical analysis from 93 nations worldwide. The completion rate was 67.25%, and the average time to complete the survey was 6 minutes. The distribution of responses to questions Q1-Q19 is presented in Table I.

TABLE I

Frequency (and percentage) distributions for question 1 (Q1) to question 19 (Q19)

Question	Variable	Items-Responses n (%)
1	Continent-wise responses	Africa - 73 (11)
		Asia - 162 (25)
		Europe - 267 (41)
		Latin America - 54 (8)
		Oceania - 36 (5)
		North America - 65 (10)
2	Gender	Male - 372 (56.62)
		Female - 281 (42.77)
		Prefer not to say - 4 (0.61)
3	Age	18 to 24 - 119 (18.11)
		25 to 34 - 280 (42.63)
		35 to 44 - 151 (22.98)
		45 to 54 - 65 (9.89)
		>54 - 42 (6.39)
4	Education	Up to higher secondary - 10 (1.52)
		Bachelor degree - 128 (19.48)
		Master degree - 270 (41.10)
		Ph.D. - 241 (36.68)
		Other - 8 (1.22)
5	Employment	Full-time employed - 409 (62.26)
		Part-time employed - 46 (7.00)
		Unemployed - 38 (5.78)
		Retired - 6 (0.91)
		Student - 145 (22.07)
		Other - 13 (1.98)
6	Car driving experience	None - 96 (14.61)
		Less than 2 years - 83 (12.63)
		2 to 5 years - 95 (14.46)
		More than 5 years - 383 (58.30)
7	People live in a household (including you)	1 - 82 (12.48)
		2 - 130 (19.79)
		3 - 155 (23.59)
		4 or more - 290 (44.14)
8	People in a household have a car driving license (excluding you)	None - 87 (13.24)
		1 - 212 (32.27)
		2 - 211 (32.12)
		3 - 89 (13.55)
		4 or more - 58 (8.82)

Question	Variable	Items-Responses n (%)
9	Cars do you usually drive	None - 152 (23.14)
		1 - 333 (50.68)
		2 - 133 (20.24)
		More than 2 - 39 (5.94)
10	Cars drive in terms of possession	Private/household car - 551 (83.87)
		Car provided by company/organization - 23 (3.50)
		Other - 83 (12.63)
11	Main role in a car	As a driver - 466 (61.26)
		As a passenger - 191 (38.74)
12	Mode of transportation use in daily life	Private/household car - 439 (43.59)
		Company car - 30 (2.98)
		Taxi (e.g., Uber, Lyft, Ola, etc.) - 138 (13.70)
		Public transport (e.g., Bus, Train, etc.) - 308 (30.59)
		Other - 92 (9.14)
13	Average trips travel per day during workdays	None - 54 (8.22)
		1 to 5 - 557 (84.78)
		6 to 10 - 31 (4.72)
		More than 10 - 15 (2.28)
14	Average trips travel per day during weekends	None - 51 (7.76)
		1 to 5 - 559 (85.08)
		6 to 10 - 38 (5.79)
		More than 10 - 9 (1.37)
15	Ride-sharing within family members	Most of the times - 265 (40.33)
		Occasionally - 290 (44.14)
		Never - 102 (15.53)
16	Car-sharing within family members	Most of the times - 291 (44.29)
		Occasionally - 204 (31.05)
		Never - 162 (24.66)
17	Car-sharing outside family members	Most of the times - 120 (18.26)
		Occasionally - 252 (38.36)
		Never - 285 (43.38)
18	Knowledge of Human-Vehicle Interaction (HVI)	Very familiar with - 167 (25.42)
		Somewhat familiar with - 298 (45.36)
		Not familiar with - 192 (29.22)
19	Knowledge of Advanced Driver Assistance Systems (ADAS)	Very familiar with - 380 (57.83)
		Somewhat familiar with - 202 (30.75)
		Not familiar with - 75 (11.42)

TABLE II

Results of analyses using the Chi-square tests for independence and Kendall's τ correlation regarding the relationship of respondent's opinion and their level of knowledge about HVI and ADAS

Question		Knowledge of Human-Vehicle Interaction (HVI) (low/medium/high)				Knowledge of Advanced Driver Assistance Systems (ADAS) (low/medium/high)			
		Chi-square		Kendall's τ_c correlation		Chi-square		Kendall's τ_c correlation	
		$\chi^2(df)$	p	τ_c	p	$\chi^2(df)$	p	τ_c	p
Q20	Useless to Useful	14.71(8)	0.065	0.082	0.022	73.41 (8)	<**0.001**	0.257	<**0.001**
	Undesirable to Desirable	7.33(8)	0.502	0.083	0.019	83.34 (8)	<**0.001**	0.283	<**0.001**
Q21	Useless to Useful	16.99(8)	**0.030**	0.101	**0.004**	64.89 (8)	<**0.001**	0.251	<**0.001**
	Undesirable to Desirable	16.07(8)	**0.041**	0.112	**0.001**	75.47 (8)	<**0.001**	0.264	<**0.001**
Q22	Useless to Useful	11.19 (8)	0.191	0.080	0.026	62.01 (8)	<**0.001**	0.204	<**0.001**
	Undesirable to Desirable	9.76(8)	0.283	0.071	0.049	55.32 (8)	<**0.001**	0.208	<**0.001**
Q23	Useless to Useful	14.90 (8)	0.061	0.087	0.015	68.97 (8)	<**0.001**	0.182	<**0.001**
	Undesirable to Desirable	14.91 (8)	0.061	0.065	0.070	61.90 (8)	<**0.001**	0.174	<**0.001**
Q24	Useless to Useful	8.46 (8)	0.390	0.052	0.139	33.48 (8)	<**0.001**	0.185	<**0.001**
	Undesirable to Desirable	11.35 (8)	0.183	0.045	0.200	38.82 (8)	<**0.001**	0.198	<**0.001**
Q25	Useless to Useful	9.01 (8)	0.342	0.077	0.025	36.64 (8)	<**0.001**	0.140	<**0.001**
	Undesirable to Desirable	14.83 (8)	0.063	0.077	0.026	40.69 (8)	<**0.001**	0.156	<**0.001**
Q26	Useless to Useful	24.89 (8)	**0.002**	0.054	0.142	34.87 (8)	<**0.001**	0.156	<**0.001**
	Undesirable to Desirable	25.51 (8)	**0.001**	0.043	0.255	32.08 (8)	<**0.001**	0.150	<**0.001**
Q27	Useless to Useful	8.21 (8)	0.413	0.058	0.108	43.29 (8)	<**0.001**	0.181	<**0.001**
	Undesirable to Desirable	5.55 (8)	0.697	0.038	0.280	36.90 (8)	<**0.001**	0.188	<**0.001**

χ^2: Chi-square statistics, df:degrees of freedom, p: level of statistical significance, τ_c: Kendall's τ_c correlation.

Apart from the socio-demographic characteristics of the respondents (including age and gender), other information was collected that may be helpful in future studies. Most respondents (around 85%) made an average of one to five trips per day on workdays and during the weekends. About 84% of respondents share a vehicle for journeys with family members most of the time or occasionally. A high percentage of respondents (about 75%) answered that family members share family-owned cars with other family members most of the time or occasionally. This percentage decreased to about 57% when asked about their willingness to share their own vehicle with other users.

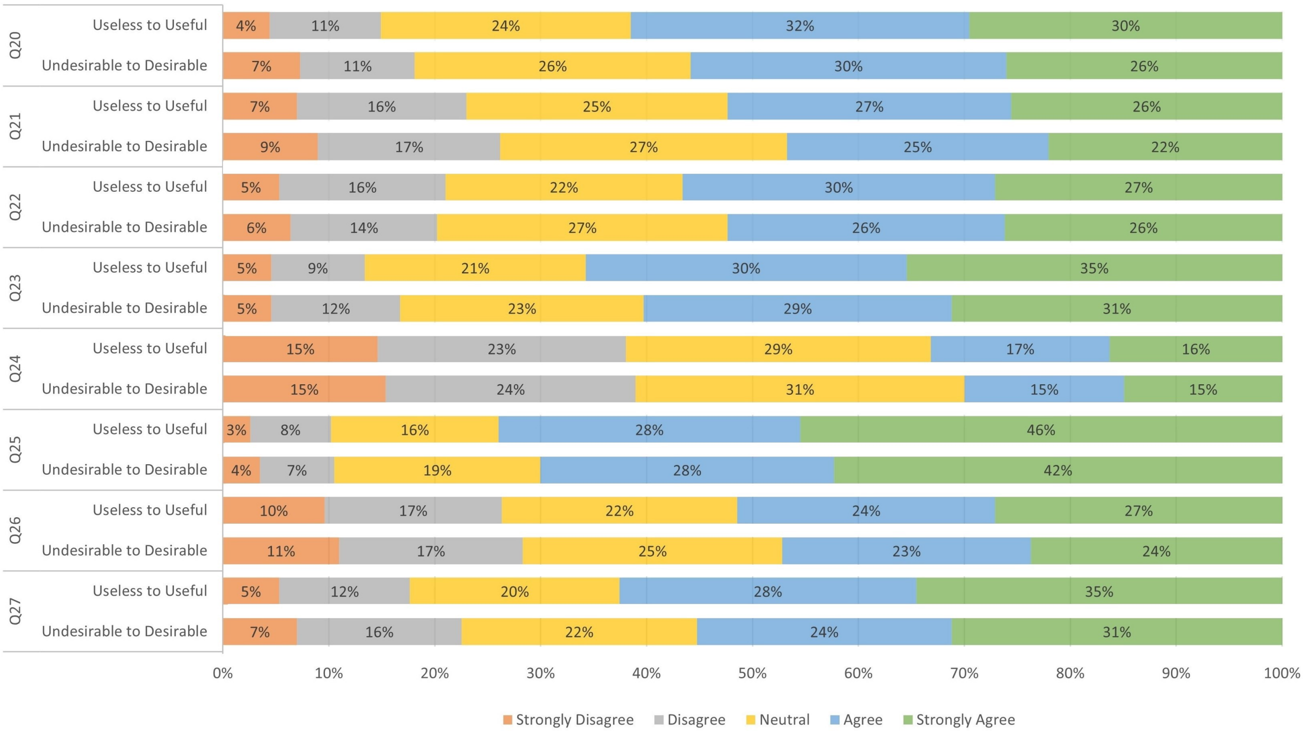

Fig. 1. The respondent's opinion on features of the cognitive vehicles

Q20: Predict when you want to depart/go to a certain destination and accordingly prepare the trip.
Q21: Learn the timestamps of your routine and predict your next destination, pre and during the trip, for both single-user and collaborative scenarios.
Q22: Learn the timestamps of your routine and automatically set the appropriate temperature inside the cockpit before it expects you to leave to your next destination.
Q23: Learn the timestamps of your routine and defrost the windows/windshield when needed before it expects you to leave to your next destination.
Q24: Remind you about your expected daily/regular passengers.
Q25: Learn the driving habits (seat position, mirror adjustment) of its different drivers and automatically change these settings according to the next expected driver.
Q26: Learn the time slots and locations when the car is parked (i.e. not in use), and hence, remind you that other potential drivers can use it.
Q27: Learn and remind the users about their daily items/objects to be carried, dropped, or forgotten (e.g. laptop, wallet, purse, school bag, gymnasium sack, etc).

B. Respondents' expectations

The percentage distribution of responses to questions Q20-Q27 is presented in Fig. 1. Except for Q24, more than half of the respondents agreed or strongly agreed that the referenced features in CVs are useful. These percentage are slightly lower when asked in terms of desirability. However, more than 47% of respondents agreed or strongly agreed that the features mentioned are also desirable. In particular, most respondents (more than 70%) found the idea of having a vehicle that learns their driving preferences (seat position, mirror adjustment) and automatically adjusts these settings, in anticipation of the next driver, to be useful and desirable (i.e., agree or strongly agree with the statement, Q25). The idea of having a vehicle that reminds the driver about their daily expected regular passengers (Q24) was found less useful and desirable by the respondents (33% and 30% agree or strongly agree, and 29% and 31% were neutral in terms of usefulness and desirability, respectively).

C. Relationship of respondent's opinion and their level of knowledge of HVI and ADAS

The analysis of the Chi-square tests for independence showed that the respondent's opinions on Q21 and Q26 were significantly related to their level of knowledge of HVI (Table II). Additionally, using the analysis of Kendall's Tau-c correlation, a significant and positive correlation was found only between respondent's opinions on Q21 and the level of knowledge of HVI ($\tau_c = 0.112, p = 0.001$ and $\tau_c = 0.101, p = 0.004$). However, there is evidence of a relationship between the knowledge of ADAS and respondent's opinions on all questions (Table II). A moderate positive correlation ($0.14 < \tau_c < 0.29, p < 0.001$) was found in all cases.

V. Discussion

The study aimed to analyze how to assist the drivers considering their daily routines and preferences in cognitive vehicles. The respondent's opinions support the idea that customers are interested in a vehicle with the capability of learning their routines and, based on that, predict their next destination. Previous studies advocated that occupants are looking for a scope in which their vehicle will predict the next destination through persons' intention sitting inside the cockpit [20], and on pre-trip and enroute information [21]–[24] is highly desirable to choose their future mobility plans. Furthermore, there is enough evidence to suggest that the level of comfort decides the acceptance of AVs [25]. Indeed, in the coming years, comfort level defined by the preferences of the users, and design of a vehicle or how a vehicle provides the necessary information to its occupants when necessary. Think how appealing it would be if, based upon daily routines, a vehicle sets the appropriate temperature of the vehicle. More than half of the respondents found the possibility of having a vehicle able to set the appropriate temperature automatically useful and desirable. Likewise, more than 50% of the participants believe that it would be helpful if the vehicle defrosts the windshield before it expects to leave for the next destination. There are previous studies on defrosting the windows [26], [27], yet no provision for learning user's timestamps. A perfect seat position setting is one of the preferred factors for a safe and comfortable ride [28]. In recent years, facial recognition-based seat adjustment techniques [29], and mirror adjustment through driver's pupil [30] were studied. From the participants' opinions, it is also highly desirable to include adjusting the seat position and mirror according to the next expected driver.

User routines are one of the critical moderating variables for choice-based decisions. There is evidence showing that routines are a sequence of actions through which we can predict future actions [12]. The outcome of the survey provides impetus to developing features like the reminder about items to be carried, dropped, or that may be forgotten. Some recent works on child-like object detection [31], and in-vehicle object and occupancy detection [32], [33] have given significant endorsement to the proposed feature. In particular, this is a substantial habitual change, as in their current busy lives, people often accidentally leave items inside the vehicle or forget to put items into the vehicle before starts the journey.

We have witnessed during the past years that the growth of car-sharing is exponential worldwide as the cost of owning a private car is becoming increasingly expensive [34]. One of the main benefits of car-sharing is to give drivers a choice to drive different types of vehicles. Moreover, car-sharing would reduce the number of vehicles on the road if a significant number of users give up vehicle ownership [35]. There are many studies on car-sharing, including the choices for car-sharing considering consumer's cultural behavior [36]; a driver's willingness to share a car [37]; booking a vehicle through GSM or SMS [38]; car-sharing on a rental basis [39]; and blockchain technology-based methods [40]. However, user's routine-based car-sharing methods have not been found so far. Findings from the survey showed that people already have a habit of sharing the car with family members and, despite being less often, with other persons. Furthermore, more than 47% of respondents found it useful and desirable to have a vehicle that reminds them when other potential drivers can use the car according to time slots and locations where the car is parked.

In general, the level of knowledge and experience with technology has been associated with greater acceptance of AVs [15], [17]. In this study, significant positive associations between the level of knowledge of ADAS and the respondent's opinion concerning the referred possible abilities of the CVs (Q20-Q27) were found. These findings suggest that the level of knowledge of ADAS may influence the acceptance of AVs and CVs.

Besides the qualitative and quantitative analyses of the results, this survey has some limitations due to its online nature. First, the sample profile is not representative of the total population, as 97% of respondents have a minimum graduate degree. Second, as the cognitive vehicle-based technology is in the initial phase of development, respondents did not physically interact with the mentioned features, which may bias results.

VI. Conclusions

Broadly, respondents revealed an overwhelmingly positive attitude towards the possibility of having a cognitive vehicle that learns their daily routines (e.g., usual destination, routine timestamps, regular driver and passengers, and their items). Then, depending upon the preferences of the driver and occupants, the cognitive vehicle performs appropriate actions to assist the driver (e.g., prepares the trip, reminds them about a possible forgotten passenger or object, and adjusts seat position and mirrors according to the next expected driver). Moreover, the results give some evidence that the higher the level of knowledge of ADAS, the higher the probability of the respondents having the opinion that the CVs' abilities are desirable and useful. The results give a relevant view of user expectations and needs that are useful for all stakeholders involved in developing future CVs.

This research raises several interesting avenues for further research. First, to develop a prototype based on the presented features of CVs. Second, to go for a simulator-based studies for further investigation into each feature. This will provide a better understanding from the human perspective towards such features. Third, it would be important to check the co-existence of a developed prototype and simulator-based results in real-time, i.e., on-road experiments.

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