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Cognitive Management Techniques for
Increasing the Acceptance of Autonomous Vehicles

Doctor of Philosophy Dissertation

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ΧΑΡΟΚΟΠΕΙΟ ΠΑΝΕΠΙΣΤΗΜΙΟ
ΣΧΟΛΗ ΨΗΦΙΑΚΗΣ ΤΕΧΝΟΛΟΓΙΑΣ
ΤΜΗΜΑ ΠΛΗΡΟΦΟΡΙΚΗΣ ΚΑΙ ΤΗΛΕΜΑΤΙΚΗΣ

Γνωσιακές Τεχνικές Διαχείρισης για την Αύξηση της Αποδοχής των Αυτόνομων Οχημάτων

Διδακτορική Διατριβή

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1) Είμαι ο κάτοχος των πνευματικών δικαιωμάτων της πρωτότυπης αυτής εργασίας και από όσο γνωρίζω η εργασία μου δε συκοφαντεί πρόσωπα, ούτε προσβάλει τα πνευματικά δικαιώματα τρίτων.

2) Αποδέχομαι ότι η ΒΚΠ μπορεί, χωρίς να αλλάξει το περιεχόμενο της εργασίας μου, να τη διαθέσει σε ηλεκτρονική μορφή μέσα από τη ψηφιακή Βιβλιοθήκη της, να την αντιγράψει σε οποιοδήποτε μέσο ή/και σε οποιοδήποτε μορφότυπο, καθώς και να κρατά περισσότερα από ένα αντίγραφα για λόγους συντήρησης και ασφάλειας.

Dedicated to

my wife, Christina-Athanasia

my children, Vivian and Panagioti-Efthimio

and my parents…

Στη σύζυγο μου, Χρηστίνα-Αθανασία

στα παιδιά μου, Βίβιαν και Παναγιώτη-Ευθύμιο

και στους γονείς μου…

"To build truly intelligent machines, teach them cause and effect"

Judea Pearl

GREETINGS

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Με τιμή,

Ηλίας Ευθ. Παναγιωτόπουλος

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ABSTRACT

Autonomous driving holds great promise to provide safe and sustainable transport. With particular interest, the international scientific community, markets and societies are monitoring the gradual integration of intelligent computerized and technologically supported driving systems with the ultimate goal of producing Autonomous Vehicles (AVs) in the future. AVs are expected to be one of the most up-to-date applications of artificial intelligence, cognitive computing and machine learning, creating a new era in on-road transport mobility, being able to operate their driving system in different levels of autonomy, but can be even driven manually when desired or when used outside the design domain of the automation.

However, the production of advanced technology has raised concerns over the risks and safety issues concerning AVs which can consequently affect public perceptions of such an "untested" and "powerful" innovation technology. As such, the scope of the present Ph.D. thesis is to increase the acceptance of AVs, by designing feasible, viable, and reliable technical solutions, through the co-existence of cognitive management principles and machine learning algorithms.

Following this direction, in order to have a deep understanding of consumers' intensions towards AVs, two appropriate theoretical models, which draw from the original well-established frameworks – Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) – were developed. The above conceptual models were tested through web-based questionnaire surveys. The results reveal that, among other factors, enjoyment of driving, trust/reliability, and performance expectancy play significant roles in shaping consumers' intentions towards AVs.

Upon the results from the aforementioned user acceptance analysis, the present research develops innovative technical solutions as follows: **(a)** a novel communication

protocol for enhancing the efficiency of vehicular communications, and therefore, increasing the acceptance of AVs in terms of the security and data privacy factors, **(b)** two novel in-vehicle intelligent platforms, through the co-existence of cognitive management principles and machine learning algorithms, for enhancing the efficiency of autonomous driving, and therefore, increasing the acceptance of AVs in terms of the road safety and driving experience factors. The proposed technical analysis aims to provide targeted assistance to drivers/users, which can increasingly change public perceptions regarding AVs, and therefore, enhance the end-user acceptance of such vehicles.

Keywords: Autonomous vehicles, cognitive management techniques, machine learning algorithms, technology acceptance, vehicular communications

ΠΕΡΙΛΗΨΗ

Η αυτόνομη οδήγηση δίνει μεγάλες υποσχέσεις για ασφαλείς και βιώσιμες μετακινήσεις. Με ιδιαίτερο ενδιαφέρον, η διεθνής επιστημονική κοινότητα, οι αγορές και οι κοινωνίες παρακολουθούν τη σταδιακή ενσωμάτωση έξυπνων, αυτοματοποιημένων και τεχνολογικά υποστηριζόμενων συστημάτων οδήγησης στα αυτοκίνητα με απώτερο σκοπό την παραγωγή αυτόνομων οχημάτων στο μέλλον. Τα εν λόγω οχήματα αναμένεται να αποτελέσουν μία από τις πιο σύγχρονες εφαρμογές της τεχνητής νοημοσύνης, της γνωσιακής πληροφορικής και της μηχανικής μάθησης, δημιουργώντας νέα εποχή στις οδικές μεταφορές και μετακινήσεις, ικανά στο να μπορεί το σύστημα οδήγησής τους να λειτουργεί σε διαφορετικά επίπεδα αυτονομίας, αλλά παράλληλα να μπορούν ακόμη και να οδηγούνται με τον κλασσικό-παραδοσιακό τρόπο όταν αυτό είναι επιθυμητό ή όταν πρόκειται να χρησιμοποιηθούν εκτός του πλαισίου επιχειρησιακής λειτουργίας της αυτόνομης οδήγησης.

Ωστόσο, η παραγωγή προηγμένης τεχνολογίας έχει εγείρει ανησυχίες σχετικά με τους κινδύνους και τα ζητήματα ασφάλειας που αφορούν τα αυτόνομα οχήματα, τα οποία μπορούν να επηρεάσουν τις αντιλήψεις του κοινού για μια τέτοια «μη δοκιμασμένη» και «ισχυρή» τεχνολογική καινοτομία. Ως εκ τούτου, ο σκοπός της παρούσας διδακτορικής διατριβής είναι η αύξηση της αποδοχής των αυτόνομων οχημάτων, σχεδιάζοντας εφικτές, βιώσιμες και αξιόπιστες τεχνικές λύσεις, μέσω της συνύπαρξης των αρχών γνωσιακής διαχείρισης και αλγορίθμων μηχανικής μάθησης.

Βάσει των ανωτέρω, προκειμένου να κατανοήσουμε εις βάθος τις προθέσεις των καταναλωτών ως προς τα αυτόνομα οχήματα, αναπτύχθηκαν δύο κατάλληλα θεωρητικά μοντέλα, τα οποία προκύπτουν από τα βασικά καθιερωμένα πλαίσια – μοντέλο τεχνολογικής αποδοχής (TAM) και ενοποιημένη θεωρία της αποδοχής και χρήσης της τεχνολογίας (UTAUT). Τα ανωτέρω εννοιολογικά μοντέλα δοκιμάστηκαν μέσω διαδικτυακών ερευνών. Τα αποτελέσματα αποκαλύπτουν ότι, μεταξύ άλλων παραγόντων, η ευχαρίστηση της οδήγησης, η εμπιστοσύνη/αξιοπιστία και η

προσδοκία απόδοσης διαδραματίζουν σημαντικό ρόλο στη διαμόρφωση των προθέσεων των καταναλωτών έναντι των αυτόνομων οχημάτων.

Σε συνέχεια των αποτελεσμάτων της προαναφερθείσας ανάλυσης αποδοχής των χρηστών, η παρούσα έρευνα αναπτύσσει καινοτόμες τεχνικές λύσεις σύμφωνα με τα ακόλουθα: **(α)** ένα νέο πρωτόκολλο επικοινωνίας για τη βελτίωση της αποτελεσματικότητας των επικοινωνιών μεταξύ οχημάτων και, ως εκ τούτου, την αύξηση της αποδοχής των αυτόνομων οχημάτων ως προς τους παράγοντες ασφάλεια και προστασία δεδομένων, **(β)** δύο νέες έξυπνες πλατφόρμες εντός του οχήματος, μέσω της συνύπαρξης των αρχών γνωσιακής διαχείρισης και αλγορίθμων μηχανικής μάθησης, για τη βελτίωση της αποτελεσματικότητας της αυτόνομης οδήγησης και, ως εκ τούτου, την αύξηση της αποδοχής των αυτόνομων οχημάτων ως προς τους παράγοντες οδική ασφάλεια και οδηγική εμπειρία. Η προτεινόμενη τεχνική ανάλυση έχει ως σκοπό το να παρέχει στοχευμένη υποστήριξη στους οδηγούς/χρήστες, η οποία μπορεί όλο και περισσότερο να μεταβάλλει τις αντιλήψεις του κοινού σχετικά με τα αυτόνομα οχήματα, και, συνεπώς, να ενισχύσει την αποδοχή τους από τους τελικούς χρήστες.

Λέξεις κλειδιά: Αλγόριθμοι μηχανικής εκμάθησης, αποδοχή τεχνολογίας, αυτόνομα οχήματα, επικοινωνίες οχημάτων, τεχνικές γνωσιακής διαχείρισης

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ACRONYMS

AD	Autonomous Driving
ADAS	Advanced Driver Assistance Systems
AI	Artificial Intelligence
ARTS	Automated Road Transport Systems
AV	Autonomous Vehicle
BNs	Bayesian Networks
CMSs	Cognitive Management Systems
CPD	Conditional Probability Distribution
CPTs	Conditional Probability Tables
CTA	Central Trusted Authority
DAG	Directed Acyclic Graph
DHKAS	Diffie-Hellman Key Agreement Scheme
DSRC	Dedicated Short Range Communication
e.g.	for example
ECAS	Eco-friendly, Connected, Autonomous, Shared
EE	Effort Expectancy
FC	Facilitating Conditions
GKe	Group Key
GPS	Global Positioning System
H	hypothesis
i.e.	that is
i-ALS	intelligent-Autonomous Level Selection
ICTs	Information and Communication Technologies
i-M	intelligent-Music
IoT	Internet of Things
IoV	Internet of Vehicles
IT	Information Technology
ITSs	Intelligent Transportation Systems
IU	Infrastructure Unit
IVI	In-Vehicle Infotainment

LoA	Level of Autonomy
MG	Music Genre
ML	Machine Learning
NB	Naïve-Bayes
OBU	On-Board Unit
PDE	Perceived Driving Enjoyment
PE	Performance Expectancy
PEU	Perceived Ease of Use
PFC	Perceived Financial Cost
PID	Pseudo IDentity
PRT	Perceived Reliability/Trust
PU	Perceived Usefulness
Q	Question
SI	Social Influence
TAM	Technology Acceptance Model
TID	True IDentity
TPM	Trusted Platform Module
UTAUT	Unified Theory of Acceptance and Use of Technology
V2E	Vehicle-to-Everything
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VCs	Vehicular Communications

FOREWORD

Road accidents are one of the leading causes of death worldwide. According to the World Health Organization (WHO), more than 1.2 million are killed in road accidents worldwide annually, while road accidents constitutes the main cause of death for young people aged 15-29 years old. The introduction of newer and innovative methodologies and investments in on-road transport mobility, from regional to international levels, is very crucial to stop this avoidable and horrendous rise in road injuries, and initiate year on year reductions.

In the light of the above, the last two decades have witnessed a huge growth in research and development of Advanced Driver Assistance Systems (ADAS) by automotive and other related companies, like adaptive cruise control, lane parking, steer assist, etc. Moreover, the individual and social demands for a safe, convenient, efficient, and eco-friendly transportation are pushing to fundamental changes in the on-road transport mobility field. In this respect, there will be a paradigm shift towards what is known as ECAS (Eco-friendly, Connected, Autonomous, Shared) technology.

Following this trend, Autonomous Vehicles (AVs) and artificial intelligence (AI) are attracting much attention from the industry, academia, and government in staging the new generation of on-road transport mobility. Future AVs could sense their local environment, could classify different kinds of objects that they detect, and could interpret sensory information to identify appropriate navigation paths. In addition, each AV is transformed into a four-wheel-drive living space where driver or/and passengers can feel safe and secure. A place where driver or/and passengers can relax, through discussion, interaction and entertainment, according to their needs and moods, leading to an active driving experience. Moreover, in the future, drivers/users will be able to choose according to their moods whether they drive their own cars or rely on Autonomous Driving (AD).

In the field of road safety, traffic collisions are expected to be drastically decreased, due to a driving automated system's increased reliability and faster reaction time compared to humans. This would also reduce traffic congestion, and thus increase roadway capacity since AVs would lead to a reduced need of safety gaps and better traffic flow management. Parking scarcity will become a historic phenomenon with the advent of AVs, as cars could drop off passengers, and park at any suitable space, and then return back to pick up the passengers. Thus, there would be a reduction in parking space. The need of physical road signage will decrease, as AVs will receive necessary information through networks. There would be also a reduction in the need of traffic police. Thus, AVs can reduce government spending on things like traffic police. The need for vehicle insurance will also decrease, along with a decrease in the incidents of car theft. Efficient car sharing and goods transport systems (as in case of taxis and trucks respectively) can be implemented, with total elimination of redundant passengers. Not everyone is suitable driving, so, AVs provide a relief from driving and navigation chores. With the benefit of free time, the driver will also be free to engage in non-driving related tasks such as relaxing, reading or working.

However, besides the numerous advantages with regard to AVs, there is a wide spectrum of challenges, social dilemmas and complicated human factors issues that have raised concerns over the risks and safety issues concerning AVs and AI, which can consequently affect public perceptions of such an "untested" and "powerful" innovative mobility technology. In this direction, it is believed that an advent of AVs would lead to a decrease of driving-related jobs. Also, situations like inability and inexperience of drivers/users to regain control of their cars, when they are to be used outside the design domain of the automation, are an important challenge. Moreover, lots of people love driving, and it would be difficult for them to forfeit control of their cars. AVs also pose challenges interacting with human-driven vehicles on the same route. Another challenge to AVs is that who is to be held liable for damage: the car manufacturing company, the car’s occupants/owner, or the government. Thus, implementation of a legal framework and establishment of government regulations for AVs is a major problem. Software reliability is also a major issue. Also, there is a risk of a car's computer or communication system being potentially compromised. There is a risk of an increase in terrorist and criminal activities, and therefore, AVs could potentially be loaded with explosives by terrorist organizations and miscreants. They could also be used as getaway vehicles and various other criminal activities.

Thus, AVs have both pros and cons. Therefore, forecasting technology usage and acceptance by the end users becomes fundamental in order to understand aspects that are likely to minimize consumer resistance and maximize adoption of driving/using AVs. In this respect, the automotive industry still lacks widely accepted and used frameworks to assess technology acceptance towards AVs.

In addition, AVs, which will operate in complex dynamic environments, require methods and techniques that generalize to unpredictable situations and reason in a timely manner in order to reach human-level reliability and react safely even in complex urban situations. To carry out successful and useful driving decisions, a variety of technologies from different disciplines that span AI, cognitive computing, mechanical engineering, electronics engineering, electrical engineering, and control engineering, should be combined. Furthermore, following the advances in internet connection technologies and vehicular networks, reliable cooperative approaches between AVs, as well as between AVs and roadside infrastructure units, where information would be shared, are crucial factors towards security protection and data privacy concerns.

With the ever-increasing popularity of machine learning techniques, complex planning and decision-making methods, and secure communication protocols for vehicular interactions, verification and guaranteed performance of the autonomous driving pipeline have become challenges still to be addressed. In that framework, on-board cognitive management techniques should be applied in AVs for enhancing the road safety, driving experience and quality of driving. As such, in-vehicle intelligent technologies provide comprehensive and at the same time targeted assistance, which can increasingly change public perceptions regarding AVs to one of interest rather than one of fear, and therefore, enhance the end-user acceptance of such vehicles.

CHAPTER 1: INTRODUCTION

Contents

1.1 Motivation and challenges

In recent years the automotive industry has seen a massive influx of new technologies being used and embedded in everyday cars. These technologies either originate from other safety critical areas, e.g. aerospace, or share significant functional characteristics with other so-called high-tech industries, e.g. robotics and artificial intelligence (AI). However, whereas the design of new products in other industries or the scaling up to reach the end user/consumer has been happening at rather low pace, i.e., a commercial aircraft requires ~10 years from conceptualization to production, the automotive world is changing extremely quickly, almost at the same pace as consumer electronics (Litman, 2017).

Over the last two decades there have been technological developments which have facilitated the gradual incorporation of various Advanced Driver Assistance Systems (ADAS) by automotive and other related companies, like adaptive cruise control, lane parking, steer assist, etc. Moreover, the individual and social demands for a safe, convenient, efficient, and eco-friendly transportation are pushing to fundamental changes in the on-road transport mobility field. In this respect, there will be a paradigm shift towards what is known as ECAS (Eco-friendly, Connected, Autonomous, Shared) technology (see Fig. 1.1).

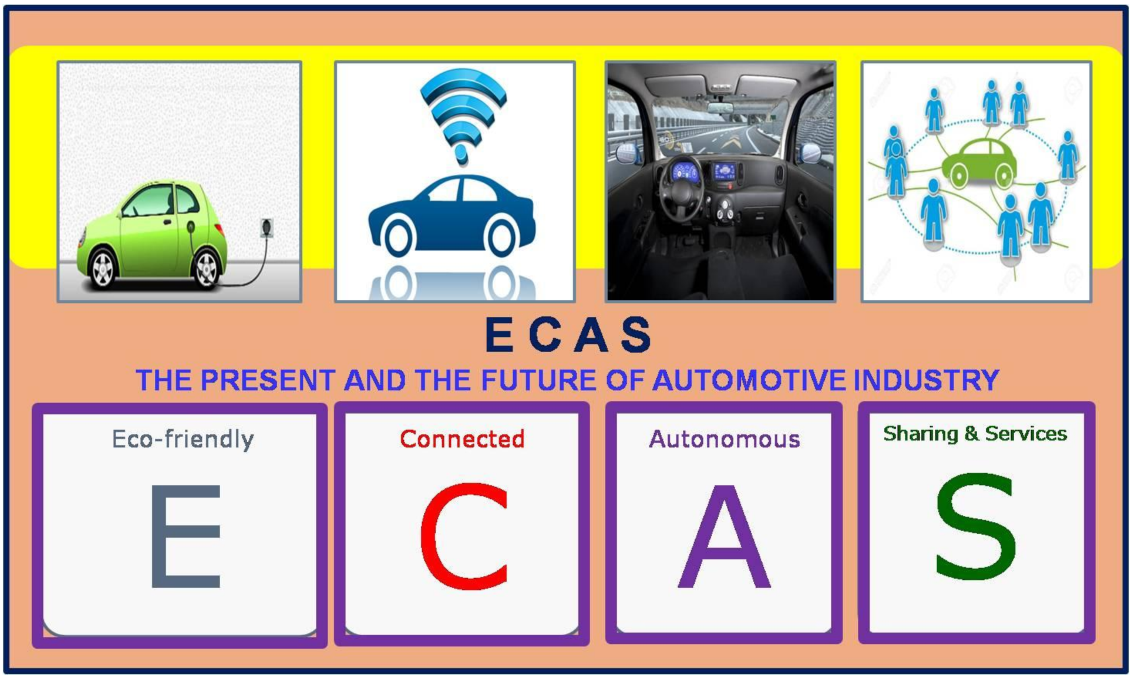


Fig. 1.1 ECAS (Eco-friendly, Connected, Autonomous, Shared) technology.

With particular interest, the international scientific community, markets and societies are monitoring the gradual integration of intelligent computerized and technologically supported driving systems with the ultimate goal of producing Autonomous Vehicles (AVs) in the future (Fagnant & Kockelman, 2015). AVs are expected to provide an alternative type of on-road transport mobility. In contrast to fully automated driving, where the human is only a passenger and the driving automation system is capable of executing all the elements of the dynamic driving task in all roadway and environmental conditions, in highly automated driving a high percentage of the driving can be performed by the embedded driving automation system, but the human is still a driver who is in control of the AV (see Fig. 1.2). Therefore, AV has the technical capabilities that it could drive fully automated, but this capability is used in certain roadway and environmental conditions, and therefore the driver/user is always meaningfully involved in the driving task.

As over 90% of road accidents come from human errors, AVs hold much promise to significantly reduce the number of traffic collisions, dead and injured drivers/users, and damage to the environment, as they could have faster reaction times and are fatigueproof in their functioning. Besides road safety and traffic congestion, AVs are expected to positively affect further social costs, like energy consumption, people's mobility, comfort and convenience for drivers/users (Piao et al., 2016). However, besides the aforementioned societal benefits, researches on the predictors influencing individuals' attitudes and willingness to adopt AVs in the future are crucial requirements for their successful diffusion in international market the next years.

Fig. 1.2 Road view inside an autonomous vehicle (AV), ***source: www.google.com*****.**

Moreover, following the advances in internet connection technologies and vehicular networks, it would be possible to adopt a cooperative approach between vehicles, as well as between vehicles and roadside infrastructure units, where information would be shared in peer-to-peer networks for enhancing transportation efficiency (see Fig. 1.3). The above cooperative applications bring the promise of improved road safety and optimized road traffic. For the successful deployment of Vehicular Communications (VCs) it is essential to make sure that "life-critical safety" information cannot be modified by external or internal within the network attackers. In this basis lack of such security and privacy in VCs is one of the key hindrances to the wide spread implementations of AVs (Papadoulis et al., 2019).

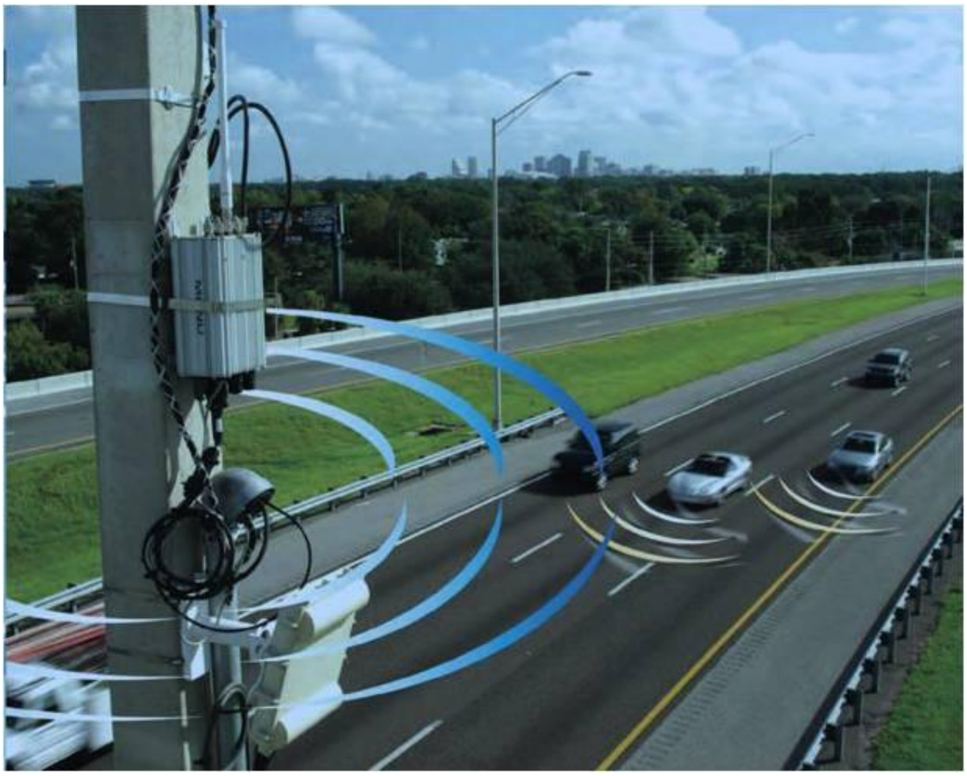


Fig. 1.3 Vehicular communications for enhancing transportation efficiency, *source: www.google.com*.

Fig. 1.4 On-board intelligent system ACC (Adaptive Cruise Control), *source: www.google.com*.

In addition, on-board intelligent systems are constantly integrated in vehicles for enhancing the driving experience and quality of driving (see Fig. 1.4). As driving decisions are time-sensitive, a variety of technologies from different disciplines that span computer science, mechanical engineering, electronics engineering, electrical engineering, and control engineering, etc. should be combined (Chen et al., 2019).

Based on the above, the Ph.D.'s motivation is justified as follows:

a) Besides the numerous advantages with regard to vehicle automation technologies, there is a wide spectrum of challenges, social dilemmas and complicated human factors issues that may arise from such an "untested" and "powerful" innovation technology. In this respect, many consumers are reluctant to drive/use AVs for a multitude of reasons; some do not trust them to be safe, secure or private, others avoid them because of social pressure and some consumers have trouble accepting them simply because they enjoy manual driving. These concerns can be critical obstacles to the market adoption and diffusion of AVs influencing consumers' intention to purchase and drive/use them. As such, more research efforts should be done in order to investigate in what extent consumers intend to drive/use AVs in the future and identify the main reasons for adapting or not adapting them for their travel activities.

b) Besides the benefits of vehicular networks, the computerization of AVs makes them prone to cyber attacks that can endanger the safety and data privacy of users (drivers and passengers). In this respect, VCs must be authenticated and authorized in order to keep unauthorized vehicles away from getting access to particular applications, services or privileges. Therefore, novel mechanisms to guarantee the primary security requirements, such as authentication, integrity, and non-repudiation needs to be developed before vehicular networks can be practically used for reliable VCs. Such mechanisms aim to increase the acceptance of AVs regarding trust/reliability focusing on security and data privacy issues.

c) Despite the establishment of extensive use of Information and Communication Technologies (ICTs) inside vehicles, automotive industry has been lately experiencing a trend towards the Intelligent Transport Systems (ITS) and intelligent In-Vehicle Infotainment (IVI) systems, which envisage cognitive management techniques in conjunction with machine learning algorithms. Such functionalities aim to attribute AVs with intelligence after gathering the necessary information from the environment through sensors and VCs. As such, the importance of investigating the design and deployment of such in-vehicle intelligent systems is increasing in order to enhance the acceptance of AVs in terms of the road safety and driving experience factors.

1.2 Research problem and objectives

Besides the numerous advantages with regard to vehicle automation technology, automotive industries realize that AVs should provide drivers/passengers with more choices for safe, reliable, pleasant, comfortable and productive driving. In this respect, reliable vehicular interactions, on-board cognitive management functionalities and intelligent IVI systems, are gaining acceptance around the automotive world and are recognized as a high priority in order to minimize consumer resistance and maximize adoption of driving/using AVs (Fagnant & Kockelman, 2015).

Based on the above, the following goals have been identified as open issues in the present Ph.D. thesis, which formed the main research objectives:

[a] provide widely accepted and used frameworks to assess consumers' acceptance towards AVs

[b] propose and validate authenticated communication protocols for enhancing the efficiency of vehicular interactions, and therefore, improving the acceptance of AVs regarding trust/reliability in terms of security protection and data privacy issues

[c] propose and validate on-board cognitive management techniques for enhancing the efficiency of autonomous driving and increasing the acceptance of AVs regarding road safety and driving experience with AVs. They operate on the basis of collecting information from various sources, intelligently processing it, integrating knowledge and experience coming from the past and, finally, issuing directives to the drivers/users

[d] prove the effectiveness and feasibility of the aforementioned in-vehicle cognitive management techniques through the implementation of realistic case studies through discrete-event simulations, mostly with regards to drivers/users with different profile data and preferences, as well as to driving scenes with different characteristics.

Based on the above, Fig. 1.5 presents the overall analysis (theoretical and technical) of the scientific field of the Ph.D. thesis, with a short description regarding each research objective.

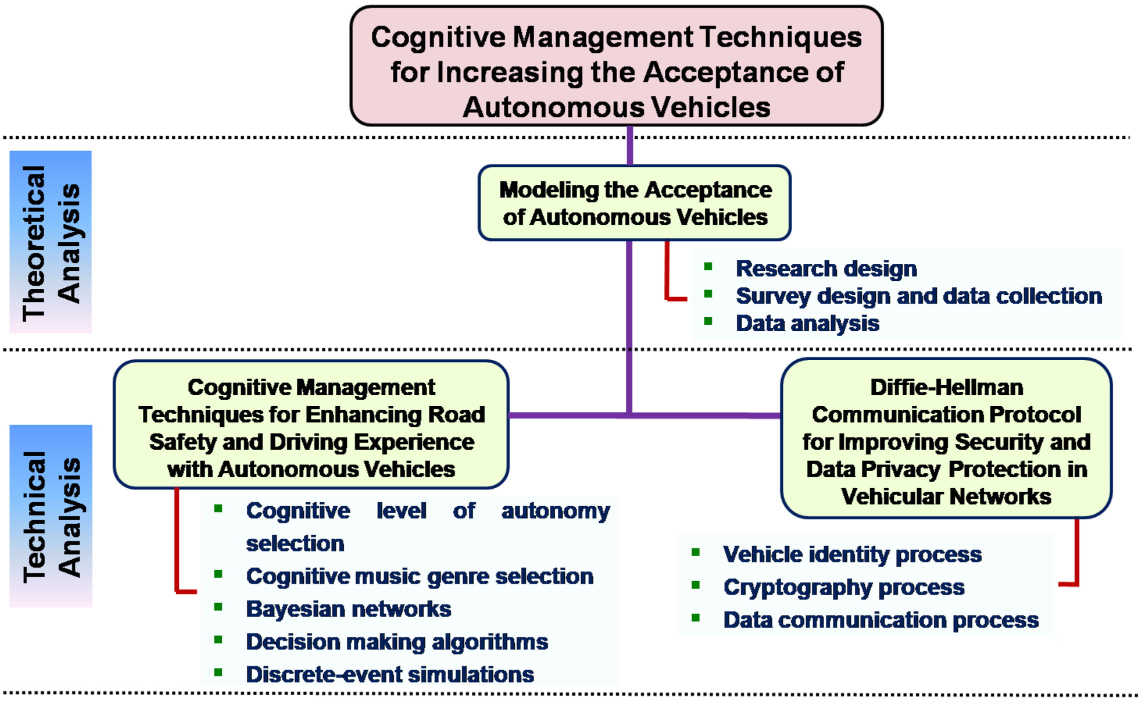


Fig. 1.5 Overall analysis (theoretical and technical) of the scientific field of Ph.D. thesis.

1.3 Contribution of this work

The contribution of the current Ph.D. thesis is summarized to the following dimensions:

i. It improves the knowledge on factors that potentially influence the user and technology acceptance of AVs. Since autonomous vehicles are currently being developed by major car manufacturers planning to be available in market diffusion the next years, the present thesis proposes two theoretical frameworks to investigate the factors that affect consumers' intension to accept and drive/use AVs.

ii. **It proposes an authenticated communication protocol for secure vehicular communications**. Since perceived trust/reliability plays a significant role in consumers' intension to accept and drive/use AVs, the present Ph.D. thesis develops a novel mechanism to guarantee the primary security requirements (authentication, integrity, non-repudiation, etc.) for reliable deployment of Internet of Vehicles (IoV) technology in the transport area. Such a protocol enhances the efficiency of vehicular interactions, and therefore, improves the acceptance of AVs regarding trust/reliability in terms of security protection and data privacy issues.

iii. **It proposes novel in-vehicle intelligent platforms, through the co-existence of cognitive management principles and machine learning algorithms**. Since cognitive management systems are a well promising area of research interest, the present Ph.D. thesis presents frameworks for two newly introduced cognitive management functionalities, i.e. i-ALS (intelligent Autonomous Level Selection) and i-M (intelligent Music), their definitions and characteristics, as well as their generic conceptual architectures. These functionalities are based on the approach for context-awareness in proactive data-driven decision making, by utilizing machine learning techniques and real-time prediction/prognostic algorithms for level of autonomy and music genre management schemes. The aforementioned architectures enhance the efficiency of autonomous driving, and therefore, increase the acceptance of AVs in terms of the road safety and driving experience issues.

1.4 Structure of the thesis

After this short introductory chapter, the Ph.D. thesis is structured as follows.

Chapter 2 presents the background in the related research areas of autonomous driving capabilities and contexts, user acceptance with regard to vehicle automation, vehicular communications, cognitive computing, intelligent transportation systems and intelligent in-vehicle infotainment systems within AVs.

Chapter 3 presents adapted versions of the original Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) social-psychological models in predicting consumers' intension to drive/use AVs. Extensive data analyses are applied to investigate in what extent consumers intend to drive/use AVs in the future, by identifying the factors that affect the uptake of such vehicles.

In **Chapter 4**, a novel communication protocol is presented, based on the Diffie-Hellman well-established popular key agreement scheme. This analysis aims to improve the efficiency of VCs and enhance the acceptance of AVs towards trust/reliability in terms of security protection and data privacy issues.

Chapter 5 presents two novel cognitive platforms that comprise mechanisms for dynamically selecting the optimal level of autonomy and optimal music genre, which are operated on the basis of collecting information from various sources, intelligently processing it, integrating knowledge and experience and, finally, reach the optimal decisions. Indicative discrete-event simulations are presented to showcase the efficiency, in terms of accuracy and speed of convergence, of the aforementioned in-vehicle cognitive functionalities, as well as the behavior of the proposed knowledge-based schemes in terms of learning the parameter capabilities associated with the in-vehicle available levels of autonomy and in-vehicle available music genres, respectively, and conducting the appropriate selections. The above architectures aim to enhance the acceptance of AVs, in terms of road safety and driving experience factors, by making service provision more seamless and stable to drivers/users when using AVs for their road journeys.

Finally, basic conclusion remarks, recommendations for future research activities, and published work as part of this Ph.D. thesis, are presented in **Chapter 6**.

CHAPTER 2: BACKGROUND AND RELATED WORK

Contents

2.1 Introduction

With advances in sensors, microprocessors, software, telecommunications and related technologies, AVs are evolving rapidly. A great benefit AVs can bring to us is that they have the potential to dramatically reduce road crashes, as AVs can avoid human shortcomings such as fatigue, distraction and other human errors that account for over 90% of all road crashes (Noy et al., 2018). It is estimated that 50-80% traffic conflicts could be reduced if 50% of vehicles on road are AVs and 90-94% reduction would be achieved if all vehicles on road are AVs (Papadoulis et al., 2019).

In addition, recent studies (Milakis et al., 2017; Van Brummelen et al., 2018) show that AVs are anticipated to increase traffic flow efficiency, increase comfort by allowing the driver/user to perform alternative tasks, and ensure mobility for all, including old and impaired individuals. Moreover, AVs are expected to be able to run on the road network, under certain or/and all driving environment conditions using sensors, software and other instruments, and successfully implement certain or/and all critical control and safety functions (e.g., steering, accelerating or braking) either without direct driver/user input or even without the intervention of driver/user (Chan, 2017).

Furthermore, the successful penetration of AVs in international market encompasses a wide range of technologies and infrastructures, capabilities and contexts, security and data privacy issues, as well as AI-enabled applications and services that sense and manipulate the dynamic driving environment. There is no single timeline for these developments: some are here today, some may be distant, and some will depend on specific technical innovations or particular policy choices. Importantly, vehicle automation is part of much larger revolutions in automation and connectivity (Van Brummelen et al., 2018).

2.2 Technologies and infrastructures

Recent developments in vehicle automation technology and ADAS (e.g. automatic braking, automatic cruise control, intelligent speed assistance, line keeping assist systems, etc.) allow the transfer of driving functions from a human driver/user to a computer, and therefore, are moving us closer to increasingly Autonomous Vehicles (AVs). Such vehicles can perform certain or/and all navigation functions (braking, acceleration, directional change), under certain or/and all driving environment conditions.

AVs, like humans, must act in three areas; namely, perception (collect information), cognition (make a decision based on that information), and action (execute that decision). In the perspective space, AVs derive Information about the surrounding environment and their own states through various senses (vehicle equipment, physical infrastructure, physical-digital infrastructure, and digital infrastructure), any of which may be public or private. Many of these technologies exist today and are capable of guiding vehicles and, in some cases, drive vehicles with minimal or no driver/user input in test situations and across diverse driving environments. In this respect, most of the traditional car companies have carried out trials or are engaged in continuous on-road testing of AV prototypes whose capacities are evolving rapidly due to improved sensor-processing technologies, self-adaptive algorithms, high-definition mapping and, in some cases, the deployment of vehicular communication technologies.

From a technical point of view, current technology for Autonomous Driving (AD) in controlled environments is quite mature. These vehicles use state-of-the-art sensors (radars, lasers, cameras) combined with high accuracy maps allowing on-board operator systems to identify appropriate navigation paths, as well as obstacles and relevant signage. These prototypes operate with a driver/user that must stand ready to take control of the vehicle though reports from trials indicate that this option is rarely acted upon. As of 2020, there is yet no consensus on the commercial maturity of highly automated and ultimately fully automated driving. Some car manufacturers have announced the arrival of highly and possibly fully AVs by as early as 2023 while others have advanced much later dates (up to 2030). Clearly there will be a first-mover advantage for pioneers in the field of AD but there are also risks linked to the safety performance of these vehicles and the possibility of regulatory action that inhibits technology development and deployment.

According to the above, a number of issues will have to be addressed in order to support the deployment of high-automation or/and full-automation driving scenarios. These include:

- **Vehicle-to-X connectivity (V2X)**: Connectivity is an important element of AVs, especially by requiring low latency and secure V2X communications. V2X technologies encompass the use of wireless technologies to achieve real-time two-way communication among vehicles (V2V) and between vehicles and infrastructure (V2I). The convergence of sensor-based solutions and V2X connectivity will enhance the successful introduction of AD in passenger vehicles.
- **Decision AI-enabled algorithms**: These include decision, planning and control algorithms for a reliable and safe vehicle automation.
- **Digital infrastructure**: Digital infrastructure includes static and dynamic digital representations of the physical world with which the AV will interact to operate (sourcing, processing, quality control, information transmission, etc.).
- **Human factors**: Human factors in automation relate to understanding the interaction(s) of humans with AVs, both from within an AV, when taking the role of a driver/user and also as a road user, when interacting with AVs. Knowledge and theories from social-psychological and behavioral sciences are useful to understand how humans interact with such systems.
- **Evaluating vehicle automation**: Automation of road vehicles has the potential to impact on lifestyles and society. Economic impacts too will be important and it will be necessary to gauge these impacts in a common cost-benefit framework with other transport investments when assessing public expenditure on supporting infrastructure or services.
- **Roadworthiness testing**: Roadworthiness testing, understood as the necessary tests to evaluate if a vehicle is legally allowed to drive on public roads is of capital importance for the deployment of new autonomous driving functionalities.

2.3 Autonomous driving capabilities and contexts

2.3.1 Levels of autonomy

The variety of driving automation technologies supporting the human driver can be classified by their Level of Autonomy (LoA), which defines the degree to which they take over the execution of the (dynamic) driving task (Eby & Molnar, 2012). Several taxonomies have been developed to define distinct degrees of driving automation. Out of these, the classification approach by SAE (2016), which is outlined in Fig. 2.1, represents the most recent and comprehensive one where six different levels of driving automation are classified. The above levels of increased autonomy differ by the execution of the vehicle control (longitudinal/lateral), the monitoring of the driving environment, and the fallback performance, which can be either controlled by the human driver or the on-board driving automation system.

Monitoring of driving environment	LoA - Short Description
Driver	**<u>LoA 0: No automation</u>** The driver/user does all the parts of the dynamic driving task in complete control, although vehicle may provide warnings **<u>LoA 1: Driver assistance</u>** Vehicle is controlled by the driver/user, but some driving assist features may be included that can assist the driver/user with either steering or braking/accelerating, but not both simultaneously **<u>LoA 2: Partial automation</u>** Vehicle has combined automated functions, like adaptive cruise control and lane centering simultaneously, but the driver/user must remain engaged with the driving task and monitor the driving environment at all times
On-Board Operator System	**<u>LoA 3: Conditional automation</u>** A driving automation system on the vehicle can itself perform all aspects of the dynamic driving task and monitor the driving environment in some instances. The driver/user is expected to be takeover-ready to take control of the vehicle at all times with notice **<u>LoA 4: High automation</u>** A driving automation system on the vehicle can itself perform all aspects of dynamic driving task in certain environments and under certain conditions. The driver/user has a reasonable amount of transition time before he/she must take the control of the vehicle **<u>LoA 5: Full automation</u>** A driving automation system on the vehicle can itself perform all aspects of dynamic driving task, under all roadway and environmental conditions, with no expectation for the driver to take control

Fig. 2.1 Levels of autonomy according to SAE International [SAE, 2016].

More in detail, the SAE automation taxonomy spans from LoA 0 (no automation), where the human driver/user executes all the elements of the driving task, to LoA 5 (full automation), where no human driver/user interaction occurs, and the vehicle's driving automation system can perform all the elements of the driving task, under all circumstances. The distinction between partial automation (LoA 2) and conditional automation (LoA 3) is considered the most meaningful one. From LoA 3, the entire driving task, including vehicle control as well as monitoring the driving environment, is performed by the on-board driving automation system with the exception of the fallback performance, which requires the human driver/user to resume the driving task any time the demands of the driving environment exceed the boundaries of the system.

This changes at the two highest levels of autonomy, on which the driving automation system is capable of executing all the elements of the driving task in some (LoA 4 – high automation) or all (LoA 5 – full automation) driving scenarios. In this case the on-board driving automation system takes over the detection and processing of the driving situation, as well as the selection and execution of adequate actions. This includes all control processes on the monitoring, regulating, and tracking level of the driving task. The human driver's task is reduced to control processes on the targeting level, which are mostly carried out prior to driving (e.g. selecting the destination of a trip). While fully automated driving (LoA 5) enables the automated execution of the driving task under all roadway and environmental conditions, a human execution of the driving task might be required under certain conditions in the context of highly automated driving (LoA 4), resulting in a higher relevance of human-centered research issues on this LoA.

2.3.2 Role of the driver/user

With the implementation of automation in vehicles, changes come in the role of the drivers in the driving task with regards to LoA (Schömig et al., 2015). According to Fig. 2.1, when the driver is performing the driving task manually (under LoA 0 or LoA 1 automation), he/she is completely responsible for the control of the vehicle and monitoring the driving environment for the safe operation of the vehicle. Driver assistance systems of LoA 1 are very common today and used in all current vehicles.

When a LoA is added, however, part of the task is taken over by the automation, leaving the driver to participate in less of an active manner and more of a passive manner during normal operating conditions. In this basis, LoA 2 automated driving technology (partial automation) allows the driver to physically (but not cognitively) disengage from the driving task and assume the role of monitoring the driving environment and vehicle performance (Banks et al., 2018). Currently, LoA 2 autonomy is available in some (but not all) vehicles on the market today from different automakers.

Furthermore, LoA 3 automated driving technology (conditional automation) allows the driver to cede both the monitoring and control role for the full driving task to the computer system under certain conditions but expect the driver to be takeover-ready when the system may request it (Blömacher et al., 2018). An example of the LoA 3 concept is traffic jam pilot, which allows drivers to engage the automation and cease monitoring the driving environment. LoA 3 autonomy is expected to be available in the near future cars.

Moreover, LoA 4 / LoA 5 driving automation technologies, which are expected to only require the driver to input a destination while the automation system monitors the driving environment and performs all safety-critical functions, do not yet exist outside of advanced research concepts (Ohn-Bar & Trivedi, 2016). It is important for the car manufacturers to join driver/user and driving automation wishes and to switch between different levels of autonomy (LoA selection) whenever he/she wants to, including during a trip. To keep the driver in-the-loop, as best as possible, enabling him or her to re-claim the control of the vehicle more quickly if necessary, the following issues are of fundamental importance:

- **(i)** what information should drivers/users receive about the transition in LoA,
- **(ii)** when should drivers/users be alerted about the transition between one LoA and another LoA, and

(iii) how should drivers/users be informed about the transition in LoA (i.e., from LoA 3 to LoA 2 or from LoA 4 to LoA 3).

2.4 User acceptance

Advancements in computational power, new sensing technologies, and increasingly capable AI-based computational methods accelerated the progress in developing advanced driver-assistance systems that automated certain aspects of the driving task while still requiring human driver oversight and an ability to resume control.

As mentioned previously, the impact of AVs could be enormous. It could help to drastically reduce road fatalities as over 90% of road accidents come from human errors such as driving under distraction, speeding, alcohol, drug involvement and/or fatigue (Piao et al., 2016). Moreover, new transport services could also be developed especially when vehicles are provided with connectivity in addition to automation, e.g. traffic safety related warnings, traffic management, new possibilities for elderly people or impaired people, more individual comfort and convenience for drivers. It could also result in new business models, such as car sharing services and shared mobility which could lead to a strong decrease of vehicles on our roads (Litman, 2017; Fagnant & Kockelman, 2015).

All these potential societal benefits will not be achieved unless these vehicles are accepted and used by a critical mass of people; thus it will be important to understand consumers' acceptance before the arrival of AVs on international market. In this context it is not yet clear to what extent users accept automation technologies in vehicles and what the factors and determinants of user acceptance of automation are (Payre et al., 2014).

Furthermore, besides the numerous challenges with regard to vehicle automation and connectivity technologies, recent studies indicate that many key factors pertaining to the interaction between human drivers and full or partial autonomous driving systems are yet to be resolved. Such challenges include the impact of automated systems on drivers' workload and situation awareness, as well as the human drivers' levels of acceptance, trust and reliance on the automated systems.

Moreover, challenges with regard to the required level of supervisory control and the role of the human drivers in the case of an emergency such as when automation fails or exceeds its functional limits (Kyriakidis et al., 2015) must be taken into account. Monitoring workload may negatively impact acceptance of AVs, as engagement with secondary tasks seems to be viewed as a primary end-user benefit of vehicle automation (Merat & Lee, 2012; Pettersson & Karlsson, 2015).

With advances in sensors, microprocessors, software, telecommunications, artificial intelligence and related technologies, AVs are evolving rapidly (Noy et al., 2018). Current technologies have allowed AVs to be operated in approximately 90% of road conditions (Litman, 2017), and the proportion is expected to increase to 99% in the foreseeable future. A great benefit AVs can bring to us is that they have the potential to dramatically reduce road crashes. It is estimated that 50-80% traffic conflicts could be reduced if 50% of vehicles on road are AVs and 90-94% reduction would be achieved if all vehicles on road are AVs (Papadoulis et al., 2019).

Although AVs could offer a potentially effective solution to improving road safety, the benefit associated with AVs can be realized only when the public accept them. Recent surveys have shown that people are still more comfortable having humans, instead of automation systems, in control of cars, and that public's intention to use or purchase AVs is generally low (Schoettle & Sivak, 2014). It is predicted that decades of years might be needed to socialize this new technology, and this process would be subject to a number of unknown social and personal factors. Therefore, to expedite AV acceptance, it is critical to investigate what factors influence public's decision to use AVs. Users' beliefs and attitudes toward the technology, perceived behavioral control, trust, usefulness and ease of use are key elements that can ultimately determine user's behavioral intention to accept and drive/use AVs.

2.4.1 Technology acceptance models

Generally, the perception of a product technology is multidimensional and includes a broad range of factors. With the advanced and dynamic growth of technologies, how fast the consumers are accepting these technologies depends on a number of factors such as availability of technology, convenience, consumers' need, trust, etc. Since the 1980s, across the domains of psychology, information systems, and sociology, a variety of well-known theories and models have been developed for explaining technology acceptance (Lai, 2017). Technology acceptance models have gained popularity and have been used in several studies to assess and gauge consumers' behavioral intentions by determining the factors which most positively influence consumers' likelihood to adopt new technologies. As such, their aim is to combine the (stated) intention of using a technology system with the person's perceived views on several key aspects of the system by investigating the acceptance rate of a new technology and finding out the reasons for accepting or not accepting this technology.

One of the most widely cited frameworks in the area of transport technology is the Technology Acceptance Model (TAM), which builds on Theory of Reasoned Action (TRA) in an effort to understand acceptance in relation to the uptake of new technologies (Ajzen, 1985; Davis, 1989). The goal of TAM is to explain the general determinants of computer acceptance that lead to explaining users' behavior across a broad range of end-user computing technologies and user populations. Using TAM, Perceived Ease of Use (PEU) and Perceived Usefulness (PU) are the two most important determinants of technology use. Adaptations of TAM have since been used to explain technology acceptance in a variety of transportation contexts, including switching intentions towards public transport (Chen & Chao, 2011), eco-driving interfaces (Hötl & Trommer, 2012; Meschtscheriakov et al., 2009), navigational systems (Park & Kim, 2014), and distraction mitigation systems (Roberts et al., 2012); explaining up to 50% of the variance in behavioral intentions around these systems.

One of the most useful aspects of TAM is the capacity to successfully extend the core constructs of the model to include additional external variables which may become relevant in different contexts (Ghazizadeh et al., 2012). A more recent and frequently used model is the Unified Theory of Acceptance and Use of Technology (UTAUT), which was proposed by Venkatesh et al. (2003) and was formulated by integrating components from eight theoretical models of acceptance, including the TRA and TAM, designed to capture all of the factors impacting on consumers' behavioral intentions to use a particular technology system. UTAUT posits that Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) all influence behavioral intentions towards technology use, which in turn predicts actual system use.

In most of cases, UTAUT model has been shown to be more accurately predictive of technology acceptance accounting for about 56% of the variance in behavioral intentions when compared with previous models, such as the TAM, which accounted for a maximum of 40% of the variance. UTAUT2, the most recent, consumer-oriented version of UTAUT, claims that there are seven main constructs that influence consumer behavioral intentions towards technology use, namely PE, EE, SI, Facilitating Conditions (FC), Hedonic Motivation, Price Value, and Habit (Venkatesh et al., 2012).

UTAUT has traditionally been applied to understanding intentions to use information systems, such as online banking (Zhou et al., 2010; Tarhini et al., 2016), open data technologies (Zuiderwijk et al., 2015), e-learning purposes (Nurkhin et al., 2017), and mobile devices/services (Carlsson et al. 2006; Abrahão et al., 2016). In recent years, a number of studies have incorporated elements of UTAUT into their understanding of user acceptance of vehicle technology (Osswald et al. 2012; Park et al., 2013; Zmud et al., 2016).

2.4.2 Factors affecting adoption of autonomous vehicles

Most companies in the automotive industry are currently being advertised the introduction of AVs, planning to be available in market diffusion the next years (Chan, 2017). Besides the numerous advantages with regard to vehicle automation technologies, AVs may also face numerous challenges before being introduced to the market, ranging from vehicle performance degradation due to unexpected situations (e.g., bad weather conditions, driving automation system failure, etc.) to security breaches against malicious attacks by cyber criminals (hackers), and legal liability issues (Milakis et al., 2017; Van Brummelen et al., 2018). These concerns can be critical obstacles to the market adoption and diffusion of AVs influencing consumers' intention to drive/use them (Pettersson & Karlsson, 2015; Kyriakidis et al., 2017).

In recent years, multiple studies have been conducted on public towards users' preferences and consumers' perceptions regarding autonomous or/and self driving vehicles (Silberg et al., 2013; Begg, 2014; Schoettle & Sivak, 2014; Haboucha et al., 2017; Hohenberger et al., 2016; Kyriakidis et al., 2015; Chowdhury & Ceder, 2016; Zmud & Sener, 2017; Leicht et al., 2018). Overall, the above surveys explored general opinions about AVs but did not focus on behavioral adaptation. In this way, as the development of the driving automation technology in vehicles advances, understanding attitudes and wider public acceptability is critical (Xu et al., 2018; Acheampong et al., 2018).

Furthermore, as found in the literature, a large majority of the population has a positive attitude towards AVs in general (Payre et al., 2014). On the other hand, privately-owned AVs may turn out to be more preferable to consumers in the near future in comparison with the car sharing mobility services and shared AVs. In this way, although AVs may be seen as a means to reduce dependence on the personal car, the literature on technology adoption suggests that private ownership of AVs is likely to prevail in the long-run (Krueger et al., 2016; Zhang et al., 2018). In addition, according to the literature on travel mode choice behavior, private car has remained the most attractive mode of individual transport (associated with sensation seeking, power, freedom, status, etc.) despite creating serious collective disadvantages, such as traffic congestion, accidents and environmental pollution (Beirão & Cabral, 2007; Steg, 2005).

Since the original UTAUT model was created for the acceptance of IT systems, adjustments need to be made to use it for testing the behavioral intention of driving/using AVs. There have been several studies which have tried to incorporate a type of attitude towards vehicle technology, driver assistance systems and automated driving characteristics in the UTAUT model. As such, Adell (2010) used the original version of UTAUT to investigate acceptance of the "Safe Speed and Safe Distance" function as part of a field trial of a driver support system. The results showed that although PE and SI affected intentions to use the system, EE did not. However, the model only accounted for 20% of the variance in behavioral intentions towards this support system, a figure much lower than that found in other industries. In addition, Osswald et al. (2012) developed and proposed the Car Technology Acceptance Model (CTAM), which extended the UTAUT model's range with a number of other attitudinal constructs, e.g. anxiety and perceived safety, to explain and predict technology acceptance of drivers regarding IT. They presented the reliability of their scales but did not investigate the impact of these factors on behavioral intentions towards driving information technology systems.

Moreover, Cho et al. (2017) applied an expanded UTAUT acceptance model about ADAS, which is the core technology of AD. In this model, the determinants anxiety, self-efficacy, perceived safety, trust and affective satisfaction were included as direct predictors of behavioral intention to use ADAS, in addition to the basic factors of the original UTAUT model. Rahman et al. (2017) assessed the utility of TAM, TPB, and UTAUT for modeling driver acceptance in terms of behavioral intention to use ADAS. Each of these models proposes a set of factors that influence acceptance of a technology. Results for this study found that all the above models (TAM, TPB, and UTAUT) can explain driver acceptance with their proposed sets of factors.

In addition, Madigan et al. (2016) assessed user acceptance of Automated Road Transport Systems (ARTS) vehicles being used in two different European cities (La Rochelle in France and Lausanne in Switzerland) as part of the CityMobil2 project using the original UTAUT framework. They found that performance expectancy had the strongest impact on consumers' behavioral intentions to use ARTS. However, the explanatory power of the model was only 22%, suggesting that this model failed to capture many of the factors influencing users' decisions around the uptake and use of ARTS. Furthermore, Madigan et al. (2017) investigated consumers' intension to use ARTS by extending UTAUT model to include the effects of facilitating conditions and hedonic motivation. The relative survey was administered to 315 users of a CityMobil2

ARTS demonstration in the city of Trikala, Greece. The results of this study indicated that hedonic motivation was the strongest predictor on consumers' intention to use ARTS. Moreover, Park et al. (2013) found a strong positive relationship between FC and drivers' intention to use car connectivity services. Similarly, it is highly likely that the resources provided to support the implementation of ARTS, including infrastructure design, implementation strategy, and consideration of social, economic, and environmental impacts, will all influence user uptake of these systems (Sessa et al., 2015). User enjoyment is also likely to play a role in such a new and innovative environment. Indeed, hedonic motivation has been shown to be the strongest predictor of consumer acceptance of technology across a variety of sectors (Van der Heijden, 2004; Venkatesh et al., 2012).

Moreover, Nordhoff et al. (2017) investigated user acceptance of driverless shuttles in public transport in an open and mixed traffic environment on real semi-public roads in Berlin-Schöneberg by using the original UTAUT framework. Results show that the acceptance and use of such shuttles is predominantly influenced by their PE, EE and SI. In addition, Leicht et al. (2018) investigated the effects of consumer innovativeness on adoption intentions of self-driving vehicles by implementing a conceptual acceptance model based on UTAUT. Results showed that PE, EE and SI are positively related with purchase intentions of autonomous cars. Consumer innovativeness moderates the relationships between the above constructs, whereas the effects are stronger when consumer innovativeness is high rather than when it is low.

Although many researchers in the existing literature have investigated and replicated the original UTAUT model and agreed that it is valid in predicting end users' acceptance, further extensions are needed, in most of cases, to fully explore the predictors influencing consumers' attitudes and willingness to use/accept innovative technologies in order to be successful in market diffusion.

2.5 Cognitive management systems for autonomous vehicles

2.5.1 Why do vehicles need artificial intelligence (AI)?

With the ever-increasing demand in urban mobility, the vehicle population has been steadily growing over the past several decades leading to increased traffic congestion. In the meanwhile, traffic accidents are plaguing the economic development as well. It is estimated that there is at least one person dying from traffic accidents worldwide every minute (Li et al., 2018).

With the help of recent developments in artificial intelligence (AI), we are able to make vehicles intelligent and capable of making decisions in situations in which humans could not do so, but we must ensure in some way that they make the right decisions so as not to put at risk the missions and the lives of drivers/users. In this respect, intelligent AVs combine AI-enabled techniques such as environmental perception (including road condition, weather condition, on-road object detection, road signs/marking detection, surrounding obstacles' locations and even predictions of their future states, etc.), map building and path planning and integrate them with multi-scale auxiliary driving services and other infotainment functions, so that vehicles are able to make intelligent decisions and trained over large data sets to perform various tasks (Oh & Kang, 2017).

As such, intelligent AVs are expected to have the capability of safe, efficient and eco-driving operations whether these are under human/operator control or in the adaptive machine control mode of operations based on the applied LoA. Such operational requirements can be met through the co-existence of cognitive management principles and machine learning algorithms (Wu et al., 2018).

2.5.2 Machine learning

In general, learning models from data is a process that traditionally involves the human mind, through what we call "physical understanding"; yet it can also be attempted in automated, computer-assisted ways and this is a major modern trend (Li et al., 2012).

On this way, cognitive management platforms need to automate big data analysis, and therefore, Machine Learning (ML) techniques can offer valuable solutions. On this way, a short definition of ML refers to a set of methods that can automatically detect patterns in data. As such, these uncovered patterns can be used to make predictions, or to perform other kinds of decision making under uncertainty (Murphy, 2012).

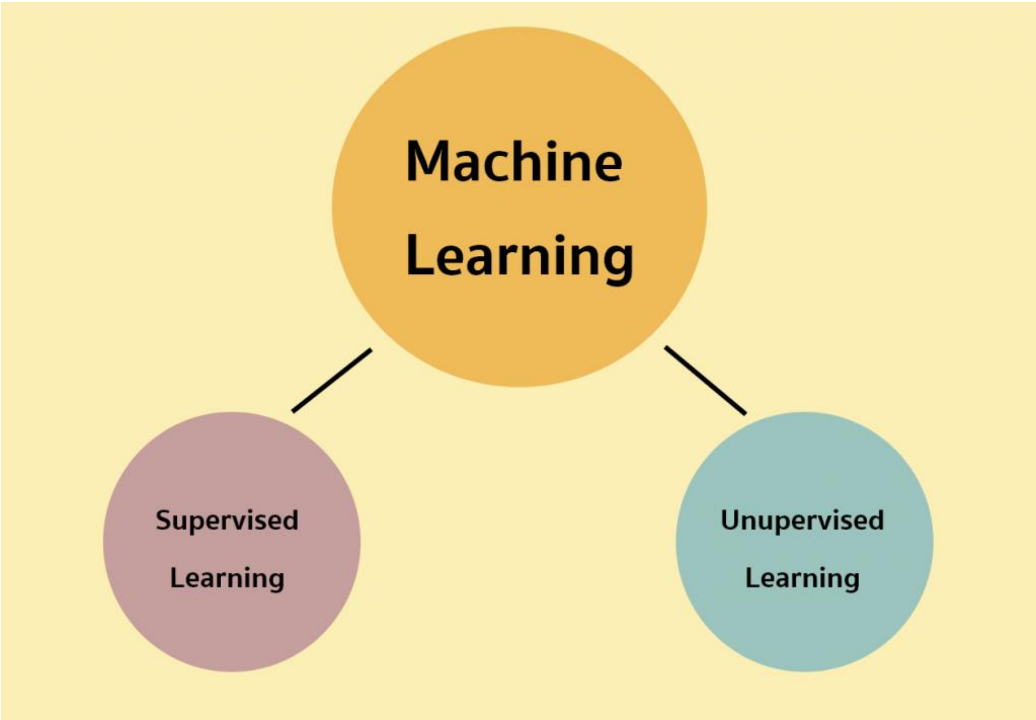


Fig. 2.2 Supervised and unsupervised machine learning methods, *source: www.google.com*.

ML methods are usually classified into two types: supervised and unsupervised learning (see Fig. 2.2). Supervised learning is based on a labelled training data set, which is used to extract a mathematical model of the data. Among the most well-known supervised methods are k-Nearest Neighbours, Naïve Bayes classifiers, Artificial Neural Networks, and Support Vector Machines (Kala & Warwick, 2015).

On the other hand, unsupervised learning doesn't use a labelled training dataset because it doesn't try to learn anything in particular. Unsupervised learning divides the dataset into homogeneous groups, which is called clustering. It is used quite regularly for data mining. For instance, it can be used to detect patterns of fraudulent behavior or in market stock analysis. K-means, mixture models or hierarchical clustering are approaches to unsupervised learning (Lantz, 2013).

2.5.3 Intelligent transportation systems and cognitive computing

With advances in AI-supported methodology, Intelligent Transportation Systems (ITSs) are gaining acceptance around the world and cognitive computing systems are recognized as a high priority research in academia and automotive industry. The overarching ITS function is to improve transportation system operations, which in turn support the transportation objectives of increasing efficiency, safety, productivity, energy savings and environmental quality (Dimitrakopoulos & Demestichas, 2010). The technical core of ITS is the application of information and control technologies to transportation system operations. These technologies include communications, automatic control, and computer hardware and software and the adaptation of these technologies to transportation requires the knowledge from many engineering fields such as civil, electrical, mechanical, industrial and their related disciplines (Lana et al., 2018).

Furthermore, Cognitive Management Systems (CMSs) are those networks that are able not only to adapt to the constantly changing users needs but also they are capable of retaining information from their interactions with environment, transforming gradually this information into knowledge and experience, and using this knowledge and experience in reaching future decisions. As such, CMSs are capable of proactively taking decisions based on the potential success or failure of previous decisions taken.

CMSs find prosperous ground in modern Information and Communication Technologies (ICT), forming the cornerstone of the new generation of ITSs (Thomas et al., 2006; Dimitrakopoulos et al., 2012). On this way, CMSs constitute major facilitators of the conception, design and implementation of innumerable ITS-enabled applications needed to support diverse requirements in terms of Quality of Service (QoS) or Quality of Experience (QoE). In this respect, it is necessary to develop and implement CMSs that will enhance the end-user experience, in terms of quality of service, availability and reliability.

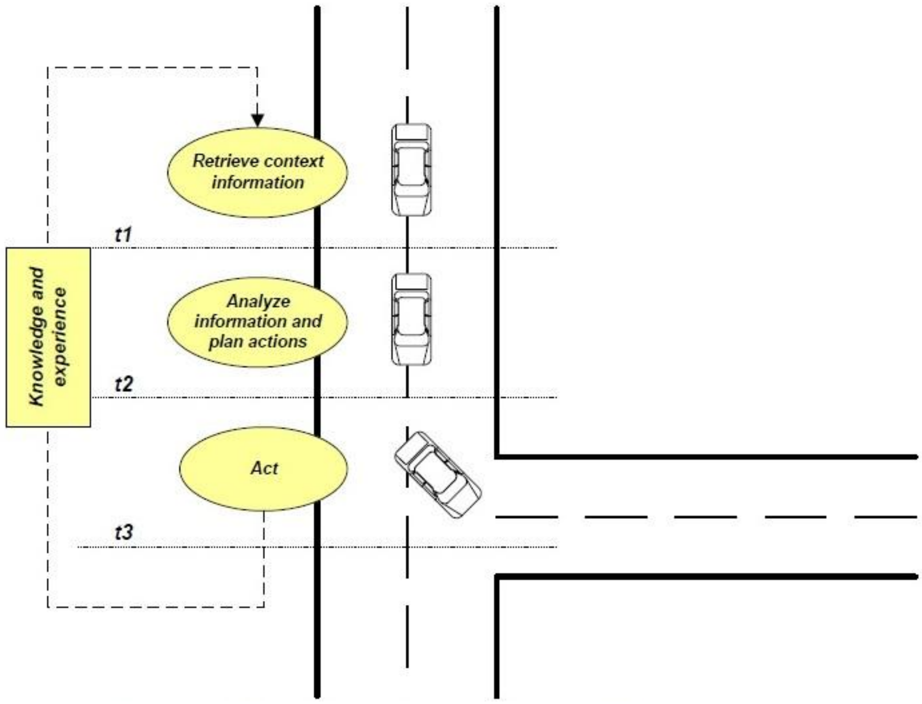


Fig. 2.3 Operation of a cognitive management system placed inside a vehicle, *source: Dimitrakopoulos, 2017*.

Indicatively, a CMS placed inside a vehicle might seem like the one shown on Fig. 2.3. CMS, at time "t1" retrieves context information, potentially on traffic, velocity of neighbouring vehicles, etc. Through the analysis of this information (at time "t2"), while taking into consideration its own preferences, goals and policies, CMS (at time "t3") decides on its actions, e.g. issue a directive towards the driver/user to change the vehicle's direction. The output of the CMS is stored on a "knowledge database", which might simply be a matrix, for future reference. This means that the system keeps track of its actions, so as to learn from their implications, in order to facilitate future decisions. This is repeated in a ML process that leads to cognition (Dimitrakopoulos, 2017).

In addition, fundamental requirements for the success of cognitive (reconfigurable) systems include self-management and learning capabilities (Thomas et al., 2006; Kephart & Chess, 2003). Self-management enables a cognitive system to identify opportunities for improving its performance and configuring/adapting its operation accordingly without the need for human intervention. ML mechanisms are essential so as to increase the reliability of decision making. ML mechanisms also provide the ground for enabling proactive handling of problematic situations, i.e. identifying and handling issues that could undermine the performance of the system before these actually occur. As such, CMSs determine their behavior (in a self-managed way), based on goals, policies, knowledge and experience (obtained through learning), reactively or proactively.

2.5.4 Intelligent in-vehicle infotainment systems

Many researchers have been developing recommender systems which supply meaningful information and the convenience of choice based on the large amount of data which are accumulated through sensors, IoT, supplement of mobile devices and the internet (Lee & Um, 2018). Based on the collected information, recommender systems provide helpful information to users for finding appropriate items, services and content, such as social networks, industry applications, cars, vacation destinations, etc. (Ding et al., 2018; Luan et al., 2017; Luan et al., 2018, Shang et al., 2019). For example, in Thomas & Vaidhehi (2018) a web based car recommendation system based on a hybrid recommender algorithm is presented by combining user-to-user and item-to-item collaborative filtering method. The user model includes demographic features, click data and browsing history, whereas item profile is built using various attributes of car (engine & transmission, capacity, comfort and safety).

Moreover, as automobile and IT industries continue to grow, vehicles have now evolved from a simple transportation means into cultural and living spaces by changing individuals' lifestyle. With this trend, IVI systems have been receiving considerable attention in the last years, which aim to improve the drivers/passengers' quality of transport mobility. Such services include navigation systems, cameras, speakers, headrest displays, air-conditioners, thermometers and heating seats, and lights.

Even though many commercial products for IVI systems have been developed by automobile manufacturers and IT companies, the existing works have mainly focused on the adaptive user interface to increase the user's convenience in the IVI systems, such as voice recognition or electronic secretary (Smith et al., 2018; Tian et al., 2014). In this respect, few studies have examined how to effectively provide intelligent recommender systems to support IVI systems. In this direction, there is a body of work on the related problem of music recommendation. For instance, Lee & Lee (2007) has improved a music recommender service with context awareness using case-based reasoning. The used context factors include the season, month, weekday, weather and temperature information. In Reddy & Mascia (2006) a music recommender system for urban environments is presented. The context factors include the location of the user, time of day, weekday, noise/traffic level, temperature and weather data.

A common feature of the aforementioned music recommender systems is the usage of a generic context model, mostly consisting of time- and weather-related information, where the choice of the most informative context factors has not been informed by any data mining experiment.

2.6 Vehicular communications

2.6.1 Challenges

Vehicular network technology is considered to be one of the most basic components of the future ITS moving us closer to increasingly AVs. The most important objective of a vehicular network system is to provide communications in the transport area between different vehicles on the roads (V2V communications), vehicles and road-side infrastructure units (V2I communications) and generally vehicles with everything (V2E communications) like pedestrians, cyclists, etc.

In doing so, in these networks each vehicle needs to have an OBU (On-Board Unit), which would integrate the vehicles' wireless communications, micro-sensors, embedded systems, and Global Positioning System (GPS) (Shen et al., 2014). By using OBUs, intelligent AVs could then communicate with each other as well as with roadside Infrastructure Units (IUs), such as traffic lights or traffic signs. In this manner IUs can be connected to a backbone network, so that many other network applications, including internet access and infotainment services, can be provided to the vehicles. Moreover vehicles could exchange messages via a Dedicated Short Range Communication (DSRC) network concerning real-time traffic conditions so that drivers would be more aware of their driving environment and take early action in response to an unusual situation (Kaur & Malhotra, 2015).

Despite the benefits of vehicular networks, the computerization of vehicles makes them prone to cyber attacks that can endanger the safety of users (drivers and passengers). In a vehicular network system there is a risk that the privacy of the users (e.g. location and identity of the driver, location and identity of the vehicle) could be impaired by an adversary intercepting the communications. Moreover, vehicular networks must be authenticated and authorized in order to keep unauthorized vehicles away from getting access to particular applications, services or privileges. For instance an adversary's vehicle could broadcast emergency vehicle approaching messages to other neighboring vehicles to get ahead in a traffic jam.

In this basis an insecure and unreliable vehicular network can be more dangerous than the system without it. Potential security measures could include a method of assuring that the packet/data was generated by a trusted source (neighbor vehicle, sensors, etc.), as well as a method of assuring that the packet/data was not tampered with or altered after it was generated. So, secure vehicular network systems are more than necessary.

Due to the constraints and requirements of the automotive life cycle, most traditional IT security solutions are not directly applicable to vehicles. This puts high demands on IT security agencies and automobile manufacturers to ensure that it is not the communications that threaten the life of passengers by affecting the safety of the in-vehicle systems. Lack of authenticated information shared in the network may lead to malicious attacks and service abuses, which could pose great threats to drivers and passengers (Raya, et al., 2006; Lin et al., 2008; Kargl et al., 2008; Zeadally et al., 2012). Furthermore, vehicular networks possess unique network characteristics that distinguish it from other traditional ad hoc networks and characterized by rapidly changing network topology, high mobility of nodes, unbounded network size, frequent exchange of information, one-time interactions and sufficient energy and computation resources.

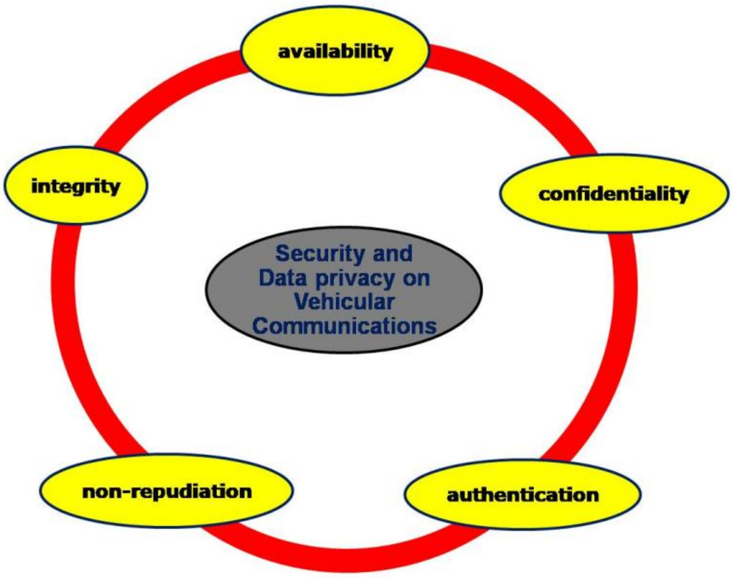


Fig. 2.4 Security and data privacy requirements on vehicular communications.

Therefore, novel mechanisms to guarantee the primary security requirements, such as authentication, integrity, and non-repudiation needs to be developed before vehicular networks can be practically used for reliable vehicular communications (Chun et al., 2008).

Vehicular Communications (VCs) have been classified in three classes as function of their scale, infrastructure support, and communication sensitivity (Yadav & Vijayakumar, 2016):

(a) Safe Mobility contains safety-of-life communications to notify drivers/users of dangerous situations. Such applications are localized, and are very sensitive to transmission impairments, delay and loss. They must also work without the help of any form of road-side equipment.

(b) Smart Mobility gathers and disseminates information related to traffic state or navigation guidelines in a decentralized way. As the precision of traffic information decays with distance and time, the scale is small to medium, and communications are delay bounded.

(c) Connected Mobility encompasses all applications providing Internet access, content exchange, or commercial advertisements. Applications in this class are fundamentally large scale, and focus mostly on throughput maximization.

Such classification also impacts the models and toolkits required to evaluate the performance of VCs applications. Given the class of the VC application, the selection of the models is a constant trade-off between performance and precision. Thus, given the constrained simulation capability, the modeling of only those behaviors that are effectively impacting the VC application should be sought.

The vehicular networks pose two major challenges as the network's deployment is not an easy task (Papadimitratos et al., 2008):

- **Dynamic network:** One of the special traits of a vehicular network is its dynamic nature, which is a result of the mobile nodes and the high speed they develop considering the fact that they are vehicles. Vehicles may also move at different directions and can quickly use or leave the network in a very short period of time, leading to frequent and fast topology changes. This results in frequent changes in network connectivity where the link between two vehicles can quickly disappear while they are transmitting information. The deployment of the infrastructure is employed to provide a level of stability to the dynamic network by coordinating the communication between its participants.
- **Security concerns:** The issue of security is really important for vehicular network deployment. While the need for data privacy and cyber-security protection is imperative to the deployment of a vehicular network, such environment cannot be guaranteed without the assistance of road-side equipments. In this case, a certain security policy is enforced on the network and the infrastructure is used to oversee it.

It is obvious that the above challenges should be taken into account for the efficient design of communication protocols in vehicular networks. The spatial-temporal constraints of this type of network and the heterogeneity of vehicles in terms of speed and mobility are design factors to be considered in the development of secure protocols for vehicle networks. For instance, cars have different speeds and tend to follow an unpredictable mobility model, whereas public transportation means, such as buses and trams, have regular and slower speeds following a predictable mobility model.

2.6.2 Applications

It is important to identify the four major categories of applications that exist in vehicular networks and provide numerous services (Papadimitratos et al., 2008):

- **Safety-oriented applications:** These applications focus on providing the vehicular network nodes with the necessary mechanisms in order to maximize accident prevention and mitigate an accident's impact on the rest of the network, i.e. emergency break warning applications, lane-change warning applications, LoA warning applications, etc.
- **Service-oriented applications:** Also known as infotainment applications, aim to provide the vehicular network participants with several services. They strive to make the driving experience of both drivers and passengers more comfortable through various applications and services. That may include Internet access, media streaming, online gaming, soundtrack entertainment, etc.
- **Traffic-efficiency applications:** These applications target at the improvement of traffic flow, reduction of road congestion, provision of alternate routes. This can be achieved in various ways such as electronic toll collection, rail intersection management, congestion awareness and information, real-time traffic conditions, etc.
- **Driver-assistance applications:** These applications aim to provide a secure and comfortable experience for the driver/user of the vehicle. Digital road maps downloading, navigation systems, parking assistance and automatic emergency calls are only some of the services that can be provided as much assistance as

possible to the driver/user, without in any case compromising the driving experience.

It must be noted that this general taxonomy is affected by the vehicle-to-infrastructure relation. It is needless to say that certain applications could not achieve the required performance of delay, throughput and other network metrics if they were left to operate only in an ad-hoc manner.

2.6.3 Threats and constraints

Data privacy in vehicular networks has to deal with various kinds of threats that try to correlate received identifiers, or to correlate them to real-world identity. The purpose of these attacks is to create problems on network for users to access the system or phishing some information (Lochert et al., 2003).

Sybil attack is the creation of multiple fake nodes broadcasting false information. In this, OBU installed in vehicle sends multiple copies of messages to other nodes and each message contains a different fabricated identity. The problem arises when attacker is able to pretend as multiple vehicles and reinforce false data. On the other hand node impersonation is an attempt by an attacker to send modified version of message and claims that the message comes from original node for the unknown purpose.

Also attackers sometimes disclose the identity of nodes in the network and track the location of the target nodes. Then it monitors the target nodes and sends a virus to the neighbors of the target nodes. When the virus attacks the neighbors of the attacker, then they take the identity of the target nodes as well as their current location. Also attackers can initiate excessive authentication requests in order to exhaust the resources.

To increase the data privacy and security protection of an ad-hoc network, we need to consider the following attributes as criteria:

(a) **availability** deals mainly with network services for all nodes comprises of bandwidth and connectivity. Technique using group signature scheme has been introduced to encounter the availability issues, prevention and detection. This scheme focuses on availability of exchanging the messages between vehicles and IUs.

(b) **confidentiality** ensures that unidentified entities can never have the access to the classified information in the network. Confidential information such as name, vehicle identification number, plate number and current location can also be prevented from unauthorized access. Pseudonyms, is the most popular technique, which is used to preserved privacy in vehicular networks. Different pseudos' are used to encrypt messages and only relevant authority could have access to them. When any earlier pseudo expires, vehicles need to obtain new pseudos from trusted authorities.

(c) **authentication** is required to verify the identity between vehicles and IUs and also for the validation of integrity of the information exchange. It also ensures that all the nodes are the authenticated vehicles to communicate within network. To establish connection between vehicles, IUs and trusted authorities, public or private keys with certificate authority are proposed.

(d) **data integrity** is very essential because it assures that the data received by nodes, IUs and trusted authorities is similar to the data which has been generated during the exchanges of the message. Digital signature which is integrated with password access is used to protect the integrity of the message.

(e) **non-repudiation** ensures the sender and receiver so that later on it cannot deny ever sending and receiving the message such as accident messages.

Moreover, a large number of authorities and service providers will emerge, making interoperability of secure communication protocols a difficult problem. A multitude of road-side infrastructure devices may be available, while vehicles from foreign administrative domains may frequently need to communicate in a secure manner.

At the same time, the deployment of those networks will be gradual: initially, only a fraction of the vehicles will be equipped with communication and processing capabilities, while only a few highways will be covered by the appropriate IUs. The cost of such equipment will be a determining factor, while broad support of vehicular communication systems is essential for their effectiveness.

2.6.4 Data privacy and security issues

In the past, several researchers addressed the security and privacy issues of vehicular networks, which review security related issues attacks, requirements, challenges, and security solutions about inter-vehicle and vehicle-IUs communication interactions (Qu & Yang, 2010; Lei et al., 2010).

In this direction, Hubaux et al. (2004) tried to address privacy problems on VCs by using anonymity schemes and, relying on temporary pseudonyms. However, with these privacy preserving proposals (Sha et al., 2006; Papadimitratos et al., 2006), malicious vehicles could still be anonymous, which would make it difficult for the central trusted authorities to track these vehicles and revoke their access. To overcome these problems, the concept of conditional privacy preservation was proposed. Lin et al. (2007) introduced a secure and conditional privacy preserving protocol for vehicular networks by integrating the techniques of group signature and identity-based signature. The trusted authorities were able to reveal the real identities of malicious vehicles and update the certificate revocation list accordingly. However, these mechanisms fell short since they required a vast amount of storage space for anonymous keys and safety message anonymous authentication. Recently, Horng et al. (2013) provided a software-based solution to reduce verification time and alleviate the computational workload of IUs, whereas Chaudhuri et al. (2012) proposed identity protocols for vehicular ad hoc networks based on the production of unique identifiers for vehicles.

In Xiong et al. (2010), a spontaneous privacy-preserving protocol based on revocable ring signature with a feature for authenticating safety messages locally was proposed.

This scheme is not scalable because every vehicle needs to participate in message verification process. Lu H. et al. (2012) proposed an ID-based authentication framework for privacy preservation for vehicular networks using adaptive self-generated pseudonyms as identifiers. Hao et al. (2012) proposed a cooperative message authentication protocol for vehicular networks to alleviate vehicles' computation burden by allowing vehicles to share verification tasks. Hsiao et al. (2011) proposed a broadcast authentication scheme to reduce communication and computation overhead using fast and selective authentication.

In another research work (Lin & Li, 2013), a cooperative authentication scheme for vehicular networks was proposed by using an evidence-token approach to distribute the authentication workload, without direct involvement of a central trusted authority. The vehicles obtain an evidence token as they make contribution to the network and benefits are given to nodes based on the tokens. In addition, in Wang & Tague (2013) a secure in-network strategy was proposed to accelerate message verification and reduce computational overhead using the aggregation structure and TESLA scheme. In a more recent study, Lim & Manivannan (2016) proposed an efficient protocol for authenticated and secure message delivery in vehicular ad hoc networks. In this protocol, IUs not only authenticate messages sent by vehicles fast, but also disseminate messages through the other IUs to the vehicles in the appropriate areas quickly.

2.6.5 Cryptographic materials

Cryptography is the practice and study of techniques for secure communication in the presence of third parties. More generally, it is about constructing and analysing protocols that overcome the influence of adversaries and which are related to various aspects in information security, such as data confidentiality, data integrity, and authentication. In this context, messages supporting a wide range of applications in vehicular networks should be authenticated, while at the same time the anonymity of the senders should be preserved.

Based on the above, cryptography processes towards the Group Key Management Protocols (GKMP) could be used through which the participants (vehicles and/or road-side equipments) exchange information, in a secure manner, to establish a common key called group key. In the literature, many solutions were proposed for secure generation and exchange of group keys. The most popular key management schemes are RSA, Diffie-Hellman and RC4 algorithms (Sasikumar et al., 2010). These solutions differ by a certain number of characteristics such as collaboration, decentralization, dynamic and hierarchy.

To cope with the famous keys management problems in vehicular communication networks, such as the limited connectivity and the sensitive communication with a central certification authority, Busanelli et al. (2011) proposed a novel key management approach to secure VCs. Their framework is designated to generate a series of short-lived secret keys, shared by all the subscribers of a specific service. Moreover, Raya & Hubaux (2007) proposed a protocol in which each vehicle needs to be preloaded with a large number of private keys, as well as their corresponding anonymous certificates. Their communication scheme is designated to pay much attention on safety-related applications in vehicular networks.

Furthermore, Shanmugapriya & Saraswathi (2017) proposed an efficient hierarchical pseudonymous authentication protocol in vehicular ad hoc networks with conditional privacy preservation, which is incorporated with the dual authentication and key management system, whereas Lu R. et al. (2012) proposed a dynamic privacy preserving key management scheme for improving the key update efficiency of location-based services in vehicular networks.

In general, most of the developed works related to cryptography materials towards V2V, V2I/I2V and V2E communication applications are related to group key generation, group key management and ID-based security frameworks (Kamat et al., 2008).

2.7 Summary

AVs are seen as a groundbreaking innovation, with the potential to change traffic environment, urban planning and even how the people see mobility. These changes represent an opportunity, but at the same time it is important to foster research efforts in order to make the change fluent and without negative surprises. Fundamental human factors challenges are to ensure safety, ease of use, trust, acceptance and comfort, for users/passengers of autonomous vehicles. Likewise, a safe and acceptable interaction with other road users including pedestrians and cyclists needs to be established.

It is predicted that decades of years might be needed to socialize this new technology, and this process would be subject to a number of unknown social and personal factors. Therefore, to expedite AV acceptance, it is critical to investigate what factors influence public’s decision to use AVs.

Furthermore, AD encompasses a wide range of technologies and infrastructures, capabilities and contexts, use cases and business cases, and products and services. There is no single timeline for these developments: some are here today, some may be distant, and some will depend on specific technical innovations or particular policy choices.

Moreover, with the help of recent developments in artificial intelligence (AI), we are able to make vehicles intelligent and capable of making decisions in situations in which humans could not do so, but we must ensure in some way that they make the right decisions so as not to put at risk the missions and the lives of drivers/users.

In addition, vehicular network technology is considered to be one of the most basic components of the future ITS moving us closer to increasingly AVs. The most important objective of a vehicular network system is to provide communications in the transport area between different vehicles on the roads (V2V communications), vehicles and road-side infrastructure units (V2I communications) and generally vehicles with everything (V2E communications) like pedestrians, cyclists, etc.

CHAPTER 3: MODELLING THE ACCEPTANCE OF AUTONOMOUS VEHICLES

Contents

3.1 Introduction

Many innovations in vehicle technology and ADAS have been developed rapidly by automotive and other related companies. The individual and social demands for a safe, convenient, efficient, and eco-friendly transportation are pushing to fundamental changes in the transportation field like the AVs, as mentioned previously.

On this basis, most companies in the automotive industry are currently being advertised the introduction of AVs, planning to be available in market diffusion the next years (Chan, 2017). As found in Chapter 2, a large majority of the population has a positive attitude towards AVs in general. In addition, with respect to travel mode choice behavior, privately-owned car has remained the most attractive mode of individual transport (associated with sensation seeking, power, freedom, status, etc.)

despite creating serious collective disadvantages, such as traffic congestion, accidents and environmental pollution (Beirão & Cabral, 2007; Steg, 2005). In this respect, privately-owned AVs may turn out to be more preferable to consumers in the near future in comparison with the car sharing mobility services and shared AVs. As such, although AVs may be seen as a means to reduce dependence on the personal car, the literature on technology adoption suggests that private ownership of AVs is likely to prevail in the long-run (Krueger et al., 2016; Zhang et al., 2018).

Therefore, forecasting technology usage and acceptance by the end users becomes fundamental in order to understand aspects that are likely to minimize consumer resistance and maximize adoption of AVs. In this respect, the automotive industry still lacks widely accepted and used frameworks to assess technology acceptance towards AVs.

With the vision to fill this research gap, the present Ph.D. dissertation aims to design and introduce adapted versions of the original well-established social-psychological frameworks – Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) – in predicting consumers' intension to drive/use AVs, as well as to investigate in what extent consumers intend to drive/use AVs in the future, by identifying the factors that affect the uptake of such vehicles.

3.2 Modifying TAM model to fit study

3.2.1 Theoretical framework

As mentioned previously in Chapter 2, TAM is one of the most widely cited frameworks in the area of transport technology. The basic TAM model included two specific beliefs:

- **Perceived Usefulness (PU)**, which indicates the extent to which consumers believe that using a particular technology system will enhance his or her job performance.
- **Perceived Ease to Use (PEU)**, which indicates to which extent consumers believe the use of a particular technology system will be free by effort.

According to the above, usage behavior is determined by the intention to use a particular system, i.e., transport technology, which in turn is determined by the factors PU and PEU.

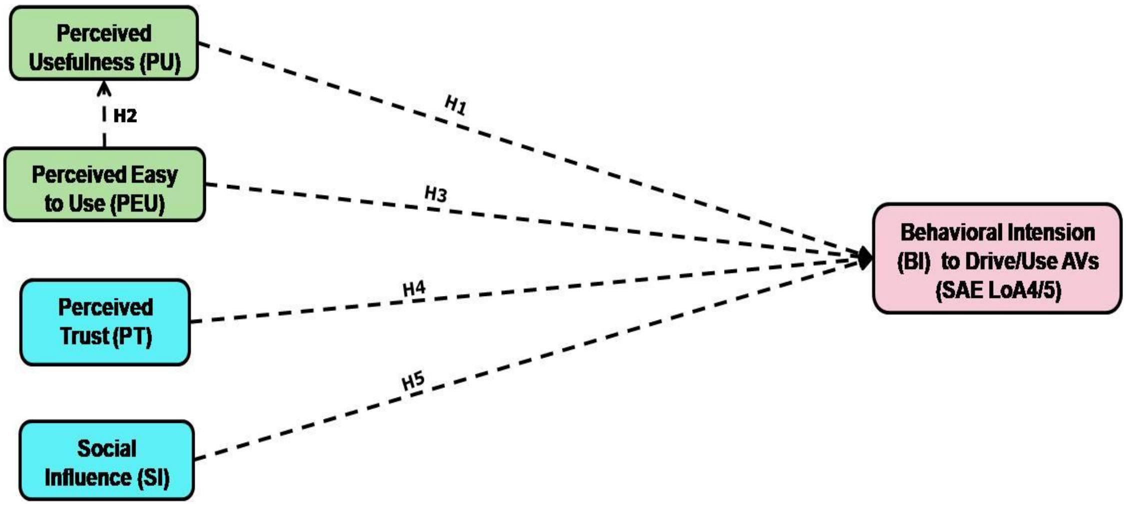


Fig. 3.1 TAM-extended research framework.

Although many researchers have investigated and replicated the TAM and agreed that it is valid in predicting the individual's acceptance towards transport technology, the TAM's fundamental constructs (PU, PEU) does not fully reflect the specific influences of technological and usage-context factors that may alter the users' acceptance (Fayad & Paper, 2015). Therefore, the present analysis, as depicted in Fig. 3.1, takes the original TAM as a starting point, and extends this model with two new factors, to enhance the understanding of consumers' behavioral intension to accept and drive/use AVs:

- **Perceived Trust (PT)**, which indicates the extent to which consumers believe that will generally trust a particular technology system.
- **Social Influence (SI)**, which indicates the degree to which an individual perceives that important others believe he or she should use a particular technology system.

Few adaptations of TAM have considered trust as a determinant of acceptance; however, those who have done so have found trust to be a determinant of intention to use, i.e. in the context of e-services and e-government applications (Mou et al., 2017; Gupta et al., 2016). According to Hoff & Bashir (2015), individuals will generally trust an automated system if it behaves in the manner they expect. However, if they experience unanticipated actions, there is a rapid drop in trust that often leads to disuse. In a similar manner individuals would intent to use AVs if they find that they can trust their technology mainly towards safety, data privacy and security protection issues.

Furthermore, there are a few studies that we are aware of which studied the role of peer pressure effects (SI) on the adoption of AVs. In this basis, Bansal et al. (2016) found that 50% of respondents would prefer their family, friends, or neighbours to use AVs before they adopt them on the basis of the theoretical propositions that mode choice behavior is partly motivated by social norms and the strong role of the car as status symbol that provides flexibility, autonomy and an interminable pull of sensory experience.

In the light of the above, according to our TAM-extended research framework, four independent variables (PU, PEU, PT, SI) and one dependent variable (Behavioral Intention, BI) were totally used, as shown in Table 3.1. Moreover, a brief (14-item) measurement scale was implemented to assess consumers' BI to accept and drive/use the AVs technology. In this context, the construct PU contained 4-items (PU1, PU2, PU3, PU4), the construct PEU contained 3-items (PEU1, PEU2, PEU3), the construct PT contained 4-items (PT1, PT2, PT3, PT4), the construct SI contained 2-items (SI1, SI2), and the construct BI contained 1-item. Items selection were adapted from or inspired by relative items in the published literature, as mentioned previously in Chapter 2, on each of the respective constructs, in order to ensure content validity, modified in a suitable manner to be specific to AVs extent.

Furthermore, five (5) hypotheses have been formed regarding the relationships between the above included factors in the proposed TAM-extended model, i.e. what impact they have on each other. These 5 hypotheses are also shown in Table 3.1. In this context PU is hypothesized to have a positive impact on BI to drive/use AVs, and this relationship is denoted as H1. Another factor with regards to the impact on a customer's adoption/rejection decision was complexity, and it was concluded that complexity has a negative impact on the likelihood to adopt. The responding factor is

PEU, which will be hypothesized to have a positive impact on BI to drive/use AVs. This relationship will be denoted as H3. Moreover, it is also hypothesized that PEU has a direct positive impact on PU. This positive relationship is expected to be as true in this case, and it will be denoted as H2. The new factor PT clearly has a positive impact on BI to drive/use AVs, and this relationship will be denoted as H4. Furthermore, another factor with regards to the impact on a consumer's adoption/rejection decision was SI. It is obvious that this has a positive impact on the likelihood to adopt AVs and this positive relationship will be denoted as H5.

Table 3.1 Items used in the TAM-extended research model and summary of hypotheses.

Construct	Items	Hypotheses
Perceived Usefulness (PU) *[Independent variable]*	PU1: I would find AVs useful in meeting my transportation needs PU2: If I were to drive/use AVs, I would feel safer PU3: Using AVs driving would be more interesting PU4: Using AVs accidents would be decreasing	H1: PU is positively correlated on BI to drive/use AVs
Perceived Ease to Use (PEU) *[Independent variable]*	PEU1: Learning to operate an AV would be easy for me PEU2: Interactions with AVs would be clear and understandable to me PEU3: It would be easy for me to become skillful at driving/using AVs	H2: PEU is positively correlated to the PU of AVs H3: PEU is positively correlated on BI to drive/use AVs
Perceived Trust (PT) *[Independent variable]*	PT1: I generally have concerns about driving/using AVs PT2: AVs are somewhat frightening to me PT3: I have concerns about safety of AVs PT4: I have concerns about system security and data privacy of AVs	H4: PT is positively correlated on BI to drive/use AVs
Social Influence (SI) *[Independent variable]*	SI1: I would be proud if people saw me driving/using an AV SI2: People whose opinions I value would like driving/using AVs	H5: SI is positively correlated on BI to drive/use AVs
Behavioral Intention (BI) *[Dependent variable]*	BI: Likelihood of driving/using AVs when they become available on the market	

3.2.2 Survey design and data collection

A 24-question survey was conducted among adults currently in their 18s to 70s. The above survey was implemented in two phases: a pilot study and a web-based questionnaire. Firstly the questionnaire was pilot-tested with 5 randomly selected individuals. Based on the feedback from the pilot test, the questionnaire was refined and a revised final online questionnaire via Google Drive format was developed. The complete questionnaire survey can be found in Appendix A. The purpose of the survey had been explained to the respondents and motivated them to reply personally. Also the confidentiality of the results had been stressed. In total, four hundred and eight-three individuals (483) completed the survey. The responses were gathered between 20 March 2017 06:00 and 30 April 2017 12:00 Central European Time.

The above 24-question survey has three main parts. In the first part a series of questions about participants' background and general attributes of the respondents about car passenger vehicles (11-questions), were included. In the second part, general experience about new technologies and concerns about internet-enabled technologies (5-questions) were taken into account. In the third part of the questionnaire 7-questions and the 14-item measurement scale, see **Table 3.1**, was administered to assess consumers' BI to accept and drive/use AVs. Responses about the 14-item measurement scale of the third part were made on a five-point Lickert scale with the anchors "strongly disagree" and "strongly agree".

3.2.3 Data analysis

Respondents

Four different demographic variables towards defining the profile of participants were considered including gender, age, household income and mode of daily commute (Table 3.2). 70.8% of respondents are males while the remaining (29.2%) are females. With respect to age, the sample stated a higher share of respondents between 18 and 30 years old (almost 56%), whereas 30.3% of the respondents were between 31 and 50 years old and 14.1% were more than 50 years old.

Table 3.2 Demographic attributes of the respondents.

Response variable	Options	Frequency (n)	Percentage (%)
Gender	Male	342	70.8
	Female	141	29.2
Age	18-30	268	55.7
	31-40	79	16.4
	41-50	67	13.9
	51-60	38	7.9
	More than 60	31	6.2
Household income (2016)	Less than 5000€	58	12.0
	5000€ to 10000€	78	16.1
	10000€ to 20000€	152	31.5
	20000€ to 30000€	122	25.3
	More than 30000€	73	15.1
Mode of daily commute	Automobiles	221	45.8
	Public transportation	228	47.2
	Walking / Biking	34	7.0

Table 3.3 General attributes of the respondents about car passenger vehicles.

Response variable	Options	Frequency (n)	Percentage (%)
Do you currently own or lease a car passenger vehicle?	Yes	270	55.9
	No	213	44.1
How often do you drive or use a car passenger vehicle?	Every day	219	45.3
	A few days a week	85	17.6
	A few days a month	64	13.3
	Almost never	115	23.8
How safe do you feel when you are driving or using car passenger vehicles today?	Not at all safe	85	17.6
	Somewhat safe	183	37.9
	Moderately safe	194	40.2
	Extremely safe	21	4.3
Had you ever heard of automated car passenger vehicles?	Yes	345	71.4
	No	117	24.2
	Don't know	21	4.3
What is your general opinion regarding automated car passenger vehicles?	Negative	36	12.0
	Neutral	168	33.6
	Positive	257	57.7

Moreover, among the respondents, 28.1% had a household income for the year 2017 less than 10000€, 31.5% had between 10000€ to 20000€, and 40.4% had more than 20000€. Furthermore almost 46% of the respondents use automobiles as drivers or passengers whereas 47.2% travel primarily by public transportation means.

Table 3.4 Respondents' attributes about using or adopting new (automation) technologies.

Response variable	Options	Frequency (n)	Percentage (%)
It is important to keep up with the latest trends in new (automation) technology	Strongly disagree	13	2.7
	Somewhat disagree	28	5.8
	Neither agree nor disagree	85	17.6
	Somewhat agree	201	41.6
	Strongly agree	156	32.3
New (automation) technology makes people waste too much time	Strongly disagree	132	27.3
	Somewhat disagree	185	38.3
	Neither agree nor disagree	121	25.1
	Somewhat agree	36	7.5
	Strongly agree	9	1.9
New (automation) technology makes life more complicated	Strongly disagree	113	23.4
	Somewhat disagree	171	35.4
	Neither agree nor disagree	121	25.1
	Somewhat agree	70	14.5
	Strongly agree	8	1.7
New (automation) technology will provide solutions to many of our problems	Strongly disagree	11	2.3
	Somewhat disagree	12	2.5
	Neither agree nor disagree	34	7.0
	Somewhat agree	207	42.9
	Strongly agree	219	45.3
Adopting new (automation) technology	Early adopter	128	26.5
	Late adopter	300	62.1
	Laggard	55	11.4

General attributes

Of the people surveyed, almost 56% of them own or lease a car passenger vehicle and 45.3% drive or use their car passenger vehicle every day (Table 3.3). Moreover, in responding to the question of "*How safe do you feel when you are driving or using car passenger vehicles today?*", almost 55% of the respondents feel not at all or somewhat safe. For the above question it has been stated to the survey participants that the feeling of safety when using car passenger vehicles is not be influenced by who is driving the vehicle. Furthermore, the majority of respondents (71.4%) had heard of vehicles with autonomous driving capabilities before participating in the present survey, and almost 58% of the respondents had a positive general opinion regarding automated car passenger vehicles whereas only 12% had a negative general opinion.

Regarding experience with the current automation technology trends (Table 3.4), almost 74% of the respondents somewhat agree or strongly agree with the statement "*it is important to keep up with the latest trends in new (automation) technology*". In the same direction almost 88% of the people surveyed somewhat agree or strongly agree with the statement "*new (automation) technology will provide solutions to many of our problems*". Moreover, the majority of the respondents somewhat disagree or strongly disagree with the statements "*new (automation) technology makes people waste too much time*" and "*new (automation) technology makes life more complicated*". Furthermore, almost 62% of the people surveyed considered themselves, late adopters on the technology adoption curve, whereas early adopters (e.g., among the first to adopt new-automation technology) comprised 26.5% of the respondents.

Table 3.5 Respondents' attributes about internet-enabled technologies or services today.

Response variable	Options	Frequency (n)	Percentage (%)
Data privacy concerns	Not at all concerned	24	5.0
	Somewhat concerned	139	28.8
	Moderately concerned	195	40.4
	Extremely concerned	125	25.9
Cyber security concerns	Not at all concerned	31	6.4
	Somewhat concerned	127	26.3
	Moderately concerned	194	40.2
	Extremely concerned	131	27.1

Moreover, in responding to the question of "*How concerned are you that your data are kept private when you use internet-enabled technologies or services today?*", almost 40% of the respondents answered that are moderately concerned, and 26% answered that are extremely concerned (Table 3.5). The same characteristics stated also to the similar question of "*How concerned are you that your data are kept resilient to* *common cyber security threats when you use internet-enabled technologies or services today?*".

Factors associated with intent to drive/use AVs

As described in Chapter 2, BI to drive/use is an important concept because AVs are not yet on the market. In this context, in responding to the questions about the perceived usefulness of AVs, almost 46% of the people surveyed indicated that such vehicles will be useful in meeting their driving needs, as depicted in Fig. 3.2. Furthermore, almost 44% of the respondents will be feeling safer on their driving trips, 38.3% answered that driving will be more interesting, and the majority 55.3% indicated that using AVs accidents would be decreasing.

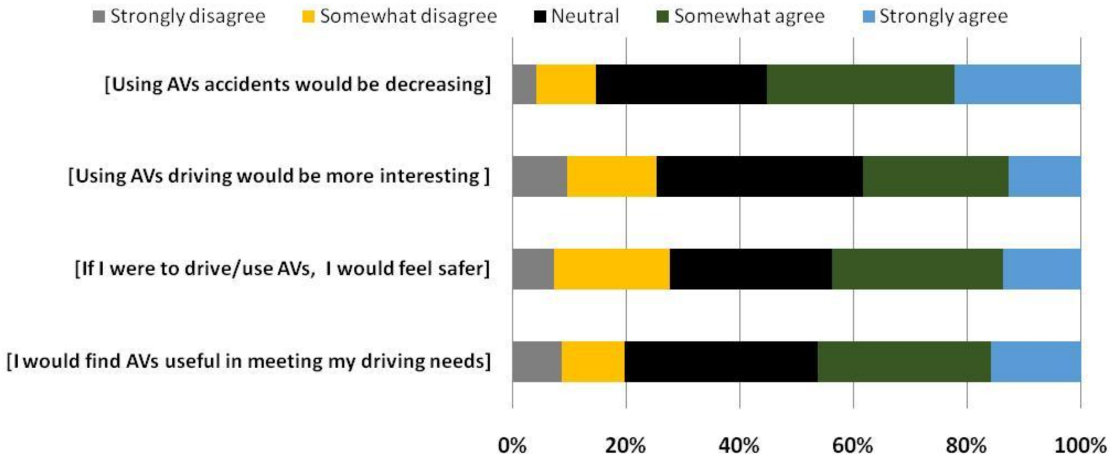


Fig. 3.2 Impact of perceived usefulness on driving/using AVs.

On the other hand, as depicted in Fig. 3.3, regarding the questions about the perceived ease to use of AVs the majority of the respondents indicated that they are strongly agree or somewhat agree against the statements "*learning to operate an AV would be easy for me*" (64%), "*interactions with AVs would be clear and understandable to me*" (69%) and "*it would be easy for me to become skillful at driving/using AVs*" (66%).

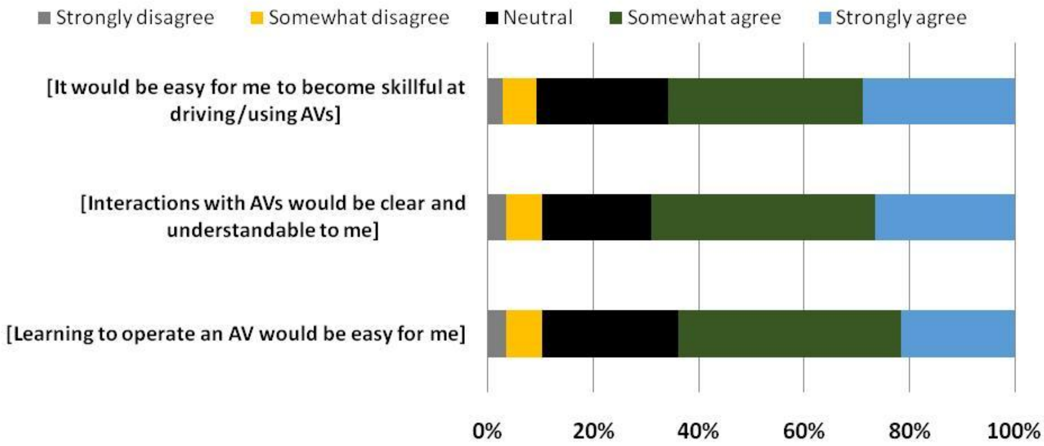


Fig. 3.3 Impact of perceived ease to use AVs.

Moreover, regarding the questions about the perceived trust of AVs, almost 48% of the respondents stated that they are strongly agree or somewhat agree against the statements "*I generally have concerns about driving/using AVs*" and "*I have concerns about safety of AVs*", whereas the corresponding percentage against the statement "*I have concerns about system security and data privacy of AVs*" was smaller (31%). Furthermore, as depicted in Fig. 3.4, only 26.7% of the people surveyed answered that the technology of AVs is somewhat frightening to them.

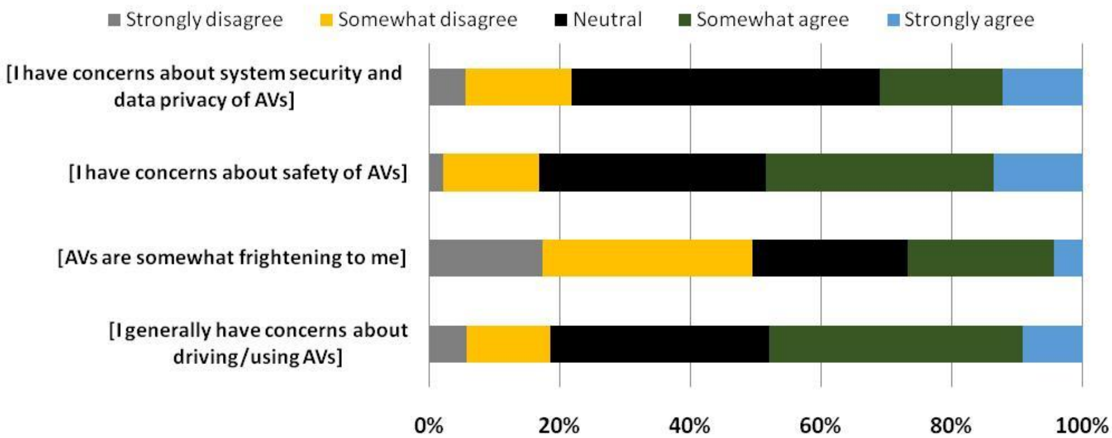


Fig. 3.4 Impact of perceived trust on driving/using AVs.

Finally, regarding the questions about the impact of social influence on using AVs almost one to third of the sample surveyed answered that they are strongly agree or somewhat agree against the statements "*I would be proud if people saw me* *driving/using an AV*" and "*People whose opinions I value would like driving/using AVs*", as shown in Fig. 3.5.

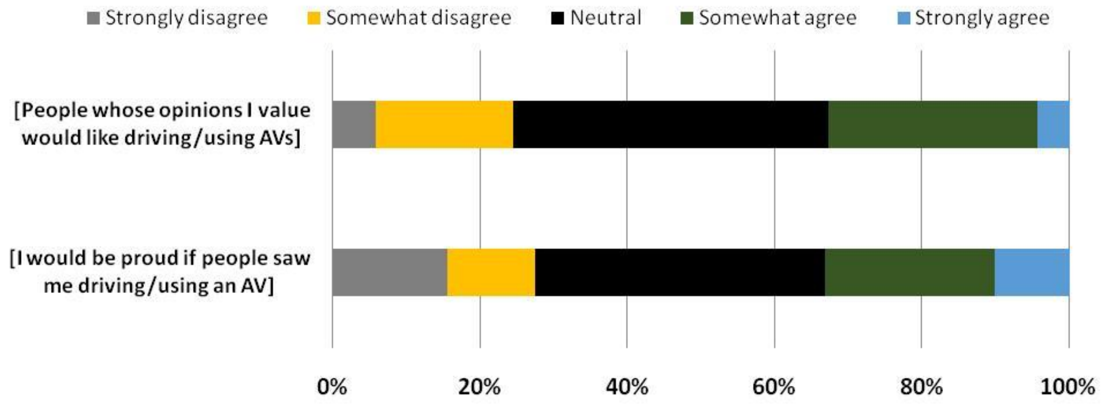


Fig. 3.5 Impact of social influence on driving/using AVs.

Respondents' likelihood of driving/using AVs when they become available on the market was assessed related to gender and age differences (see Table 3.6). Females, more than males, are somewhat or extremely likely to drive/use AVs with 18.4% of males were enthusiasts (extremely likely), compared to almost 12.5% of females. Furthermore, respondents between 18 and 40 years old are more likely to drive/use AVs when they become available on the market than those who are over 40 years old.

Table 3.6 Intension to drive/use AVs related to gender and age differences.

Response variable	Options	Gender		Age	
		Male (n = 342)	Female (n = 141)	18-40 (n = 346)	More than 40 (n = 137)
What is the likelihood of driving/using AVs when they become available on the market?	Not at all likely	13.3%	15.0%	13.3%	22.6%
	Somewhat unlikely	28.1%	17.5%	26.6%	21.9%
	Somewhat likely	40.3%	55.0%	45.4%	34.3%
	Extremely likely	18.4%	12.5%	14.7%	21.2%

Hypotheses testing

Cronbach's Alpha was chosen to analyze the degree of consistency among the items in a construct for reliability analysis. The calculated value of Cronbach's Alpha coefficient for the whole 14-item structured measurement scale is 0.757 and meets the general rule of thumb of .70 (Hair et al., 2006).

For the main group items of the questionnaire survey the descriptive statistics revealed that all dimensions charted higher than the midpoints of their respective scales (Table 3.7). It shows that respondents are generally optimistic about PU and PEU of AVs. Additionally, PT and SI factors were rated lower than the technological acceptance dimensions of PEU and PU.

Table 3.7 Descriptive statistics for the main variables in TAM-extended research model.

Constructs	Mean	Standard Deviation
Perceived Usefulness (PU)	3.33	1.132
Perceived Ease to Use (PEU)	3.79	1.001
Perceived Trust (PT)	3.14	1.077
Social Influence (SI)	3.04	1.061
Behavioral Intention (BI)	2.59	0.945

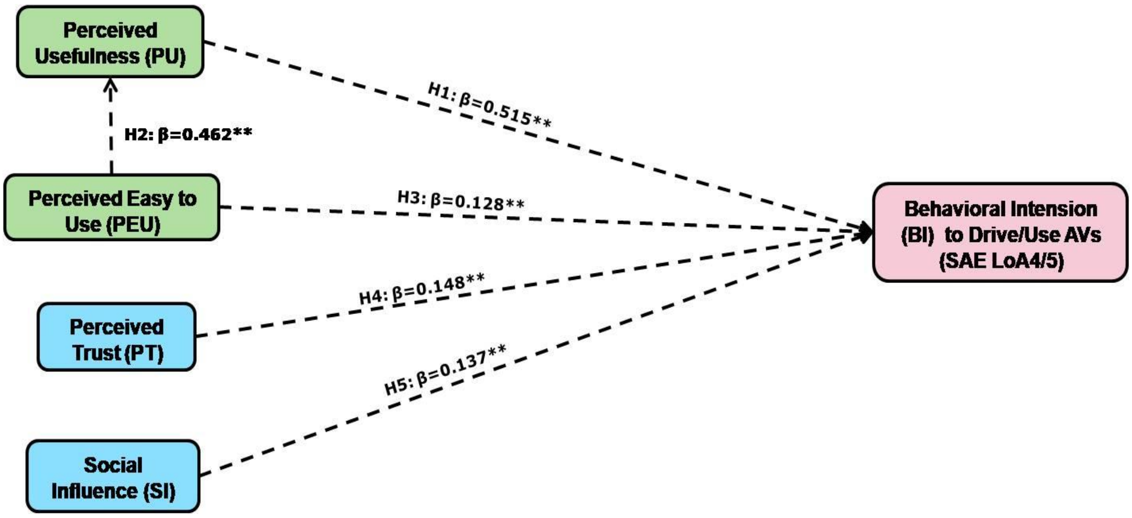
The Pearson product moment inter-correlations in Table 3.8 suggested that all variables other than PT-BIU are related to each other. In addition, the independent variables of PU, PEU, PT and SI do not show any multicollinearity problems associated with them.

Table 3.8 Pearson product moment inter-correlations of the main variables in TAM-extended research model.

	PU	PEU	PT	SI	BIU
Perceived Usefulness (PU)	1.000				
Perceived Ease of Use (PEU)	0.462**	1.000			
Perceived Trust (PT)	-0.148**	-0.157**	1.000		
Social Influence (SI)	0.546**	0.272**	-0.115*	1.000	
Behavioral Intention (BI)	0.627**	0.380**	0.036	0.436**	1.000

** $p<0.01$, * $p<0.1$

The concern of our analysis is whether the variables have an influenced as hypothesized. For this purpose, two multiple regression analyses (MRAs) were conducted using standardized coefficients. The first MRA is used to analyse the relationship between PEU and PU and the second is between PEU, PU, PT and SI with BI to drive/use AVs (Fig. 3.6).



** p<0.01

Fig. 3.6 Results of relationships in the TAM-extended research model.

The analysis show that PU had a positive effect on the BI to drive/use AVs (β = 0.515, p < 0.01), and that PT had also a positive effect on the BI to drive/use AVs (β = 0.148, p < 0.01). Therefore, hypotheses H1 and H4 were supported. Moreover, PEU had a positive effect on the BI to drive/use AVs (β = 0.128, p < 0.01), and that SI had also a positive effect on the BI to drive/use AVs (β = 0.137, p < 0.01). These values mean that hypotheses H3 and H5 were supported. PEU had a positive effect on PU (β = 0.462, p < 0.01) where this means that hypothesis H2 was supported.

Furthermore PEU accounted for approximately 21 per cent of the variance in PU (R^2 = 0.213), while PU, PEU, PT and SI managed to explain 43.7 per cent of the variance in BIU (R^2 = 0.437). Additionally, the impact is such that PU has the largest impact on the BI to drive/use AVs, followed by PT, SI and PEU.

3.2.4 Main findings – discussion

AVs have not been commercialised yet and hence only few people had interactions with this technology so far. For this reason, the present TAM-extended research model aimed to predict consumers’ intentions to drive/use such vehicles. Almost 62% of survey respondents considered themselves, late adopters on the technology adoption curve, which is almost at the same level compared to the findings (66%) obtained by

Zmud & Sener (2017). This implication has to do with the fact that the majority of consumers wait awhile before adopting new (automation) technology, and so are not necessarily eager to jump on AVs emerging technology. Moreover, it was found that females (almost 78%) were more likely to drive/use AVs, when they become available on the market, whereas the corresponding percentage about males' likelihood was smaller (almost 59%). This finding is opposite to other related studies towards acceptance and use of autonomous (self-driving) vehicles (Piao et al., 2016). This statement suggests that the gender gap with respect to AVs technology acceptance is lessening.

Furthermore, safer driving is one of the major driving forces for the development of AVs and would be a prerequisite for implementation of AVs on public roads in the future. From the survey, 44% of the respondents indicated that if they were to drive/use AVs they would be feeling safer. This finding underlines the necessity to convince the potential consumers what AVs can do in real conditions, especially the safety benefits. Additionally, the majority of the people surveyed are concerned about cyber security and data privacy issues regarding online technologies or services that they use today. This implication is followed by the finding that almost 47% of the respondents were stated neutral against their concerns about system security and data privacy of AVs. According to the above results, which are similar to what Kyriakidis et al. (2015) have studied, it is obvious that gaining trust from end users about safety, security and data privacy concerns will be critical to the widespread deployment of AVs in the future.

Moreover, according to the proposed TAM-extended research model, the results of this analysis indicated that the four constructs PU, PEU, PT, and SI impact on BI to drive/use AVs. PU is the strongest predictor, suggesting that the most important factor that potential consumers will consider in deciding whether or not to drive/use AVs is how well they believe it will be useful in comparison to other transportation solutions. In this context consumers who think that AVs are useful tend to be more willing to use these technologies when they will be available on the market. While this finding is perhaps not surprising, it nevertheless underlines the importance of AVs' potential to provide functional benefits in terms of freeing up consumers' time and simplifying their lives, similar to what Piao et al. (2016) have studied.

Additionally, PT had also a positive impact on BI, indicating that perceptions of how trusted the system is to use will influence consumers' decision to use AVs technology. In this manner, it is obvious that individuals would drive/use AVs if they find that they can trust AVs technology towards safety, data privacy and security protection concerns. The above confirm the results of what Ghazizadeh et al. (2012) have studied about the important role of trust on automation along with other determinants of acceptance.

Furthermore, the variable SI had a positive impact on BI, indicating that the influence of others, influence consumers' likelihood of driving/using AVs when they become available on the market. This may stem from the car often being regarded as a status symbol which highlights the connection between intent to use and the social environment. This implication is consistent with what Zmud & Sener (2017) have studied. Moreover, it should be noted that SI and PT constructs have a negative interaction (-0.115*). This implication is in line with the fact that the more trust someone gets on his/her intension to drive/use AVs, the less will be influenced by social norms (family, friends, etc.).

Moreover, the construct PEU seems to have the smaller influence on the attitudes of consumers towards the driving/usagevof AVs. The notion that individuals are more influenced by the ease to use of the products instead of its usefulness had been challenged. This implication is similar to what Choi & Ji (2015) demonstrated that perceived usefulness and trust were necessary precursors to drive/use an AV, with a weak effect of perceived ease to use on behavioral intent to use such a vehicle. The above finding indicates that car developers need to pay attention to the user-friendliness of AVs. Furthermore, this result is similar to previous studies in the driving domain (Chen & Chen, 2011), which have found a greater effect of PEU on BI, compared to PU) Moreover the results also showed a significant relationship between the two variables PEU and PU. This implication is consistent with what Solbraa Bay (2016) has studied showing that PEU has indirect effects on BI to drive/use AVs via PU.

In conclusion, the results demonstrated that, in keeping with the hypotheses, PU plays the major role in determining consumers' BI to drive/use AVs. PT, PEU and SI constructs were also determinants of use intentions. These findings are consistent with what Nordhoff et al. (2018) have investigated by conducting a survey with 7,755 respondents from 116 countries on the acceptance of driverless vehicles. The above results show that the proposed TAM-extended framework could be applied to increase understanding of user's BI towards AVs. However, similar to Madigan et al. (2016) investigation of Automated Road Transport Systems (ARTS), the explanatory power of the proposed TAM-extended research model was 43.7 per cent. This suggests that the current manifestation of TAM-extended framework is not capturing all of the factors which influence individual's behavioral intentions to drive/use AVs, so there may be a need to find additional variables to improve the accuracy of our predictions on usage intentions.

3.3 Modifying UTAUT model to fit study

3.3.1 Theoretical framework

The original UTAUT model (Venkatesh et al., 2003), as shown in Fig. 3.7, incorporates four key constructs which play a significant role as direct determinants of user acceptance and usage behavior:

- **Performance Expectancy – PE (intention):** "the degree to which an individual perceives that using the system could help improve his/her performance"
- **Effort Expectancy – EE (intention):** "The extent to which an individual perceives that the system will be easy to use"
- **Social Influence – SI (intention):** "The degree to which an individual perceives that important others believe he or she should use the new system"
- **Facilitating Conditions – FC (use behavior):** "the degree to which an individual perceives that organizational assistance is there to facilitate use of the system"

According to the original UTAUT model, these constructs are hypothesized to positively affect behavioral intention and usage behavior, shown to be important predictors of technology adoption. In addition, external variables such as Gender, Age, Experience and Voluntariness of Use are used to moderate the impact of each key component.

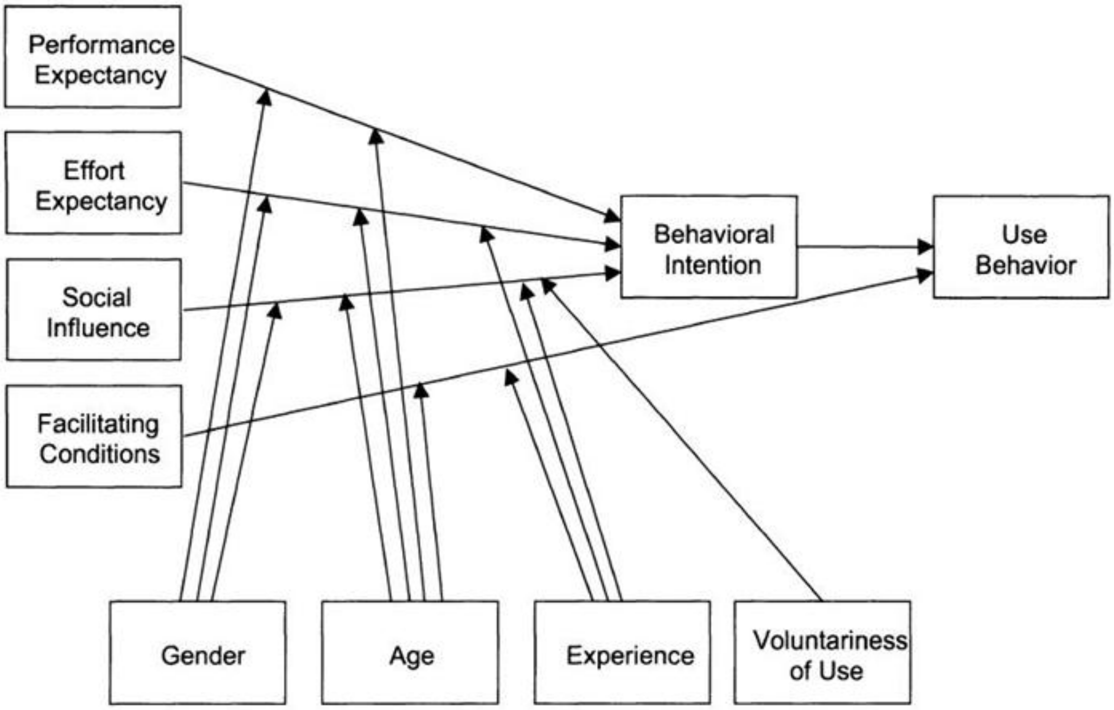


Fig. 3.7 The original UTAUT model.

Although previous studies in the existing literature have investigated and replicated the original UTAUT model and agreed that it is valid in predicting end users' acceptance towards vehicle technology and autonomous driving (Chapter 2), further extensions are needed, in most of cases, to fully explore the predictors influencing consumers' attitudes and willingness to use/accept innovative vehicle technologies in order to be successful in market diffusion. In this respect, based on the literature review regarding the intension of potential users to adopt AVs, further indicators should be incorporated to determine the construction of the modified-UTAUT theoretical model. These factors are expected to play a vital role on consumers' behavioral intention to accept and drive/use AVs in the (near) future, by identifying the most important impacts and which variables of the UTAUT model have had the biggest impact on acceptability. Therefore, the questions in the user acceptance survey should be formulated accordingly.

Performance Expectancy (PE)

According to UTAUT model, PE is driven from perceived usefulness (TAM/TAM2), relative advantage (IDT), extrinsic motivates (MM), job-fit (MPCU), and outcome expectations (SCT). For the present analysis, **PE is defined** as "***the degree to which driving/using AVs will provide benefits to individuals in performing their travel activities***".

Previous research studies in the area of transport technology (Chapter 2) have shown that the factor PE was affected significantly consumers' behavioral intention to use/accept new transport applications like ADAS and ARTS vehicles (Adell, 2010; Cho et al., 2017; Madigan et al., 2016; Madigan et al., 2017). Moreover, various studies in the existing literature point to the perceived advantages of AVs relating to different dimensions of users' driving performance, e.g. traffic safety, driver productivity, traffic flow, etc. In this context, Schoettle & Sivak (2014) investigated public opinion about autonomous and self-driving vehicles in the US, UK and Australia, and their results indicated that respondents expected automated vehicles to lead to crash reduction (70%), fewer emissions (64%), fuel consumption (72%), improved traffic congestion (52%), and reduced travel time (57%). In addition, according to the survey study of Bansal et al. (2016), the reduction in crashes received the highest support with 63%, whereas the ability of automated vehicles to reduce traffic congestion was questioned by 31%.

Taken the above together, the present analysis posits the following **hypothesis H1**:
"Performance expectancy (PE) significantly affects individual behavioral intention (BI) to accept and drive/use AVs"

Effort Expectancy (EE)

This determinant is important in user acceptance analysis as prior studies (Chapter 2) have shown that complexity of technology and information loading discourages customers to adopt new technology systems. In UTAUT model, EE is driven from perceived ease-of-use (TAM), complexity (MPCU), and easy-of-use (IDT). In the present analysis, **EE is defined** as ***"the degree of ease associated with the driving/usage of AVs"***.

It is of intrinsic importance AVs to be able to perform driving tasks quickly without lasting periods of trial and error. In this way, as secondary tasks affect the driving performance, it is mandatory for AVs to be easy to use and clearly to understand. So, if the consumers found that AVs are easy to use and do not require much effort, then they are more likely to adopt them.

Regarding the effects of factor EE on the adoption of new applications in the area of transport technology context, mixed results were observed. For example, Madigan et al. (2016) found that the factor EE had an effect on consumers' behavioral intention to use ARTS but it was not the strongest predictor. In contrast, Adell (2010), Cho et al. (2017) and Madigan et al. (2017) failed to support the relationship between EE and consumers' behavioral intention to use/accept new applications like ADAS and ARTS vehicles.

As a result, in the present analysis, it is plausible to formulate the **hypothesis H2**:
"Effort expectancy (EE) significantly affects individual behavioral intention (BI) to accept and drive/use AVs"

Social Influence (SI)

Venkatesh et al. (2012) used SI to represent subjective norm in TRA, TAM2, TPB, and C-TAM-TPB, social factors in MPCU, and image in IDT. SI relates to the social pressure coming from external environment which surrounds the individuals and may affect consumers' propensities to adopt new technology systems. In the present analysis, **SI is defined** as ***"the extent to which individuals perceive that important others believe that they should drive/use AVs"***.

Much of the empirical research studies in ADAS and ARTS found SI to be an important antecedent of behavioral intension (Adell, 2010; Cho et al., 2017; Madigan et al., 2016;

Madigan et al., 2017). Moreover, according to the study of Bansal et al. (2016) about the role of SI on the adoption of AVs, findings showed that 50% of survey respondents would prefer their family, friends, or neighbors to drive/use AVs before they adopt them.

Moreover, on the basis of the theoretical propositions that mode choice behavior is partly motivated by social norms and the strong role of the car vehicle as status symbol, it is obvious that the consumers will be highly influenced by the uncertainty that will be created from innovations in vehicle automation technology (such as AVs) and this will force these consumers to interact with their social network to consult on their adoption decisions.

Accordingly, the present analysis posits the following **hypothesis H3**:
"Social influence (SI) significantly affects individual behavioral intention (BI) to accept and drive/use AVs"

Facilitating Conditions (FC)
By capturing the concepts of perceived behavioral control (TPB, C-TAM-TPB), facilitating conditions (MPCU), and compatibility such as work style (IDT), Venkatesh et al. (2012) defined FC as the degree to which an individual believes that an organizational and technical infrastructure exists to support technology use. In the present analysis, **FC refers** to ***"the extent to which individuals believe that an organizational and technical infrastructure should exist to support the driving/usage of AVs"***.

There is no doubt that driving/using AVs requires appropriate resources and knowledge, technical infrastructure design and implementation strategies. As found in the literature (e.g., Fagnant & Kockelman, 2015), AVs barriers suggest that if the aforementioned facilitating conditions are available, the intention to drive/use AVs will be higher. On the other hand, when facilitating conditions are not in place, the barriers are likely to be too high and, consequently, the intentions of potential AVs users to use such innovative technologies is expected to be lower.

Although prior research (Chapter 2) has shown that FC is not the best predictor for the behavioral intention to use different information technology contexts, we do expect that FC influence the intention to drive/use AVs. To enhance our expectation, in the most relevant study available, Madigan et al. (2017) found that the factor FC makes positive contribution to consumers' intension to use ARTS. In a similar study, it is highly likely that the resources provided to support the implementation of ARTS will influence user uptake of these systems (Sessa et al., 2015).

Consequently, the present analysis denotes the following **hypothesis H4**:
"Facilitating conditions (FC) significantly affects individual behavioral intention (BI) to accept and drive/use AVs"

Perceived Driving Enjoyment (PDE)

With regards to a car vehicle, the main instrumental value is individual mobility or, in other words, a person's freedom to get safely and independently to his/her desired destinations whenever he/she likes. Additionally, car vehicles also offer hedonic benefits, since they can be used for fun and exciting activities such as cruising around or enjoying the thrill of speed (Hagman, 2010).

With the expected widespread availability of vehicles with advanced high automation driving technology becoming ever-closer, the way we travel is set to be revolutionized. In this context, driving pleasure is also likely to play a role in such a new and innovative environment. This specific kind of hedonic motivation, which ultimately contributes to the overall enjoyment of a car vehicle, is called as **Perceived Driving Enjoyment (PDE)**, and is defined as ***"the degree to which individuals perceive enjoyment and pleasure derived from driving/using AVs"***.

As found in the literature (Chapter 2), hedonic motivation has been shown to be one of the most important factors influencing consumers' acceptance of technology across a variety of sectors (Venkatesh et al., 2012). According to the study of Madigan et al. (2017), in the context of vehicle automation, hedonic motivation, or users' enjoyment of the system, was the strongest predictor on consumers' behavioral intensions to use ARTS. Furthermore, Kyriakidis et al. (2015) found that manual driving is considered to be the most fun part of driving and full automation is the least enjoyable mode.

In this vein, the present analysis assumes the following **hypothesis H5**:
"Perceived driving enjoyment (PDE) significantly affects individual behavioral intention (BI) to accept and drive/use AVs"

Perceived Financial Cost (PFC)
Academics generally investigate consumer adoption of AVs from psychological and sociological theories, but empirical evidence has also revealed that AVs adoption is highly encouraged by economic factors such as purchasing costs and driving/usage costs like operating costs, maintenance costs, insurance costs, fuel costs, etc. (Zmud & Sener, 2017). Due to the fact that the present analysis focuses on AVs, PFC is also likely to play an important role in consumers' willingness to purchase and drive/use AVs in the future. In this way, the factor **Perceived Financial Cost (PFC)** is **defined** as ***"the degree to which individuals perceive financial costs derived from purchasing and driving/using AVs"***.

Previous studies in Chapter 2 have shown that perceived financial cost is one of the most important concerns influencing consumers' acceptance of autonomous and self-driving technology. More in detail, according to the study of Howard & Dai (2014), which public perceptions towards self-driving cars were explored, the cost factor was one of the least attractive features. Moreover, just above 40% of the participants said they would wish to either purchase self-driving technology in their next vehicle or retrofit their current vehicle with such technology. Furthermore, Ahmed (2018) investigated automotive engineers' perspectives on the awareness, demand and trust on AVs in the current sharing infrastructure with conventional vehicles. Results show that the cost factor was one of the most important customer requirements for the successful deployment of AVs in the future.

Taken the above together, we believe that PFC will be one of the most influential factors that may affect the adoption of AVs by potential customers. In this way, the present analysis formulates the following **hypothesis H6**:

"Perceived financial cost (PFC) significantly affects individual behavioral intention (BI) to accept and drive/use AVs"

Perceived Reliability/Trust (PRT)

Driving automation represents a novel and complex technology and, contrary to flight automation in aviation, its users will not be experts who have a deep understanding of its functionality and principles. Thus, its use represents a situation of uncertainty and vulnerability in which the driver/user entrusts his well-being to the driving automation system (Walker et al., 2016). Moreover, according to Hoff & Bashir (2015) individuals will generally trust an automation technology system if this system behaves in the manner they expect. However, if they experience unforeseen actions, there will be a rapid drop in confidence that often leads to the disuse of the automation technology system.

Several previous studies (Chapter 2) shown that trust is a crucial contributor to an individual's acceptability in the context of e-services and e-government applications (Mou et al., 2017; Gupta et al., 2016), as well as in consumers' intentions towards driving automation technology and AVs (Ghazizadeh et al., 2012; Choi & Ji, 2015; Körber et al., 2018). In the present study, **PRT** is **defined** as ***"the degree to which individuals believe that AVs will ensure safe and reliable travels by protecting them from potential misuse and problems"***.

According to the study of Zmud & Sener (2017), most of the people surveyed (82%) are not at all or only somewhat concerned that their data would not be kept private when using self-driving cars. Furthermore, the study by Choi & Ji (2015) supports the claim that trust is a major determinant to predicting the reliance on and adoption of AVs. In addition, the study of Kaur & Rampersad (2018) found that the ability of the driverless cars to meet performance expectations and their reliability were important adoption determinants in conjunction with significant concerns such as privacy (autonomy, location tracking and surveillance) and security (from hackers).

Accordingly, the present analysis posits the following **hypothesis H7**:

"Perceived reliability/trust (PRT) significantly affects individual behavioral intention (BI) to accept and drive/use AVs"

With the help of the above statements a theoretical model is made based on the original UTAUT. The complete theoretical framework can be found in Fig. 3.8. The presented framework takes the initial UTAUT model with the main four determinants (PE, EE, SI, FC) as a starting point, and incorporates three further direct determinants (PDE, PFC, PRT). Figure 3.8 shows how the respondent's answers to the indicators influences the 7 main constructs (PE, EE, SI, FC, PDE, PFC, PRT). The UTAUT-extended model will also reveal if the stated importance of each indicator will have an impact on the behavioral intention.

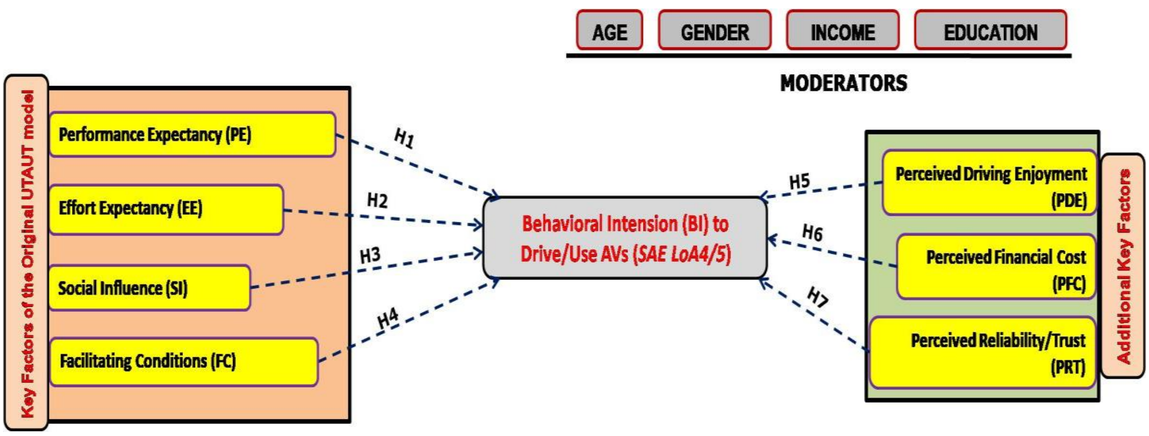


Fig. 3.8 UTAUT-extended research framework.

Furthermore, in the above extended UTAUT-model, along with the external variables - moderators (age, gender, income and education) measured during the survey the relation between the constructs and BI can then be determined. It must be noted that while the original UTAUT model also included voluntariness of use and experience as moderators, these external variables were not included, in light of the fact that the vast majority of potential consumers have no concrete and real experience with AVs, which are the focus of the present analysis, due to their low dispersion in international markets. It should be noted that the highest levels in vehicle automation that are currently being commercialized are SAE LoA2 and SAE LoA3 (semi-automated vehicles) with the next step being now adding more automated features to realize SAE LoA4/5 (highly/fully automated vehicles).

3.3.2 Survey design and data collection

With the help of the research design and final theoretical research model formulated in subsection 3.3.1, the survey design will be constructed. An overview of the final survey, including the relevant questions for each indicator variable, will be given. Before the data collection a description of AVs that will be presented during the survey is formulated. In the last part data collection process is detailed.

Survey requirements

To formulate the right questions that will be asked during the survey several requirements are taken into consideration. These requirements will help to find an answer to the research questions and make sure that the survey questions align with earlier findings.

- All respondents of the survey should be aged 18 years old and up
- Survey will be held in Europe
- All the elements found in the literature study must be considered (indicators found in the theoretical model)
- It must contain multiple questions on the usage intention towards AVs including performance expectancy, effort expectancy, social influence, facilitating conditions, perceived driving enjoyment, perceived financial cost and perceived reliability/trust

- AVs have to be properly explained with their corresponding levels of automation and how they could be used in the future
- A five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), will be used to reduce complexity of survey questions and making it faster to fill
- The survey should take no longer than twenty (20) minutes to complete taking into account that the number of respondents should be high enough.

Survey design and procedure

Regarding observer bias and error, an online survey with structured, close-ended questions was used to collect data, thus limiting the risk of observer bias by avoiding the subjective interpretation linked with open-ended questions. Furthermore, all data was imported automatically into SPSS and Microsoft Excel software packages, thereby removing the danger of data plotting errors associated with manual entry.

In terms of participant bias, a general concern for this type of research is social desirability bias, which refers to respondents' providing answers that may not hold true for them, but which they perceive to be the correct or socially acceptable answer to a question (Moreau et al., 2001). Several steps were taken to diminish the potential for such bias in the present research. First, in order to avoid answers that were deemed socially acceptable, anonymity of responses was guaranteed both in the invitations to participate and in the introduction text to the survey, and participants were not observed while answering the online survey. Moreover, to avoid researcher-desirable answers, participants were not informed about the true purpose of the survey, but rather asked to simply provide their opinions on the factors towards intension to accept and drive/use AVs by indicating how much they agreed with a set of statements.

Regarding participant error, a potential concern is that the newness of the innovation may imply that consumers have not yet fully acquired an understanding of AVs or formed opinions about them (Fraedrich & Lenz, 2014; Kyriakidis et al., 2015). If respondents lack experience in thinking about the topic, find the topic difficult to understand or see no personal relevance of the issue, systematic errors can occur.

Thus, an introductory text to the topic (see Appendix B) was displayed before the survey started to ensure that all respondents could more easily understand what an AV is and see its relevance to their personal lives and transportation activities.

Another potential source of participant error or method bias regards the respondents' ability to comprehend the meaning of questions and making judgments, which may be affected by issues of complex or abstract questions, item ambiguity or doubled-barreled questions. All measures used in the survey were based on previously validated scales, and effort went into ensuring that all items were worded in a way that would not trigger any confusion for the respondents.

Survey outline

In Table 3.9 an outline of the UTAUT-based questionnaire survey is shown. The complete UTAUT-based questionnaire survey can be found in Appendix B. The survey has been divided in four sections with each section having its own purpose. Firstly in the introduction section the objective of the research is explained showing why respondents are filling in the survey. To ensure survey respondents had a clear understanding of the different levels of driving automation technology, respondents were required to read the simplified definitions of vehicle automation, according to SAE taxonomy, as defined in Chapter 2.

Furthermore, participants were not able to continue to the next sections of the survey without confirming a relative control question that they have read and understood the definition regarding AVs (SAE LoA 4/5), where the present Ph.D. focus.

After the introduction section, the second section of the questionnaire survey is followed, which aimed to identify the socio-demographic characteristics of the participants (age, gender, income, education, etc.), as well as the general attributes of the respondents about car passenger vehicles and transportation mobility. After the second section, the third part of the questionnaire is followed, which assessed with multiple choice questions the general experience and concerns of the participants towards automation technologies in general and ADAS.

Table 3.9 UTAUT-based questionnaire survey outline.

Section	Components / Indicators
1. Introduction	• Explain objective of the survey • Explain content of survey and how to fill in the survey
2. Demographic information and Transportation profile	• Personal characteristics (*gender, age, income, education, degree of involvement with the automotive field*) • General attributes about car vehicles (*level of interest in vehicle automation, car ownership, etc.*)
3. Automation and experience	• Current experience and concerns with automation technologies in general • Current experience and concerns with ADAS (*cruise control system, lane keeping system, park assist system, etc.*)
4. Intension to drive/use AVs and acceptance	• **Performance Expectancy** PE1: *AVs will be useful for my travels* PE2: *Driving/using AVs, my travels will take place in less time* PE3: *AVs will allow me to perform other tasks (working, reading, etc.) while driving* PE4: *Driving/using AVs, my driving behavior and performance will be improved* PE5: *Driving/using AVs, my safety on the road will be improved* • **Effort Expectancy** EE1: *AVs will be easy to drive/use* EE2: *I would find AVs easy to drive/use* EE3: *My interaction with AVs would be clear and understandable* EE4: *It would be easy for me to learn how to drive/use AVs* • **Social Influence** SI1: *Having people who are important to me driving/using AVs will make me more likely to drive/use such vehicles as well* SI2: *People who are important to me would think that I should drive/use AVs* SI3: *People in my environment would support me in driving/using AVs* SI4: *The trends of the global automotive community towards vehicle automation influence my behavior and will make me more likely to drive/use AVs as well* • **Facilitating Conditions** FC1: *I would drive/use AVs if specific and appropriate regulatory frameworks are existing and supporting their driving/usage* FC2: *I would drive/use AVs if appropriate road and roadside infrastructures are existing and supporting their driving/usage* FC3: *I would drive/use AVs if there are compatible with the advanced driver assistance systems which are currently used in human-operated vehicles* FC4: *I would drive/use AVs if I could have the necessary resources and knowledge to drive/use them* • **Perceived Driving Enjoyment** PDE1: *Driving/using AVs will be exciting* PDE2: *Driving/using AVs will be comfortable and relaxing* PDE3: *Driving/using AVs will be enjoyable* • **Perceived Financial Cost** PFC1: *I would like to invest money for the purchase / rental of AVs* PFC2: *The benefits of driving/using AVs outweigh the cost of their purchasing / renting* PFC3: *The cost of purchasing / renting AVs will be at reasonable prices similar to currently used human-operated vehicles* PFC4: *The operating cost of driving/using AVs will be at reasonable prices similar to currently used human-operated vehicles* • **Perceived Reliability / Trust** PRT1: *I trust that AVs can get me safely to my destinations, even in the most challenging and demanding driving scenarios* PRT2: *I trust that AVs can drive better than me and they can interact better with the external driving environment* PRT3: *I trust that AVs can maintain the full control of the vehicle, at any moment, against cyber attacks (hacking)* PRT4: *I trust that AVs can ensure data privacy protection against cyber attacks (hacking)* • **Behavioral Intension to Drive/Use** BI1: I intend to drive/use AVs when they become available BI2: I predict I will drive/use AVs when they become available BI3: I plan to drive/use AVs when they become available

After this section, the fourth and last part of the questionnaire is followed, where a 31-item measurement scale was administrated covering each indicator specified in the proposed UTAUT-extended theoretical framework (PE, EE, SI, FC, PDE, PFC, PRT, and BI to drive/use AVs). Items selection (see Table 3.9) was based on relative statements in the existing literature (Venkatesh et al., 2012; Choi & Ji, 2015; Madigan et al., 2017) on each of the above indicators. Additionally, these items were modified in a suitable manner due to the fact that the present Ph.D. research focus on AVs (SAE LoA 4/5), which can perform and control all critical driving functions in certain (LoA 4 – high automation) or all (LoA 5 – full automation) traffic and environmental conditions.

Data collection

After completion of the above survey outline, a version of the UTAUT-based questionnaire survey was worked out on paper and tested in two (2) test surveys to see if there could be any improvements made to the setup of the final survey.

Results from these test surveys showed:

- Roughly how long it took to complete them
- If all the questions where clear and interpreted correctly for all respondents
- How different formats such as a face-to-face survey or a on-line survey were respondents fill in the survey by themselves (or a combination of these two) impact the completion time and clarity of the survey

Furthermore, the above test surveys showed that there were a few questions that were unclear and some questions suffered from poor translation, and therefore, these issues were corrected for the final survey. The face-to-face method where the interviewer asked each of the questions to the respondents proved to take a long time to complete (45 min to 1 hour). There was also some confusion during the interview due to the repetitive nature of some questions which worked better if the respondents read and fill in the questions by themselves. A combination of face-to-face and independently filled in survey also took a long time due to the fact that there are a lot of separate sections in the survey (explanation of survey, gathering of personal information, gathering of transportation profile information, etc.).

With help of the test surveys the choice was made to conduct an online survey which lets respondents to fill in the survey independently wherever they are and was shown to take the least amount of time to complete (estimation of around 20 min). An online survey also helps reaching a larger response group and thus acquiring a larger sample. With the help of the questionnaire outline found in Table 3.9, an online survey was set-up with the help of Google Drive format.

After the survey was constructed respondents were recruited trough online means of communication (i.e. websites, social media) with the intent of targeting adults aged 18+ residing in Europe, in order to test the hypotheses and assess consumers' perceptions and attitudes towards AVs (SAE LoA 4/5). Results from the online survey were gathered for a period of four (4) months (from September to December 2018).

Out of the 847 on-line collected responses, 829 valid answers were used for final analysis, indicating a 97.8 per cent acceptance rate. 18 respondents, who had answered only the first four questions, as they expressed their wish not to participate in the present survey, were eliminated from the final sample. It should be noted, that no compensation or prizes were offered for participation in the above survey, so it was completely voluntary. On average, each participant of the final sample took between 15 and 20 minutes to complete the relative questionnaire.

3.3.3 Data Analysis

The data gathered from the survey will be used to analyse the relations between constructs, indicators and moderators found in the theoretical UTAUT-extended model. The model will be analysed with the help of Structural Equation Modelling (SEM). SEM is useful in this case because it is suitable to answer more complicated questions with regard to the relations between individual constructs and the behavioral intention (BI). SEM is a path analysis method that can deal with the multiple relationships (between indicator variables) that are found in the model simultaneously. It can also account for the unreliability of measurement.

Since UTAUT-extended theoretical model has been constructed with both the help of the literature review and argumentation the proposed framework (Fig. 3.8) will be validated with the use of Confirmative Factor Analysis (CFA). Following the above, first Cronbach's alpha (Brown, 2002) was used to measure the consistency of the constructs of the proposed UTAUT model. Then, Principal Component Analysis (PCA) was used to investigate the extent to which the total variance of the research model was explained by the predictors included in the proposed framework. Varimax factor rotation was used to examine the loading of the predictors (Field, 2013). Furthermore, multiple regression analysis was used to test the hypotheses. Additionally, the moderating effects of the proposed UTAUT model (age, gender, income, education) were investigated.

Demographic statistics

Background demographic information of the respondents are described and provided in Table 3.10. As such, the gender split was 57.5% males, 41.4% females, whereas 1.1% responded "I prefer not to answer". With respect to age, 47.8% of the respondents were between 18 and 30 years old, 29.1% between 31 and 40 years old, 22.7% more than 40 years old, whereas 0.4% responded "I prefer not to answer".

According to the educational level options, most respondents were M.Sc. or/and Ph.D. holders (53.9%), whereas 32.6% were university/college diploma holders, 12.8% had secondary education or less, and 0.7% responded "I prefer not to answer". Moreover, among the respondents, 41.8% had a net average monthly personal income below 1000€, 27.1% between 1000€ and 2000€, and 20.7% more than 2000€, whereas 10.4% responded "I prefer not to answer". Furthermore, with respect to the options of involvement with the automotive field, 38.7% of the respondents answered that they have no active involvement, 37.5% responded that they are working in sectors relative to the automotive field (e.g. automakers, research institutions, sales, marketing, insurance companies, etc.), whereas 23.8% indicated that they attend the automotive sector by personal interest.

Table 3.10 Demographic information of the respondents.

Variable	Options	Frequency (n)	Percentage (%)
Gender	Male	466	57.5
	Female	336	41.4
	I prefer not to answer	9	1.1
Age	18 - 30 years old	388	47.8
	31 - 40 years old	236	29.1
	40 years old and older	184	22.7
	I prefer not to answer	3	0.4
Educational	High school graduate or less	104	12.8
	University/college diploma	264	32.6
	Higher education diploma (M.Sc., Ph.D.)	437	53.9
	I prefer not to answer	6	0.7
Monthly personal income	Less than 1000€	339	41.8
	1000€ – 2000€	220	27.1
	More than 2000€	168	20.7
	I prefer not to answer	84	10.4
Involvement with the automotive field	I am working in sectors related to the automotive field (e.g. automakers, research institutions, sales, marketing, insurance companies, etc.)	304	37.5
	I am attending the automotive sector by personal interest	193	23.8
	None of the above	314	38.7

Based on the above results, a good representation of gender and involvement with the automotive field was observed, as well as an overrepresentation of the age category under 30 years old, higher levels of education and lower monthly incomes, possibly due to the online method of survey distribution. The above underline that the present sample represents a younger population than would be representative for the European population. However, younger consumers are an interesting target group considering that AVs are still expected to be in the international market a few years away. Moreover, young consumers may be the first to adopt AVs, as novices in a new product category are more likely to adopt technology innovations early (Moreau et al., 2001).

Table 3.11 Transportation profile of the respondents.

Variable	Options	Frequency (n)	Percentage (%)
Vehicle ownership	Yes	677	83.5
	No	134	16.5
Hours a week (on average) driving a car passenger vehicle	Less than 5	442	54.5
	5 to15	310	38.2
	More than 15	59	7.3
How often do you use for your travels car passenger vehicles?	Rarely/Never	33	4.1
	Few times a year	57	7.0
	Few times a month	131	16.2
	Few times a week	189	23.3
	Every day	401	49.4
What is the usual purpose of your travels with car passenger vehicles?	I do not drive/use vehicles	61	7.5
	Professional (work, education, etc.)	404	49.8
	Personal (medical, family, shopping, etc.)	222	27.4
	Leisure (travels, walks, etc.)	124	15.3
How safe do you feel when you are driving/using car passenger vehicles today?	Not at all safe	17	2.1
	Slightly safe	58	7.2
	Moderately safe	276	34.0
	Quite safe	402	49.6
	Extremely safe	58	7.2
To what extent technology progress, until now, has contributed to improving the safety of your travels with car passenger vehicles?	Not at all improved	8	1.0
	Slightly improved	50	6.2
	Moderately improved	111	13.7
	Quite improved	386	47.6
	Extremely improved	256	31.6
Had you ever heard of AVs before participating in the survey?	Yes	707	87.2
	No	79	9.7
	I do not know - I'm not sure	25	3.1
Had you ever any experience on driving/using AVs before participating in this survey?	Yes	229	28.2
	No	562	69.3
	I do not know - I'm not sure	20	2.5
Level of interest in AVs before participating in the survey	Not at all interested	83	10.2
	Slightly interested	129	15.9
	Moderately interested	172	21.2
	Quite interested	231	28.5
	Strongly interested	196	24.2
Level of interest in issues related to vehicle automation before participating in the survey	Not at all interested	32	3.9
	Slightly interested	88	10.9
	Moderately interested	143	17.6
	Quite interested	248	30.6
	Strongly interested	300	37.0
What is your general opinion regarding AVs?	Positive	524	64.6
	Neutral	167	20.6
	Negative	64	7.9
	I do not know - I'm not sure	56	6.9

Transportation profile

Additional information towards the transportation profile of the respondents are provided in Table 3.11, where 83.5% of the respondents stated that they own a passenger car, 49.4% indicated that they use car passenger vehicles as a daily commute transportation mode, 54.5% responded that they are driving less than 5 hours per week (on average), and 49.8% stated that the usual purpose of their travels with car passenger vehicles is professional (work, education, etc.).

Furthermore, 56.8% of the respondents stated that they feel quite safe or extremely safe when they are driving/using car passenger vehicles today, whereas the vast majority of respondents (79.2%) believe that technology progress, until now, has extremely improved (31.6%) or quite improved (47.6%) the safety of their travels with car passenger vehicles. Moreover, the vast majority of respondents (87.2%) had heard of AVs before their participation in the present survey, whereas 9.7% answered "No" and 3.1% responded "I do not know – I'm not sure".

Moreover, many respondents (almost 70%) had not any previous experience on driving/using AVs before participating in this survey. Regarding the level of interest in AVs before participating in the survey, 52.7% answered that they strongly interested (24.2%) or somewhat interested (28.5%).

In addition, 67.6% of the people surveyed answered that they are strongly interested or somewhat interested with the trends of the global automotive community towards vehicle automation before participating in the survey. Finally, almost 65% of the total sample had a positive general opinion regarding AVs, whereas only 7.9% had a negative general opinion and 6.9% responded "I do not know – I'm not sure".

Experience with automation technologies and ADAS

In this section, the experience of potential users towards automation technologies and ADAS is investigated. Based on the survey results, almost 54% of the respondents stated that they are keeping up with the latest trends in automation technologies, and 70% are strongly/somewhat agreed with the statement "*Automation technologies provide solutions to many of my problems in my daily life*". Moreover, the majority of the respondents (almost 70%) stated that it is easy for them to use and apply automation technologies and they do not waste too much time with their use.

Moreover, almost three-to-four respondents considered themselves, late adopters on the technology adoption curve (e.g., they wait before adopting a new automation technology).

Additionally, in responding to the question "*To what extent do you trust the automation technologies in terms of tracking - interception of sensitive information?*", only 28.0% of the respondents answered that they somewhat trusted or strongly trusted. Almost the same levels of trust towards automation technologies were stated also to the options of "*cyber security and data protection*" and "*data loss - system failure (software, databases, etc.)*". Based on the above percentages, it is obvious that more than two-to-third respondents are concerned about security and data privacy issues regarding automation technologies or services in general.

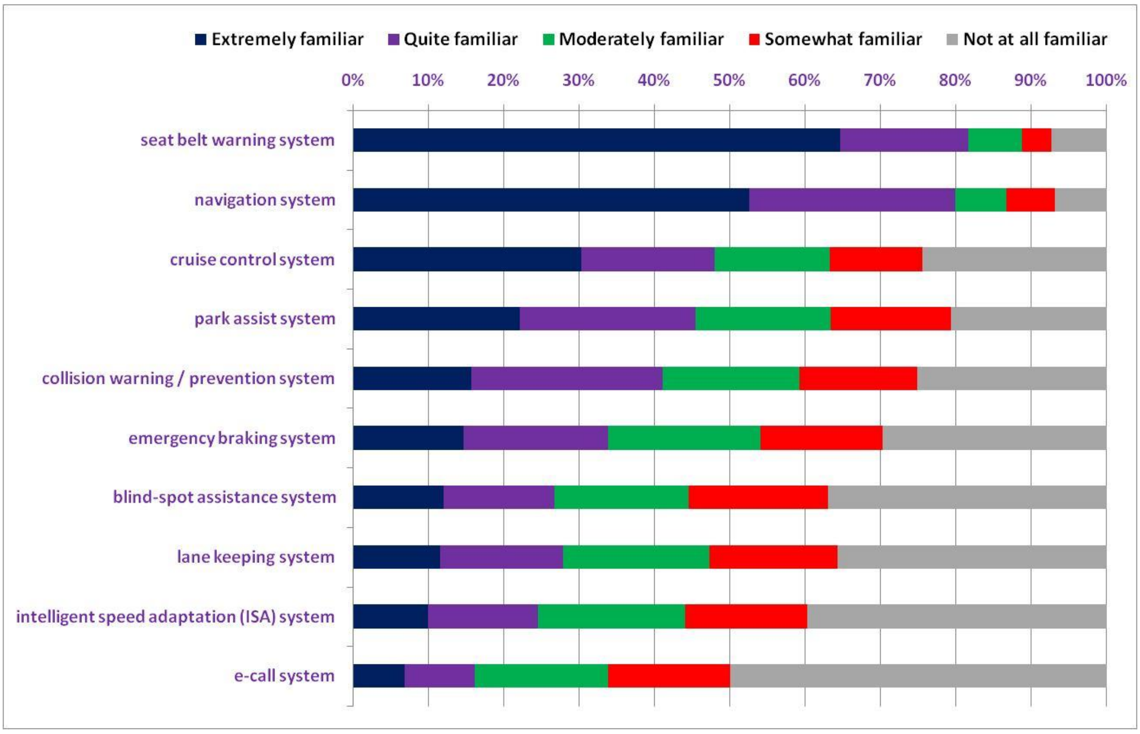


Fig. 3.9 Responses on level of familiarity with ADAS.

In a similar basis with respect to experience with automation technologies, almost 40% of the respondents stated that they are keeping up with the latest trends in ADAS, and 60% indicated that they are strongly agreed or somewhat agreed with the statement "*ADAS make easier my driving*". Moreover, the majority of the respondents (almost

70%) stated that it is easy for them to use and apply ADAS in driving and they do not waste too much time in driving with their use.

In addition, of the people surveyed, the majority of respondents indicated that only two driver assistance systems, which are offered today on human-operated passenger cars, are exceeding the threshold of 50%, as the most quite/very familiar ADAS for the respondents, “seat belt warning system” (81.6%) and “navigation system” (80.0%), respectively (Fig. 3.9). On the other hand, it should be noted that the level of respondents’ familiarity towards all the other available ADAS being offered by the automotive industry (e.g., cruise control system, park assist system, etc.) are not exceed the threshold of 50%.

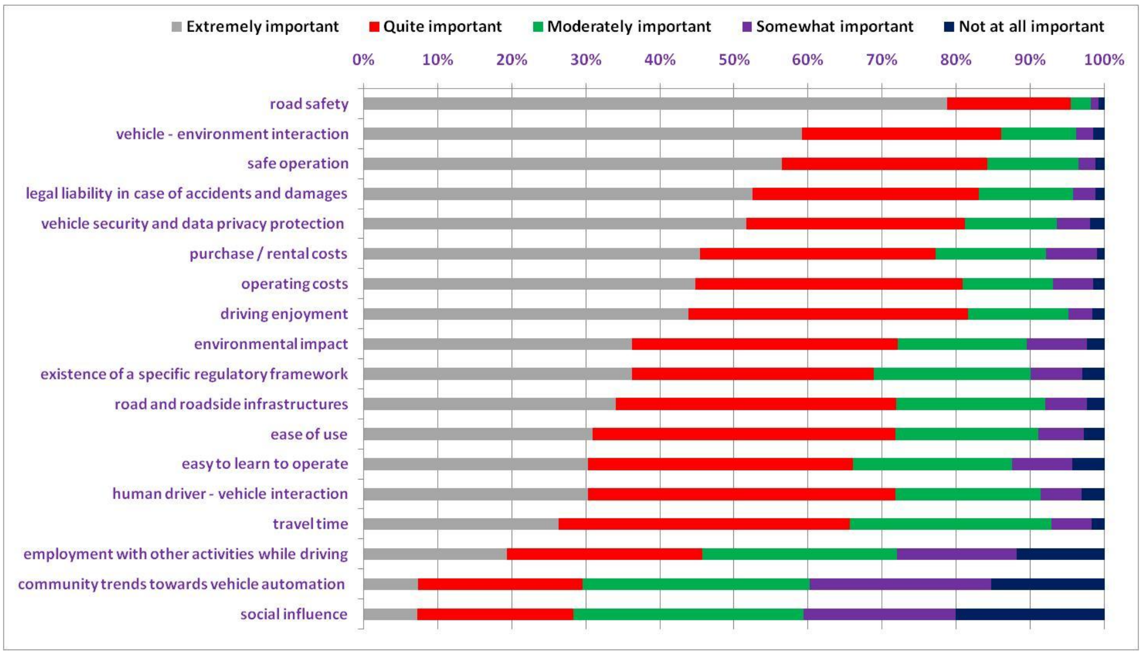


Fig. 3.10 Responses on "How important are the following features for you regarding AVs?".

General attributes about AVs

With respect to the level of automation on vehicles that make respondents feel more comfortable, the majority of them (34.7%) responded LoA3 (conditional automation), where the human driver remains always in the loop and is ready to take back the control of the vehicle when the driving automation system requests. Only 4.2% of the participants answered that they feel comfortable with LoA0 (no automation, driver only).

In addition, of the people surveyed, the majority of respondents indicated that "road safety" (78.8%), "vehicle-environment interaction (59.2%), "safe operation" (56.5%), "legal liability in case of accidents and damages" (52.5%), and "vehicle security and data privacy" (51.7%) were the most extremely important features for the respondents towards the driving/usage of an AV. On the other hand, a small portion of respondents indicated that "employment with other activities while driving" (19.4%), "community's trends towards vehicle automation" (7.4%) and "social influence" (7.3%) were the least important features regarding the driving/usage of an AV, as shown in Fig. 3.10.

Table 3.12 Impact of performance expectancy construct on driving/usage of AVs.

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
PE1	2.5%	4.6%	18.9%	**43.0%**	31.1%
PE2	7.9%	16.2%	**39.6%**	25.4%	11.0%
PE3	12.1%	12.7%	18.6%	**33.4%**	23.2%
PE4	14.5%	17.9%	**28.4%**	26.3%	12.9%
PE5	3.3%	10.0%	29.7%	**37.9%**	19.1%

Behavioral intentions towards AVs

As described in Chapter 2, behavioral intension to drive/use is an important concept before AVs being introduced and launched on mass consumer markets. In this context, with regards to the performance expectancy (PE) relative items (PE1, PE2, PE3, PE4, PE5), 74.1% of all respondents stated that they strongly agreed (31.1%) or somewhat agreed (43.0%) with the statement "*PE1: AVs will be useful for my travels*", as depicted in Table 3.12. Only 7.1% of the respondents disagreed with the above statement PE1. More than half of respondents also strongly agreed (23.2%) or somewhat agreed (33.4%) with the statement "*PE3: AVs will allow me to perform other tasks (working, reading, etc.) while driving*". Moreover, many respondents (57%) believe that "*PE5: Driving/using AVs, my safety on the road will be improved*". Only 13.3% of the respondents disagreed with the above statement PE5. In addition, the majority of the respondents neither disagreed nor agreed with the statements "*PE2: Driving/using AVs, my travels will take place in less time*" and "*PE4: Driving/using AVs, my driving behavior and performance will be improved*" (39.6% and 28.4%, respectively).

Table 3.13 Impact of effort expectancy construct on driving/usage of AVs.

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
EE1	2.0%	6.9%	28.9%	**41.3%**	21.0%
EE2	1.5%	5.2%	29.5%	**39.1%**	24.8%
EE3	1.4%	5.9%	31.7%	**42.4%**	18.6%
EE4	3.9%	10.2%	25.2%	**34.8%**	25.9%

According to the results presented in Table 3.13 regarding the effort expectancy (EE) relative items (EE1, EE2, EE3, EE4), most respondents strongly agreed (21.0%) or somewhat agreed (41.3%) with the statement "*EE1: AVs will be easy to drive/use*". In addition, the majority of the respondents strongly agreed (24.8%) or somewhat agreed (39.1%) with the statement "*EE2: I would find AVs easy to drive/use*". Furthermore, 18.6% of the respondents strongly agreed and 42.4% somewhat agreed with the statement "*EE3: My interaction with AVs would be clear and understandable*". In addition, the majority of respondents strongly agreed (25.9%) or somewhat agreed (34.8%) with the statement "*EE4: It would be easy for me to learn how to drive/use AVs*".

Table 3.14 Impact of social influence construct on driving/usage of AVs.

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
SI1	13.6%	10.6%	**33.5%**	33.2%	9.1%
SI2	14.7%	12.8%	**37.5%**	28.2%	6.8%
SI3	6.9%	10.2%	**43.9%**	28.4%	10.6%
SI4	11.3%	13.6%	29.7%	**35.1%**	10.2%

Moreover, according to the Table 3.14 regarding the social influence (SI) relative items (SI1, SI2, SI3, SI4), most respondents neither disagreed nor agreed with the statements

"*SI1: Having people who are important to me driving/using AVs will make me more likely to drive/use such vehicles as well*" (33.5%), "*SI2: People who are important to me would think that I should drive/use AVs*" (37.5%) and "*SI3: People in my environment would support me in driving/using AVs*" (43.9%). Moreover, the majority of the respondents agreed with the statement "*SI4: The trends of the global automotive community towards vehicle automation influence my behavior and will make me more likely to drive/use AVs as well*" (45.3%).

Table 3.15 Impact of facilitating conditions construct on driving/usage of AVs.

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
FC1	3.2%	5.4%	20.3%	**42.3%**	28.7%
FC2	2.6%	3.1%	15.4%	**39.8%**	39.1%
FC3	3.0%	6.2%	25.8%	**40.4%**	24.7%
FC4	3.3%	3.6%	20.7%	**39.0%**	33.4%

Regarding the facilitating conditions (FC) relative items (FC1, FC2, FC3, FC4), Table 3.15 reveals that the majority of the respondents agreed with the statements "*FC1: I would drive/use AVs if specific and appropriate regulatory frameworks are existing and supporting their driving/usage*" (71.0%), "*FC2: I would drive/use AVs if appropriate road and roadside infrastructures are existing and supporting their driving/usage*" (78.9%), "*FC3: I would drive/use AVs if there are compatible with the advanced driver assistance systems which are currently used in human-operated vehicles*" (65.1%), and "*FC4: I would drive/use AVs if I could have the necessary resources and knowledge to drive/use them*" (72.4%). Only 5.7% to 9.2% of the respondents strongly disagreed or somewhat disagreed with the above statements FC1, FC2, FC3 and FC4.

Furthermore, according to the results displayed in Table 3.16 regarding the perceived driving enjoyment (PDE) relative items (PDE1, PDE2, PDE3), most respondents agreed with the statement "*PDE1: Driving/using AVs will be exciting*" (79.3%). Moreover, more than half of the respondents agreed with the statements "*PDE2: Driving/using AVs will be comfortable and relaxing*" and "*PDE3: Driving/using AVs will be enjoyable*".

Table 3.16 Impact of perceived driving enjoyment construct on driving/usage of AVs.

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
PDE1	3.0%	4.1%	13.7%	37.0%	**42.3%**
PDE2	1.8%	14.2%	29.1%	**36.0%**	18.9%
PDE3	2.6%	7.9%	33.0%	**37.6%**	18.9%

Table 3.17 Impact of perceived financial cost construct on driving/usage of AVs.

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
PFC1	9.0%	16.6%	**32.7%**	30.3%	11.3%
PFC2	8.9%	16.8%	**44.0%**	22.6%	7.8%
PFC3	13.3%	**26.4%**	26.3%	22.4%	11.6%
PFC4	11.1%	21.7%	**34.4%**	22.4%	10.4%

Moreover, regarding the perceived financial cost (PFC) relative items (PFC1, PFC2, PFC3, PFC4), Table 3.17 presents that almost four-to-ten respondents agreed with the statement "*PFC1: I would like to invest money for the purchase of AVs*", whereas a small portion of respondents (30.4%) strongly agreed or somewhat agreed with the statement "*PFC2: The benefits of driving/using AVs outweigh the cost of their purchasing*". In addition, a small portion of respondents agreed with the statements "*PFC3: The cost of purchasing AVs will be at reasonable prices similar to currently used human-operated vehicles*" (34.0%), and "*PFC4: The operating cost of driving/using AVs will be at reasonable prices similar to currently used human-operated vehicles*" (32.8%).

Table 3.18 Impact of perceived reliability/trust construct on driving/usage of AVs.

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
PRT1	14,3%	20,0%	22,9%	**31,1%**	11,7%
PRT2	10,5%	21,6%	26,5%	**29,0%**	12,5%
PRT3	11,6%	23,3%	**32,4%**	27,6%	5,1%
PRT4	14,3%	24,3%	**33,2%**	23,3%	6,0%

Finally, with regard to the perceived reliability/trust (PRT) relative items (PRT1, PRT2, PRT3, PRT4), results in Table 3.18 show that almost four-to-ten respondents agreed with the statements "*PRT1: I trust that the driving automation system on AVs can get me safely to my destinations, even in the most challenging and demanding driving scenarios*" (42.8%) and "*PRT2: I trust that the driving automation system on AVs can drive better than me and it can interact better with the external driving environment*" (41.5%). On the other hand, most respondents neither disagreed nor agreed with the statements "*PRT3: I trust that the driving automation system on AVs can maintain the full control of the vehicle, at any moment, against cyber attacks (hacking)*" (32.4%) and "*PRT4: I trust that the driving automation system on AVs can ensure data privacy protection against cyber attacks (hacking)*" (33.2%).

Respondents’ intension to purchase and drive/use AVs when they become available on the market was assessed related to gender and age differences (see Table 3.19). There are no noticeable differences between females and males with regards to the level of agreement with their intension to purchase and drive/use AVs. Furthermore, respondents more than 40 years old are more likely to purchase and drive/use AVs (33.6% strongly agreed or somewhat agreed) when they become available on the market than those who are under 30 years old (22.7% strongly agreed or somewhat agreed).

Table 3.19 Intension to drive/use AVs related to gender and age differences.

Variable	**Options**	**Gender**		**Age**		
		Male (n = 193)	**Female (n = 258)**	**18 – 30 (n = 216)**	**31 – 40 (n = 129)**	**More than 40 (n = 110)**
Consumers’ intension to drive/use AVs	Strongly disagree	21.8%	25.6%	24.5%	20.9%	25.4%
	Somewhat disagree	19.7%	19.4%	23.6%	17.8%	12.7%
	Neither agree nor disagree	32.1%	29.1%	29.2%	36.4%	28.2%
	Somewhat agree	21.2%	22.5%	18.5%	21.7%	28.2%
	Strongly agree	5.2%	3.5%	4.2%	3.1%	5.4%

Table 3.20 Intension to drive/use AVs related to income and education differences.

Variable	Options	Education			Income	
		Secondary education or less (n = 80)	**University / college diploma (n = 168)**	**Higher education diploma (n = 206)**	**Less than 1000€ (n = 255)**	**More than 1000€ (n = 164)**
Consumers' intension to drive/use AVs	Strongly disagree	37.5%	15.5%	25.2%	25.5%	23.8%
	Somewhat disagree	22.5%	17.9%	18.9%	22.4%	14.6%
	Neither agree nor disagree	18.8%	35.0%	32.5%	28.9%	30.5%
	Somewhat agree	20.0%	26.8%	18.4%	19.6%	26.8%
	Strongly agree	1.2%	4.8%	4.9%	3.6%	4.3%

In addition, respondents' intension to purchase and drive/use AVs when they become available on the market was assessed related to income and education differences (see Table 3.20). According to the results, survey respondents with a net monthly personal income above 1000€ are more likely to purchase and drive/use AVs (31.1% strongly agreed or somewhat agreed) than those who have a lower income below 1000€ (23.2% strongly agreed or somewhat agreed). Furthermore, respondents which are university/college diploma holders are more likely to purchase and drive/use AVs (31.6% strongly agreed or somewhat agreed) when they become available on the market than those who have secondary education or less (21.2% strongly agreed or somewhat agreed).

Measurement validation

The measurement instruments' reliability and internal consistency was evaluated by calculating Cronbach Alphas. These values are also known as the reliability coefficients. For all eight factors, these coefficients were above the cut-off criterion of 0.7 (Hair et al., 2006), indicating high reliability. More in detail, as shown in Table 3.21, the results indicate that PE yielded 0.734 indicating 73.4% of internal consistency, EE yielded 0.837, representing 83.7% internal consistency, SI gave a reliability coefficient of 0.782

depicting 78.2% reliability, FC yielded 0.879 depicting 87.9% reliability, PDE gave a coefficient of α = 0.873 indicating 87.3% of internal consistency, PFC yielded 0.818 representing 81.8% internal consistency, PRT gave 0.869 depicting 86.9% reliability, and BI yielded 0.934 depicting 93.4% of internal consistency.

Table 3.21 Items coding of the proposed UTAUT-extended model, scale reliabilities and factor loadings.

Construct	Cronbach's α	Items coding	Factor Loading
PE	0.734	PE1	0.646
		PE2	0.553
		PE3	0.707
		PE4	0.606
		PE5	0.606
EE	0.837	EE1	0.756
		EE2	0.800
		EE3	0.787
		EE4	0.742
SI	0.782	SI1	0.897
		SI2	0.888
		SI3	0.467
		SI4	0.455
FC	0.879	FC1	0.794
		FC2	0.850
		FC3	0.764
		FC4	0.842
PDE	0.873	PDE1	0.512
		PDE2	0.595
		PDE3	0.571
PFC	0.818	PFC1	0.476
		PFC2	0.856
		PFC3	0.566
		PFC4	0.867
PRT	0.869	PRT1	0.584
		PRT2	0.645
		PRT3	0.826
		PRT4	0.855
BI	0.934	BI1	0.843
		BI2	0.888
		BI3	0.895

Additionally, to ensure that the aforementioned eight UTAUT dimensions investigated were distinct, Principal Component Analysis (PCA) was performed, and the loading of the variables on each dimension was conducted, using maximum likelihood extraction and varimax rotation. It can be seen in the Table 3.21, that all the factor loadings were greater than 0.4, indicating high construct validity (Field, 2013).

Furthermore, the descriptive statistics calculations about the main group items of the applied measurement scale revealed that all determinants charted higher than the midpoints of their respective scales expect for the constructs PRT (M = 2.96) and BI (M = 2.56). Moreover, results show that respondents are generally optimistic about FC (M = 4.01), EE (M = 3.70) and PDE (M = 3.65) in relation to AVs, while the factors of PE, SI and PFC were rated lower than the technological acceptance dimensions of FC, EE and DPE.

Table 3.22 Descriptive statistics and Pearson product moment correlations of the main variables in the proposed UTAUT-extended research model.

PE	M	SD	PE	EE	SI	FC	PDE	PFC	PRT	BI
EE	3.70	0.895	0.512**	1						
SI	3.20	0.871	0.439**	0.366**	1					
FC	4.01	0.813	0.441**	0.403**	0.538**	1				
PDE	3.65	0.862	0.693**	0.610**	0.421**	0.500**	1			
PFC	3.03	0.880	0.561**	0.309**	0.349**	0.295**	0.573**	1		
PRT	2.96	0.968	0.647**	0.412**	0.434**	0.319**	0.626**	0.575**	1	
BI	2.56	1.086	0.456**	0.305**	0.373**	0.241**	0.498**	0.464**	0.475**	1

**: p-value < 0.01, M: Mean, SD: Standard Deviation

Prior to evaluating the model as a whole, the Pearson product moment inter-correlation analysis was run to check for multicollinearity. As shown in Table 3.22, the independent variables of PE, EE, SI, FC, PDE, PFC and PRT do not show any multicollinearity problems associated with them. There were no correlations larger than 0.7 and lower than 0.2.

Hypotheses testing of the modified UTAUT-model

A multiple linear regression analysis was conducted for predicting behavioral intentions towards AVs taking into account the predictors of PE, EE, SI, FC, PDE, PFC and PRT. In the first phase of the regression, a baseline model was run without the presence of the four moderating effects (age, gender, education, income). The regression standardized path coefficients without moderating effects are demonstrated in Table 3.23.

Table 3.23 Summary results of the two multiple regression analyses before and after adding the four moderating effects (age, gender, education, income).

Path / hypothesis	Independent variable	Dependent variable	Modified UTAUT-model *(standardized path coefficients β before adding moderating effects)*	Modified UTAUT-model *(standardized path coefficients β after adding moderating effects)*	Decision
H1	PE	BI	0.075#	0.067#	Rejected
H2	EE	BI	-0.019#	-0.009#	Rejected
H3	SI	BI	0.176***	0.177***	Supported
H4	FC	BI	-0.098*	-0.106*	Supported
H5	PDE	BI	0.247***	0.242***	Supported
H6	PFC	BI	0.178**	0.197***	Supported
H7	PRT	BI	0.132*	0.138*	Supported
	Age	BI		-0.068#	
	Gender	BI		0.088*	
	Education	BI		-0.015#	
	Income	BI		0.102*	

Note: *p-value < 0.05, **p-value < 0.01, ***p-value < 0.001, # p-value non-significant

Hypothesis 5 (H5) states that PDE significantly affects individual BI to accept and drive/use AVs. Our results supported this hypothesis (β = 0.247, p-value = 0.000). Likewise, the results supported Hypotheses H6 and H3 which stipulates that the determinants PFC and SI significantly affect individual BI to accept and drive/use AVs (β = 0.178, p-value = 0.001 and β = 0.176, p-value = 0.000, respectively).

Besides, Hypotheses H7 and H4 which hypothesized that the determinants PRT and FC significantly affect individual BI to accept and drive/use AVs (β = 0.132, p-value = 0.019 and β = -0.098, p-value = 0.049, respectively), were also supported. The above show that the five factors PDE, PFC, SI, PRT and FC influence consumers' BI to adopt and drive/use AVs. Meanwhile, the remaining two constructs PE (β = 0.075, p-value = 0.210) and EE (β = -0.019, p-value = 0.708) are rejected given that they were found to be statistically insignificant. And this also implies that PE and EE do not significantly influence consumers' BI to drive/use AVs.

In the second phase, a second regression was run in which the moderating influences of age, gender, income and education were examined. To test these effects, the four moderators (age, gender, income and education) with the aforementioned seven independent predictors were added to the model. As demonstrated in Table 3.23, an examination of the new standardized beta weights (β) about the second regression analysis indicate that the demographic variables Gender (β = 0.088, p-value = 0.032) and Income (β = 0.102, p-value = 0.040) had a significant positive effect influencing consumers' BI to drive/use AVs. Moreover, the same factors as in the first multiple regression analysis, PDE (β = 0.242, p-value = 0.000), PFC (β = 0.197, p-value = 0.000), SI (β = 0.177, p-value = 0.000), PRT (β = 0.138, p-value = 0.015) and FC (β = -0.106, p-value = 0.034), remain the most significantly influencing predictors of behavioral intentions towards the driving/usage of AVs.

In conclusion, according to the results of the above multiple regression analyses, hypotheses H3, H4, H5, H6 and H7 were supported whereas hypotheses H1 and H2 were not supported.

Comparison analysis with the original UTAUT-model

In this subsection the results derived by the application of the modified UTAUT model are compared to the original UTAUT model. Since we were not able to integrate the moderating variables in our modified model, we will compare our model to the original UTAUT model without these. Since Venkatesh et al. (2003) stated that in the presence of EE construct the factor FC becomes non-significant in predicting intention, we removed FC from this model. Table 3.24 provides the multiple regression results of the original UTAUT model without FC.

Results show that the constructs of PE (β = 0.337, p-value = 0.000) and SI (β = 0.204, p-value = 0.000) are both useful predictors of BI to drive/use AVs, with PE having the strongest impact. The above result about PE is in contrast to the findings of the modified UTAUT-model where the analysis demonstrated that the factor PDE was the strongest predictor of consumers' BI towards driving/usage of AVs. Furthermore, the factor EE (β = 0.058, p-value = 0.235) seems not to affect significantly consumers' intension to adopt and drive/use AVs which supports the corresponding finding of the modified UTAUT-model.

Table 3.24 Summary results of the multiple regression analysis towards the original UTAUT-model.

Path / hypothesis	Independent variable	Dependent variable	Original UTAUT-model *(standardized path coefficients β)*	Decision
H1	PE	BI	0.337***	Supported
H2	EE	BI	0.058#	Rejected
H3	SI	BI	0.204***	Supported

Note: ***p-value < 0.001, # p-value non-significant

3.3.4 Main findings – discussion

Although there is much excitement surrounding the introduction of AVs, there are largely unknown at the moment which determinants of user acceptance will influence the uptake of AVs, where car ownership as a relevant category should be taken into consideration. In this respect, it should be noted that the majority of people (potential consumers) have no real interactions and actual experiences with AVs so far due to their low dispersion in international markets.

According to the survey results, almost 75% of respondents considered themselves, late adopters on the technology adoption curve, which is at a higher level compared to the findings obtained by other studies (e.g., Zmud & Sener, 2017; Panagiotopoulos & Dimitrakopoulos, 2018a). This implication has to do with the fact that the majority of consumers wait awhile before adopting a new technology, and so are not necessarily eager to jump on driving/using AVs.

Furthermore, safer driving is one of the crucial factors for the development of vehicles with driving automation systems and would be a prerequisite for the widespread implementation of AVs when they will come to public roads. According to the survey results, less than half of the respondents indicated that they feel safe today when they are using car passenger vehicles for their travels, whereas the corresponding percentage when they are using public transport means is much higher (almost 75%). This implication underlines the necessity of safety benefits and how this factor convinces the end users (potential consumers) what AVs can do in real conditions.

Additionally, more than 80% of the respondents believe that technology progress, until now, has improved the safety of their travels with car passenger vehicles. This finding shows that new well-studied technologies in car passenger vehicles, such as the driving automation systems, could enhance the safety perspectives of potential consumers towards the deployment of AVs in the future. Additionally, the majority of the people surveyed (almost two-to-third respondents) are concerned about security and data privacy issues regarding automation technologies or services that they use today. These notes are similar to the findings obtained by other recent studies (Kyriakidis et al., 2015; Panagiotopoulos & Dimitrakopoulos, 2018a).

One of the main purposes of the present Ph.D. thesis was to gain a more detailed understanding of the factors that will affect potential end users' future acceptance of AVs, by extending the original UTAUT model trough the incorporation of PDE, PFC and PRT constructs. Most of the path coefficients in the proposed research model were found statistically significant except the paths from PE to BI and EE to BI.

More specifically, five of the model's predicted relationships were supported, with PDE, PFC, SI, PRT and FC all making significantly unique (positive or negative) contributions to users' behavioral intentions towards AVs. Similar to Venkatesh et al. (2012), PDE was the strongest predictor, suggesting that the most important factor influencing positively consumers' BI to drive/use AVs is how exciting, comfortable and enjoyable will find them. The above confirm the results of what Madigan et al. (2017) have studied about the factor of hedonic motivation and its impact on users' acceptance towards ARTS. In a similar manner, the aforementioned finding supports the results of Nordhoff et al. (2018), where the majority of survey respondents indicated that driverless vehicles would take away the driving pleasure or enjoyment.

Furthermore, our results show that PFC has a positive influence on BI towards AVs, indicating that the adoption of AVs is highly affected by economic factors such as purchasing costs and driving/usage operating costs (maintenance, insurance, fuel, etc.). It should be noted that a small portion of respondents (almost three to ten) strongly agreed or somewhat agreed that the cost of purchasing AVs, as well as the operating cost of driving/using AVs will be at reasonable prices similar to currently used human-operated vehicles. The above finding is also confirms the results of what Howard and Dai (2014) have explored about the cost factor and its impact on consumers' perceptions towards self-driving cars. In this manner, the challenge of car manufacturers towards AVs research is not only to develop better and effective driving automation technology systems, but also to develop economic insights that will lead to widespread private ownership of AVs in comparison with other transportation options (human-operated cars, car-sharing services, etc.).

Furthermore, our results show that SI has a significant positive influence on BI towards AVs, indicating that the opinions of others will have an effect on consumers' likelihood on driving/using car passenger vehicles with autonomous driving technology when they become available on the international market. The above finding supports previous research studies, which found that social norms had a significant impact on behavioral intentions towards autonomous driving (Panagiotopoulos & Dimitrakopoulos, 2018a) and ARTS vehicles (Madigan et al., 2017). In an attempt to attract more end users, developers, manufacturers and other stakeholders related to the automotive sector need to focus on generating social norms, through effective marketing campaigns, that include the driving/usage of AVs as a valid transportation choice for their personal travels.

In addition, this study found that PRT has a significant positive influence on BI towards the driving/usage of AVs, indicating that perceptions of how trusted the autonomous driving system is to use will affect consumers' decision to drive/use AVs. The above confirm the results of other studies about the important role of trust in autonomous and driverless vehicles along with other determinants of acceptance (Ghazizadeh et al., 2012; Kaur & Rampersad, 2018; Nordhoff et al., 2018; Panagiotopoulos & Dimitrakopoulos, 2018a). It is noted that car manufacturers should enhance consumer confidence and trust towards AVs by providing secure and reliable driving automation systems. In this respect, potential customers' intension to drive/use AVs will be greater.

Furthermore, this present analysis found that the factor FC has a significant negative influence on BI towards AVs, indicating that facilities which support the effective driving/usage of AVs like appropriate resources, infrastructures and implementation strategies are unlikely to be a deciding factor in potential consumer's intension to purchase and use such vehicles. The above result is in line with previous research (Madigan et al., 2017), which showed that facilitating conditions are not the best predictor for behavioral intention to use ARTS.

Regarding the PE, this study found to have a statistically insignificant positive impact on BI towards AVs, within the proposed UTAUT-extended research model, suggesting that respondents are not expected AVs will provide significant potential benefits (road safety, usefulness, etc.) in performing their travel activities. Our results are in contrast with other findings of previous research studies (Piao et al., 2016; Cho et al., 2017; Madigan et al., 2017; Panagiotopoulos & Dimitrakopoulos, 2018a) where PU and PE were important predictors in potential consumer's intensions towards AVs and driving automation technology. The foregoing shows that car manufacturers have improved the quality of the embedded driving systems on currently used human-operated vehicles, which have already met consumers' expectations and needs in performing their own travels.

In addition, the factor EE failed to reach significance in this study, suggesting that difficulty in driving or/and using AVs is becoming less of a concern for the potential consumers as they become more user-friendly. The above result is in contrast to other findings, where EE (Madigan et al., 2016) and PEU (Panagiotopoulos &

Dimitrakopoulos, 2018a) did have an impact on BI towards ARTS and autonomous driving technology, respectively. On the other hand, our result is similar to other related studies (Adell, 2010; Choi & Ji, 2015) where EE and PEU were insignificant predictors of customers' intention towards vehicle automation. The foregoing shows that car passenger vehicles are well-designed for public understanding, and that the level of effort required is unlikely to be a deciding factor in consumers' decision to purchase and drive/use AVs.

Moreover, the relationship between the predictor variables PDE, PFC, SI, PRT, FC, PE, EE and BI was found to be affected by moderating factors such as gender and income. On the other side, age and education moderating factors was found not to affect the relationship between the above predictor variables and BI. Regarding the effects of the age moderator, the above finding is in contrast to previous studies by Venkatesh et al. (2012). However, other studies have also failed to find any effects of age and gender moderating variables on end users' interactions with autonomous systems in vehicles (Adell, 2010; Madigan et al., 2016). In this respect, results from this study imply that targeted campaigns to increase the acceptability of AVs for specific gender and income groups are likely to be required.

3.4 Summary

Autonomous car passenger vehicles have enormous potential to enhance privately-owned mobility, and therefore, are rapidly becoming a topic of international research, making studies of this nature an area of need. Gaining experiences with automation technologies in car passenger vehicles over the coming years, could lead us to better understand consumers' willingness to drive/use AVs. Therefore, forecasting technology usage and acceptance by the end users becomes fundamental in order to understand aspects that are likely to minimize consumer resistance and maximize adoption of AVs.
In the present chapter, adapted versions of the original well-established social-psychological frameworks – Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) – were designed and introduced in predicting consumers' intension to drive/use AVs, as well as to investigate in what

extent consumers intend to drive/use AVs in the future, by identifying the factors that affect the uptake of such vehicles.

Conclusions regarding TAM-extended research framework

The implications of the present analysis show that PU, PEU, PT and SI all appear to have an impact on behavioral intentions to drive/use AVs, with PU having the strongest impact. Furthermore, the results suggest that additional variables should be considered to improve the accuracy of our predictions on usage intentions of the AVs due to the fact that the explanatory power of the proposed TAM-extended research model was 43.7 per cent.

Part of this work regarding TAM-extended research framework has been published in Elsevier Transportation Research Journal (Part C: Emerging Technologies) (Panagiotopoulos & Dimitrakopoulos, 2018a), as well as in the proceedings of the 13th Intelligent Transport Systems (ITS) European Congress, which was held in Eindhoven, NETHERLANDS, from 3 June to 6 June 2019 (Panagiotopoulos & Dimitrakopoulos, 2019d) and in the proceedings of the 25th Intelligent Transport Systems (ITS) World Congress, which was held in Copenhagen, DENMARK, from 17 September to 21 September 2018 (Panagiotopoulos & Dimitrakopoulos, 2018c).

Conclusions regarding UTAUT-extended research framework

The implications of the present analysis show that PDE plays a big part in consumers' desire to drive/use AVs for their travels. In this context, it is obvious that consumers will still want to enjoy the driving/usage of vehicles equipped with advanced driving automation technologies. Rather than stripping away the pleasure of driving, car manufacturers realize that AVs will simply provide drivers with more choices for comfortable driving towards the use of a clear and understandable human-machine interface (HMI) which enhancing the collaboration between the driver/user and the embedded autonomous driving system in the vehicle.

Furthermore, the financial purchasing and operating cost, the trust in automation technology and the social popularity all appear to be important deciding factors.

Therefore it is hoped that in order to maximize AVs uptake, designers and developers in the automotive field can consider the above issues when implementing more permanent versions of private transportation choices like vehicles with autonomous driving technology.

It should be stated, that part of this work regarding UTAUT-extended research framework has been published in the proceedings of the 6th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2020), which was held as a web-based streaming event, from 2 May to 4 May 2020 (Panagiotopoulos et al, 2020).

Limitations

Like any other studies, the above research efforts have some limitations that should be considered before interpreting the findings. In this manner, the presented implications need to be evaluated in light of the quite futuristic character of AVs at the time of the surveys. AVs are not yet launched on mass consumer markets. Hence, our respondents did not have any hands-on experience with them and could only state their guesses based on the descriptions provided at the beginning of the questionnaire surveys, as well as on information they might have gathered on their own. In this direction real demonstrations are needed to test such vehicle technologies (e.g. in operational speed and under different road/weather/traffic conditions) in order to convince the public what AVs can do in real conditions. Furthermore, our surveys were conducted via online means of communication (websites, social media, etc.) and, hence, excluded people that do not use the Internet.

Also, majority of our sample individuals on both surveys were relatively young (under 40 years old). In addition, since only European people were surveyed, our results might not hold true for non-European people as consumers' opinions and preferences also vary among different geographical regions. In this direction, future efforts and assessments should be done by targeting larger, more diverse populations and examining how attitudes may differ by gender, education level, occupation, household income, driving experience, involvement into accidents, etc.

As communities and individuals learn more about these new vehicle-based technologies, their perceptions and expected/stated behavioral responses are likely to change, in some cases rapidly. As such, future analysis should be done to delve deeper into secondary topics about AVs such as productivity, efficiency, environmental impact, etc. In this respect, due to the ever-changing technology in the areas of transportation and mobility, the findings of our research studies could significantly contribute to ongoing research related to technology acceptance of AVs and are expected to allow automobile industries to improve their design and technology.

CHAPTER 4: DIFFIE-HELLMAN COMMUNICATION PROTOCOL FOR IMPROVING SECURITY AND DATA PRIVACY IN VEHICULAR NETWORKS

Contents

4.1 Introduction

It is now widely accepted by academician and industry that connectivity, provided by intelligent vehicles, is enabled, facilitated and supported by the latest advances in Information and Communication Technologies (ICTs), forming the cornerstone of the new generation of Intelligent Transport Systems (ITSs). Such systems can fundamentally improve road safety, traffic management efficiency and life quality (Wang et al., 2006).

In the field of vehicular networks, future ITSs are constructed to manage Vehicular Communications (VCs) among nearby vehicles on the roads (V2V communications), between vehicles and roadside Infrastructure Units (IUs) and trusted agencies or certificate authorities (V2I communications), and generally between vehicles with everything (V2E communications) like pedestrians, cyclists, etc. In doing so, in these networks each vehicle needs to have an OBU (On-Board Unit), which would integrate the vehicles' wireless communications, micro-sensors, embedded systems, and Global Positioning System (GPS) (Shen et al., 2014).

By using OBUs, intelligent vehicles could then communicate with each other as well as with roadside IUs, such as traffic lights or traffic signs. In this manner IUs can be connected to a backbone network, so that many other network applications, including internet access and infotainment services, can be provided to the vehicles. Moreover vehicles could exchange messages via a Dedicated Short Range Communication (DSRC) network concerning real-time traffic conditions so that drivers/users would be more aware of their driving environment and take early actions in response to unusual situations (Kaur & Malhotra, 2015).

Despite the benefits of VCs, the computerization of vehicles makes them prone to cyber attacks that can endanger the safety of users (passengers and drivers). In a typical vehicular network system there is always a risk that the privacy of the users (e.g. location and identity of the driver, location and identity of the vehicle) could be impaired by an adversary intercepting the communications. Moreover, VCs must be authenticated and authorized in order to keep unauthorized vehicles away from getting access to particular applications, services or privileges. For instance an adversary's vehicle could broadcast emergency vehicle approaching messages to other neighboring vehicles to get ahead in a traffic jam.

On this basis, an insecure and unreliable vehicular network can be more dangerous than the system without it. Potential security measures could include a method of assuring that the packet/data was generated by a trusted source (neighbor vehicle, sensors, etc.), as well as a method of assuring that the packet/data was not tampered with or altered after it was generated. So, secure vehicular network systems are more than necessary.

Owing to the constraints and requirements of the automotive life cycle, most traditional IT security solutions are not directly applicable to vehicles. This puts high demands on IT security agencies and car manufacturers to ensure that it is not the communications that threaten the life of users (passengers and drivers) by affecting the safety of the in-vehicle systems. Lack of authenticated information shared in the network may lead to malicious attacks and service abuses, which could pose great threats to drivers and passengers (Raya et al., 2006; Lin et al., 2008; Kargl et al., 2008; Zeadally et al., 2012).

Furthermore, vehicular networks possess unique network characteristics that distinguish it from other traditional ad hoc networks and characterized by rapidly changing network topology, the high mobility of nodes, unbounded network size, frequent exchange of information, one-time interactions and sufficient energy and computation resources. Therefore, novel mechanisms to guarantee the primary security requirements, such as authentication, integrity, and non-repudiation needs to be developed before vehicular networks can be practically used for reliable VCs (Chun et al., 2008).

With the vision to build on the aforementioned approaches, as well as on the implications of the Chapter 3, where trust/reliability plays a big part in consumers' desire to drive/use AVs in the future, the present Ph.D. dissertation presents a novel communication protocol, based on the Diffie-Hellman well-established popular key agreement scheme, towards the deployment of Internet of Vehicles (IoV) technology in the transport area. The above analysis aims to enhance the efficiency of vehicular interactions and improve the acceptance of AVs regarding trust/reliability in terms of security protection and data privacy issues.

4.2 Modelling approach

In this section, we introduce the vehicular network scheme, assumptions, and problem statement.

4.2.1 Vehicular network scheme

Though various schemes have been proposed, the basic ideas in securing vehicular networks have many similarities. A typical vehicular network model (Fig. 4.1) mainly consists of three nodes; Central Trusted Authority (CTA), roadside IUs, and Vehicles. CTA and IUs are considered as stationary nodes and Vs are low-speed or high-speed mobile nodes.

- **Central Trusted Authority (CTA)** refers to a trusted agency with sufficient computational and storage resources, which covers a specific geographical region, and where all vehicles moving in this area register and get their digital certificates for vehicular network usage. CTA also manages all private information about vehicles and shares them securely with IUs upon request within the covering range. IUs can verify vehicles' certificates via CTA and also can obtain identities of Vs from CTA.

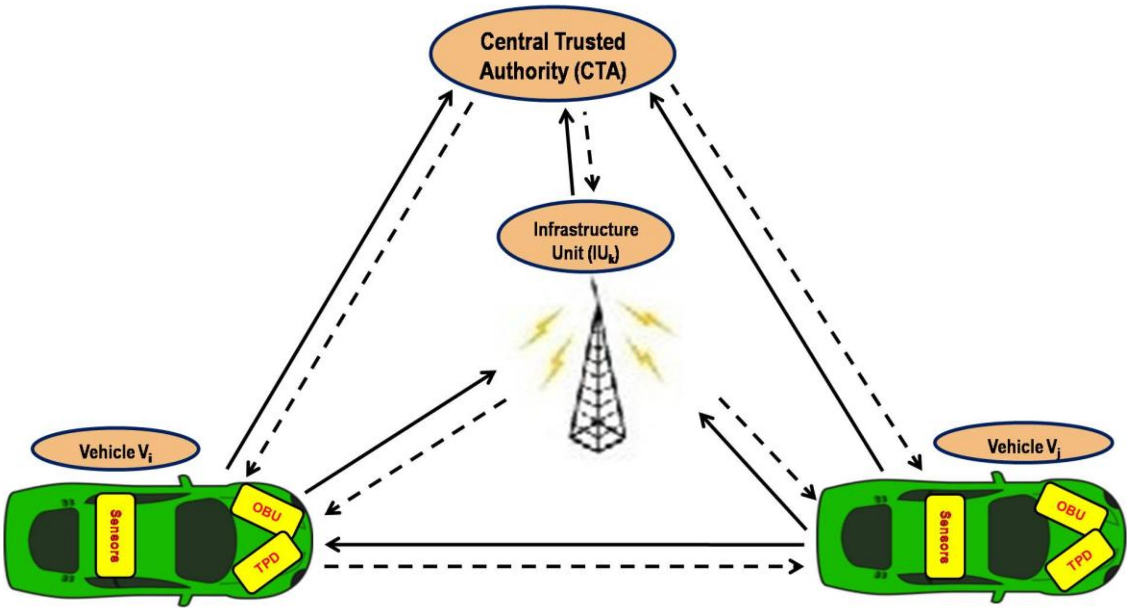


Fig. 4.1 Typical vehicular interaction scheme.

- **Infrastructure Units (IUs)** act as intermediates between vehicles and CTA and also transfer information about environment conditions and traffic information to the vehicles (nodes) of its region. For enhanced security, IUs could directly communicate with a specific CTA and if CTA considers that a specific IU has been compromised, it could revoke the IU's access. The IUs are located along the roads and play an important role in verifying the authenticity and integrity of messages sent by vehicles and forwarding them to other vehicles within its transmission range. Each IU creates a group key (GKe) and shares it with all vehicles within its transmission range, so the IU can encrypt messages using GKe and broadcast them to the vehicles within its transmission range.

- **Vehicles** are moving nodes in the network, which are equipped with three different devices. Firstly, they are equipped with a communication unit, denoted as OBU that enables V2V, V2I, I2V and generally V2E communications. An OBU is assumed to have significantly shorter communication range and less computation power than IUs. Moreover, vehicles are equipped with a set of sensors to measure their own status (e.g. fuel consumption) and its environmental condition (e.g. slippery road, safety distance). These sensorial data can be shared with other vehicles to increase their awareness and improve road safety. Finally, a Trusted Platform Module (TPM) is often mounted on vehicles to store the secret information cryptographic materials and process cryptographic operations. This device is especially interesting for security purposes, as it offers reliable storage and computation.

The above vehicular network scheme is followed as basic architecture in order to design and establish the following proposed identity and data communication protocol for secure vehicular interactions.

4.2.2 Assumptions

We assume that any vehicle that is within a target IU's transmission range is capable of sending/forwarding messages to the IU through other vehicles using a routing protocol suitable for vehicular networks (Tian et al., 2003; Bernsen & Manivannan, 2012). IUs have larger storage space and computation power than OBUs. Our protocol utilizes IUs not only to verify the authenticity and integrity of the messages received from Vs, but also to disseminate those messages to the other vehicles within their transmission ranges, when necessary.

Moreover, we make the following assumptions.

(i) The CTA and IUs are totally trusted and are assumed to be not compromised.

(ii) When a vehicle is registered, the locations of IUs and their public keys are stored in the OBU installed in the vehicle and they are updated during renewal of vehicle registration. So, at any given time, the OBU of a vehicle knows the nearest IU.

4.2.3 Problem statement

When a vehicle senses an incident such as accident, bad road condition due to weather, traffic jam, etc., it needs to send that information to other vehicles in appropriate regions so their drivers (or vehicles themselves, if they are self-driving or autonomous-driving) can take appropriate actions. When such messages are sent, the integrity and authenticity of the messages should be verified while at the same time the anonymity of the senders of these messages should be preserved, i.e. the real identities of the vehicles (or drivers/users) should not be revealed to any other vehicle (or driver).

Moreover, the proposed protocol should prevent all possible attacks, due to the nature of messages in vehicular networks, ensuring security and data privacy protection. To preserve the anonymity of the vehicles, the designed protocol uses pseudo IDs (PIDs) of the vehicles for message transmission. Since IUs have more computation power, authentication of messages and dissemination of messages to neighbor Vs are carried out by the IUs.

4.3 Proposed protocol

This section aims at exemplifying the context in which the proposed protocol is envisaged to operate. The presented protocol has been structured following past research attempts (Chapter 2) which have been performed on the development of various vehicular networks protocols with reference to real-time based communications (Yadav & Vijayakumar, 2012). It is thus divided into three main phases, for facilitating its operation.

4.3.1 First phase: vehicle identity process

The first step in the proposed protocol is vehicle to provide the required identity information, i.e. its unique True IDentity (TID), to the CTA. In the second step CTA verifies the TID information and in the third step CTA issues a unique Pseudo IDentity (PID) to the vehicle. For security reasons PID should not reveal the vehicle's true identity and must be different from its TID. Figure 4.2 presents in detail the overall vehicle identity process.

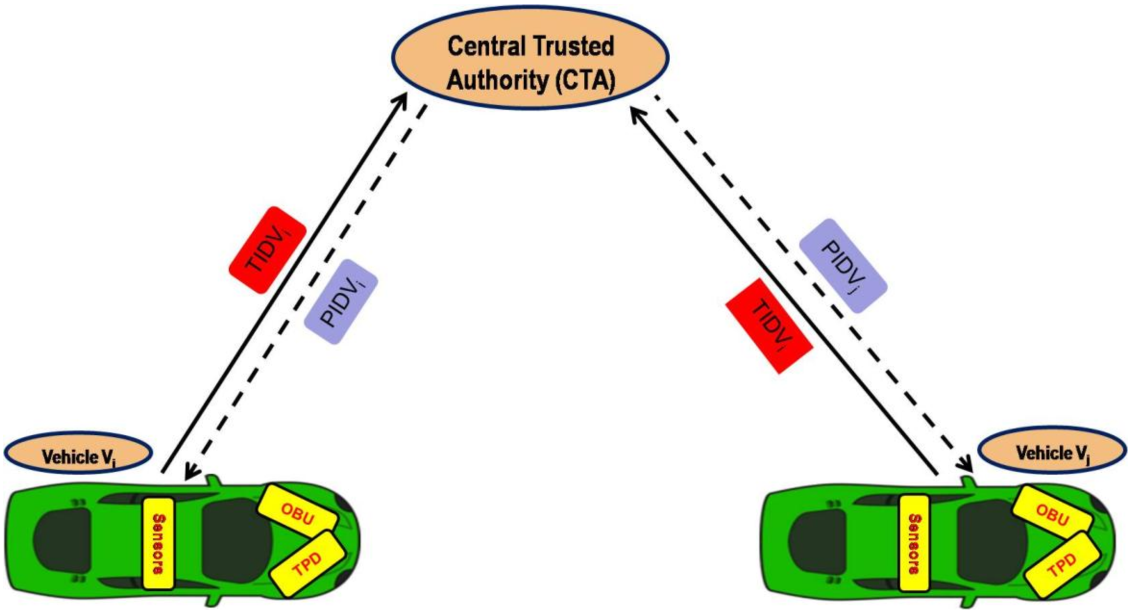


Fig. 4.2 Vehicle identity process.

The above registration process is the initial protection step and should be necessary for each vehicle because services in vehicular networks are only to be provided to valid clients. It ensures that all mobile units are authenticated vehicles to communicate within network.

The protocol for the above presented registration scheme is described in the below:

<u>Protocol – Part A</u>: "Vehicle (V_j) registration to CTA"

1.	Vehicle V_j sends a registration request to CTA providing its $TIDV_j$ (True IDentity of Vehicle V_j)
2.	CTA verifies $TIDV_j$ via Vehicle Manufacturers Agencies (VMA)

If Verification = Successful then
CTA signs a unique $PIDV_j$ (Pseudo Identity of Vehicle V_j)
CTA sends $PIDV_j$ to the Vehicle V_j and stored in $OBUV_j$ (On-Board Unit of Vehicle V_j)
Else
CTA discards the request
End If

$PIDV_j$ can only be modified by local CTA covering a specific region. The vehicle uses its $PIDV_j$ in all communications within the CTA's region. For communications in different geographical regions vehicle V_j should be registered with the specific CTAs that covers these regions. Then CTAs issue different unique Pseudo Identities (PIDs) to the vehicle which send and stored in $OBUV_j$.

4.3.2 Cryptography process

Public Symmetric Key Cryptography Process (PSKCP), based on Diffie-Hellman Key Agreement Scheme (DHKAS), is the basic idea behind our proposed protocol (Fig. 4.3). In this method the same key is used for encryption and decryption of a shared secret (message) at both ends of a vehicular communication link (Diffie & Hellman, 1976).

In the first phase Group Key and Symmetric Key are established. When a vehicle V_j enters an area covered by a specific IU_k, it initiates communication with the IU_k sending its $PIDV_j$, as described above. $PIDV_j$ is verified by IU_k via communication with CTA, and establishes a shared symmetric key with the V_j. In this basis V_j can send encrypted messages using the symmetric key to the IU_k. It also gets the GKe from the IU_k. GKe is used by the IU_k to encrypt messages and send them to other vehicles in the area covered by the IU_k.

In the second phase vehicles can send messages to IUs for dissemination. After completing the first phase, a vehicle V_j can send messages to the IU_k. It uses the shared symmetric key established in the first phase to encrypt the message as well as compute the digest of the messages it sends. This message digest helps the IU_k in verifying the authenticity and the integrity of the messages.

The third phase is the verification and dissemination of messages by IUs. When an IU_k receives the message sent by the vehicle V_j, it verifies the authenticity and integrity of the message and forwards directly the message to the Vs inside its region.

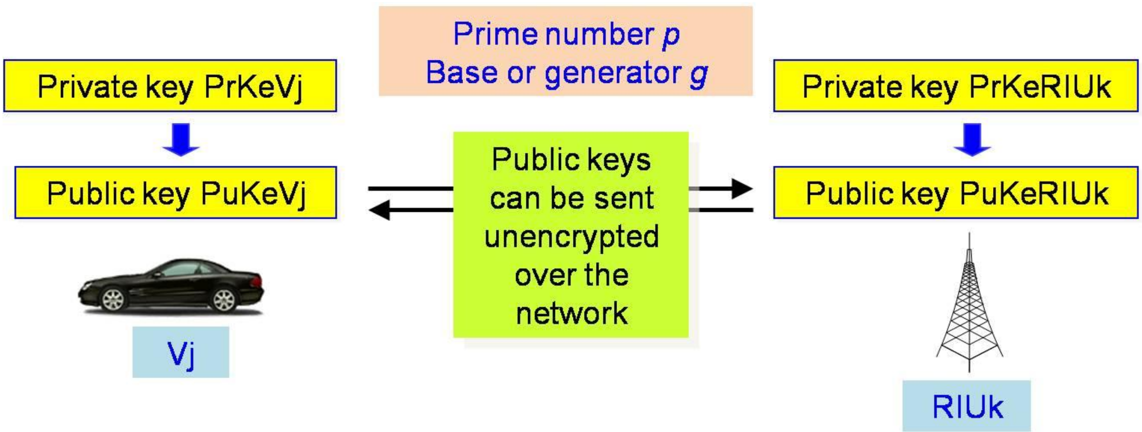


Fig. 4.3 Cryptography process.

When a vehicle V_j enters a region covered by a roadside infrastructure unit, called IU_k, it initiates the key establishment process, as described in the first phase, based on six numbers p, g, private key of vehicle $PrKeV_j$, private key of infrastructure unit $PrKeIU_k$, public key of vehicle $PuKeV_j$, and public key of infrastructure uint $PuKeIU_k$. In this process p is a prime number, g is base or generator, $PuKeV_j = gPrKeV_jmodp$, and $PuKeIU_k = gPrKeIU_kmodp$. Vehicle V_j calculates the shared secret key KeV_j using vehicle V_j's private key and IU_k's public key according to $KeV_j = PuKeIU_kPrKeV_jmodp$. On the other hand infrastructure unit IU_k calculates the shared secret key $KeIU_k$ using IU_k's private key and V_j's public key according to $KeIU_k = PuKeV_jPrKeIU_kmodp$. It turns out that $KeV_j = KeIU_k$, where the shared secret key takes the name $KeV_{j}\_IU_k$. From the attacker point of view, it is quite difficult to find out the value of $KeV_{j}\_IU_k$ by using $PuKeV_j$ and/or $PuKeIU_k$, provided the numbers are sufficiently large.

After the key establishment phase between a vehicle V_j and an infrastructure unit IU_k, V_j can send messages to IU_k securely and without revealing its identity as follows.

When V_j wants to send a message about a sensed incident such as accident, bad road condition due to weather, traffic jam, etc., it computes M_j as follows and sends it to IU_k:

$$M_j = \{PIDV_j\ ,\ KeV_{j}\_IU_k\}$$

To compute M_j, the secret key $KeV_j\_IU_k$ established between V_j and IU_k is used. Note that when IU_k receives the message, it will be able to verify the authenticity of the sender and the integrity of the message based on the pseudo ID of the vehicle V_j ($PIDV_j$) and the secret key $KeV_j\_IU_k$ used for encryption.

When the IU_k receives a message M_j sent by a vehicle V_j, since it has a shared key with each vehicle which forwarded the message, it can decrypt the signatures attached by all nodes on the route one-by-one and verify the authenticity of each node and the integrity of the message received. After it verifies the authenticity and integrity of M_j, it disseminates the message to the other vehicles within its transmission range. Since the IUs have higher computation power than the OBUs, IUs can verify messages more quickly than OBUs.

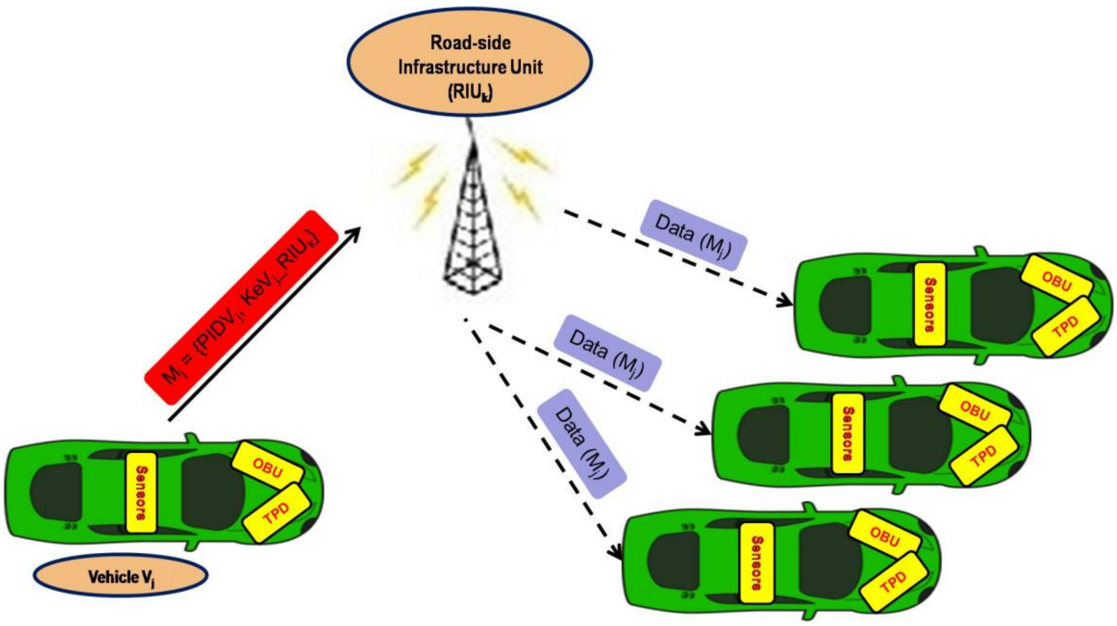


Fig. 4.4 Data communication process.

4.3.3 Data communication process

After become registered with CTA vehicle has the ability to communicate with a nearby roadside IU (V2I communication) about a sensed incident such as accident, bad road condition due to weather, traffic jam, etc. (Fig. 4.4). This communication is based on the aforementioned DHKAS, where a common secret key $KeV_j\_IU_k$ is used for encryption messages.

The protocol for the above communication scheme is described in the below:

<u>Protocol – Part B</u>: "Vehicle (V_j) to nearby Infrastructure Unit (IUk) Communication"

1.	Vehicle V_j sends an "traffic jam" message M_j to nearby IU_k providing its $PIDV_j$ (unique Pseudo Identity of Vehicle V_j) and the secret key $KeV_j\_IU_k$
2.	IU_k verifies the secret key $KeV_j\_IU_k$
3.	If Verification = Successful then
4.	IU_k uses the Group Key (GKe) and sends the message M_j within its transmission range to other neighboring vehicles
5.	Else
6.	IU_k discards the message M_j
7.	End If

In general, under our protocol, when a vehicle enters a region covered by an IU (i.e., the area that lies within the transmission range of the IU), it initiates key establishment with the IU and establishes a symmetric key with the IU so that it can encrypt all the messages it needs to send to the IU while in its region. It also obtains a pseudo ID from CTA. The vehicle uses only its pseudo ID in all communications and hence the anonymity of the vehicle is preserved. The IU uses the GKe to encrypt messages it sends to the vehicles in its region. So all messages are encrypted and no intruder can decrypt the messages.

In this respect, when a vehicle senses an event and wants to disseminate it to other neighboring vehicles, it simply sends it to the nearby IU. The nearby IU authenticates the vehicles sending the message and also checks the integrity of the message and then disseminates the message to the vehicles within its transmission range. A vehicle never broadcasts any message to other vehicles. In this way dissemination of messages to other vehicles is the responsibility of the IUs and hence this approach is scalable. Messages exchanged are generally small so OBUs can use symmetric key for encryption without incurring much computation overhead.

4.4 Main findings – discussion

Under the above protocol, CTA verifies the authenticity of each vehicle providing its PID. A vehicle never uses its real ID in any communication and hence the anonymity of vehicles is preserved. Also, a PID is issued again from CTA, if a vehicle enters another IU's region, and the issued PID is re-issued frequently if a vehicle stays in a IU's region for a long time to prevent tracking of the same pseudo identity.

Moreover, any observed phenomena are only sent by vehicles to the IUs for further dissemination. So, IUs can determine and suppress propagation of redundant messages. In this basis, when a node senses an event, it sends a message to the nearby IU about the event so that the IU can forward this message to other neighboring vehicles. The message is encrypted with the shared secret key between the vehicle and the IU. Messages forwarded by the IUs to vehicles in their regions are encrypted using GKe. So, integrity of messages is ensured.

Furthermore, in the introduced protocol, the authenticity and integrity of the messages are verified by IUs that have higher computation power than OBUs. Also, they can communicate and send the appropriate messages to neighboring vehicles securely. Therefore, fast verification and efficient dissemination are achieved.

As mentioned previously, the symmetric key establishment process in the presented protocol uses DHKAS. Even though DHKAS is vulnerable to man-in-the-middle attack (Diffie & Hellman, 1976), the introduced protocol does not suffer from this weakness because of the following reasons: When a vehicle V_j enters the region covered by an IU_k, it encrypts g, p and its public key $PuKeV_j$ using its private key $PrKeV_j$. An intermediate vehicle can carry out the man-in-the-middle attack only if it is also an authentic vehicle which has a public/private key pair already established by the CTA, in which case the IU_k can trace the messages to the intruder.

In addition, the aforementioned protocol prevents some other types of attacks in vehicular communications (Papadimitratos et al., 2008), such as:

- **Sybil attack:** This is a type of security threat that exists when a malicious node can present multiple identities at once. In our protocol, each vehicle is assigned a PID by CTA and vehicles encrypt outgoing messages using a symmetric key established with the IU. Hence, a malicious node is not able to use multiple identities at once.
- **Message fabrication / alteration attack:** In this attack, an attacker tries to modify, delete, or alter existing messages. In our protocol, when a vehicle sends a message, it encrypts it and the IU (receiver) can verify the integrity of the message received. Hence, fabrication / alteration attack is prevented.
- **Fake IU attack:** An adversary may pretend to be a real IU in this type of attack. In our protocol, however, a fake IU attack is infeasible to succeed because an IU appends its signature using its private key during symmetric key establishment process so the receiver knows who actually sent the signed message by decrypting it using the IU's public key. Hence the fake IU attack is prevented. In the present analysis, IUs are assumed to be reliable and not compromised.

4.5 Summary

Nowadays, vehicular networks are being developed and improved. Several new applications are enabled by this new kind of communication networks bringing the promise of improved road safety and optimized road traffic. For the successful deployment of vehicular communications it is essential to make sure that "life-critical safety" information cannot be modified by external or internal within the network attackers. In this basis lack of such security and privacy in vehicular networks is one of the key hindrances to the wide spread implementations of AVs. Moreover specific operational parameters (highly moving vehicles, frequently and fast changed connectivity) make the problem very novel and challenging.

With the vision to tackle this challenge, this chapter presented a novel communication protocol for propagating phenomena, such as accidents, road conditions, etc., observed by vehicles in vehicular networks, to other vehicles in appropriate regions so they can use them to make informed and proactive decisions. The proposed approach is based on Diffie–Hellman key agreement scheme, where the concepts of vehicle identity process, cryptography process and data communication process were extensively presented and identified throughout the design and operation scheme. The above analysis aims to enhance the efficiency of vehicular interactions and improve the acceptance of AVs regarding trust/reliability in terms of security protection and data privacy issues.

In particular, the presented protocol utilizes IUs that have higher computation power than OBUs to disseminate authenticated messages about the observed phenomena by vehicles within an IUs' transmission range. Moreover, in the proposed approach, the IUs have the ability to verify the authenticity of the sender and the integrity of the message before disseminating it to the other vehicles. In this respect, the anonymity of the senders is preserved, whereas message integrity, source authentication, fast verification and efficient dissemination of messages are achieved.

Finally, it should be stated that the aforementioned approach towards secure vehicular communication networks has been published in IET Intelligent Transport Systems Journal (Panagiotopoulos & Dimitrakopoulos, 2018b), as well as in the proceedings of the 1st IEEE International Conference on Industrial Cyber-Physical Systems (ICPS), which was held in Saint Petersburg, RUSSIA from 15 May to 18 May 2018 (Panagiotopoulos & Dimitrakopoulos, 2018d).

CHAPTER 5: COGNITIVE MANAGEMENT TECHNIQUES FOR ENHANCING ROAD SAFETY AND DRIVING EXPERIENCE WITH AUTONOMOUS VEHICLES

Contents

5.1 Introduction

Automotive industry has been lately experiencing a trend related to the extensive use of Information and Communication Technologies (ICTs) inside vehicles. The results of this trend are reflected on the terms "Intelligent Transportation Systems (ITSs)" and "In-Vehicle-Infotainment (IVI) systems", which envisage cognitive management functionalities that are used inside vehicles traveling on road, attributing vehicles with intelligence after gathering the necessary information from the environment through sensors and vehicular communication technologies. Such functionalities should have the ability to learn and make predictions by adapting to traffic scenarios of different characteristics (Chen et al., 2019).

However, despite the establishment of ITSs and IVI systems, there is still way to go for efficient on-board intelligent functionalities in order to maximize driving experience and interaction with AVs. As such, the importance of investigating the design and deployment of such in-vehicle intelligent systems is increasing (Fagnant & Kockelman, 2015).

With the vision to build on the aforementioned trends, as well as on the implications of the Chapter 3, where performance expectancy and perceived driving enjoyment play important roles in consumers' desire to drive/use AVs in the future, the present Ph.D. dissertation presents two novel on-board cognitive functionalities for enhancing the efficiency of autonomous driving, and therefore, increasing the acceptance of AVs in terms of the road safety and driving experience factors. In this respect, these functionalities aim to enhance travel experience with AVs and improve

either the drivers/passengers' safety, or the drivers/passengers' quality of traveling through entertainment, or both, as follows:

[a] As driving decisions are time-sensitive, AVs should be able to adapt its Level of Autonomy (LoA), even frequently, to tackle traffic scenes with complex environment circumstances. On the other hand, driver/user's profile data and personal preferences towards driving automation should be assessed and managed appropriately, in order to increase their productivity and comfort inside AVs. On this basis, an in-vehicle cognitive management functionality, namely 'i-ALS', is introduced, which automatically and dynamically proposes the optimum LoA to the drivers/users when they wish to have a certain road journey with their AVs, by responding quickly to changing environment situations and driver/user's preferences according to previous knowledge and experience.

[b] As novel infotainment services and applications enhance quality of traveling, an in-vehicle cognitive management functionality, namely 'i-M', is proposed, which automatically and dynamically recommends the optimal Music Genre (MG) to the drivers/users when they want to make a certain journey with their AVs. The proposed IVI cognitive management functionality utilizes drivers/users' profile data and current situation, drivers/users' personal preferences, external environment information, and previous knowledge and experience.

Based on the above, the aforementioned intelligent functionalities are operated on the basis of collecting information from various sources, intelligently processing it, integrating knowledge and experience and, finally, selecting the optimal LoA and MG, respectively, improving thus the quality of on-road transport mobility. Knowledge is obtained through the exploitation of Bayesian networking principles in combination with a practical implementation of the Naive-Bayes law. The overall approach is presented in detail, whereas a novel heuristic is proposed for the algorithmic process towards reaching decisions.

More in detail, the objective of this chapter is to showcase the efficiency, in terms of accuracy and speed of convergence, of the proposed cognitive management functionalities ('i-ALS', 'i-M'), as well as the behavior of the supported LoA and MG selection schemes. The focus is mainly on the knowledge developed and acquired in various situations, the corresponding computational effort required, and the selections conducted. To do this, discrete-event simulations are being implemented to evaluate and validate our models, concerning those specific criteria. The goal of these simulations is to show how fast 'i-ALS' and 'i-M' functionalities can converge to certain solutions and find the best possible matches during the decision-making phase.

5.2 Cognitive selection of autonomy level

5.2.1 Motivation and challenges

AVs are expected to be operated in the collaborative and at the same time efficient usage of on-board intelligent systems in tackling emerging situations and different driving scenarios, even if different levels of autonomy will co-exist. In particular, in-vehicle intelligent systems should have the ability to operate in advanced driving environments, being able and “inform” the drivers/users effectively on real-time crucial information extracted from the vehicle’s driving environment.

On the other hand, due to the fact that AVs in the future will have different on-board levels of autonomy, drivers/users need to be able to “tell” the vehicle effectively how they want to be driven in order to maintain a high level of trust and comfort. This statement is further reinforced by the fact that the factor "perceived driving enjoyment" plays the biggest role in consumers’ desire to accept and drive/use AVs in the future, according to the survey results presented in Chapter 3. In this respect, rather than stripping away the pleasure of driving, automotive industries realize that AVs should provide drivers/users with more choices for pleasant, comfortable and productive driving towards the use of a clear and understandable Human-Vehicle Interface (HVI), which enhances the collaboration between the driver/user and the AV’s embedded autonomous driving system.

The aforementioned statements call for a very effective communication between the "intelligent vehicle" and the driver/user, especially during the handoff of driving responsibility and the transfer of driving functions to the on-board computer operator system (Sm. Desai & Sh. Desai, 2017; Dimitrakopoulos & Demestichas, 2010; Kala & Warwick, 2015).

In the light of the above, it is obvious that several attributes/parameters related to the vehicle's driving environment and the driver/user's personal preferences can be changing with time, in a random manner, during the AV's ride, and therefore, affects the LoA. In this way the AV's operational capabilities will change dynamically based on the software that will be enabled each time. The selection of the capabilities that will be enabled requires advanced management functionality. Moreover, the importance of those parameters may specify the effective operation of AVs. Therefore, an on-board cognitive functionality that can dynamically and proactively recommend, in an automated manner, the transition (downgrading or upgrading) between different levels of autonomy, is of fundamental importance. Regardless of social or legal issues which arise with in-vehicle cognitive management techniques, this functionality should act fast and effectively, increasing the reliability of its decisions.

With the vision at solving the above specified problem, the present Ph.D. dissertation aims to specify and design the architecture of such a novel driver-oriented on-board cognitive functionality, as well as the development of the software entities required. This functionality aims to be capable in proposing the optimal LoA when an individual drive/user wishes to make a certain journey with his/her AV, by taking into consideration a predefined set of attributes/parameters (driver/user personality features, driver/user personal preferences, real-time driving environment information), as well as the policies, and previous knowledge turned into experience. It should be noted that this operation will be autonomous and driver/user's intervention will not be required. At the same time this operation will be designed in order to be human-centric by satisfying simultaneously driver/user's preferences and on-board operator system's requirements.

According to what mentioned above, it is necessary that such an on-board cognitive functionality will be able to monitor the driving environment and driver/user's preferences and requirements, and make decisions on which is the best LoA in each case, using previous knowledge and experience. The platform that incorporates such functionality is named 'i-ALS' (intelligent Autonomous Level Selection) and its architecture and specifications will be specified in the following. In particular, 'i-ALS' functionality aims to contribute in improving the driving/usage and interaction with AVs, through the exploitation of a dynamic, real time, automatic selection of driving automation level among the in-vehicle available levels of autonomy. This is justified as follows:

- Intelligence embedded in AVs towards the effective communication between the vehicle and its driver/user is still at a low level, especially during the handoff of driving responsibility and the transfer of driving functions to the on-board operator system. As such, 'i-ALS' contributes to a significant increase in AV's intelligence, through its valuable help and support that provides to the driver/user a priori.
- High complexity is involved in AV's motion, and this means that, in principle, on-board intelligent functionalities demand a high amount of crucial information from the vehicle's driving environment, including road network type, road condition, weather condition, etc. As such, vehicle's surrounding needs to be assessed in real-time. In this context, 'i-ALS' functionality aims to exploit all the above information by adapting to driving environment changes, fast and successfully, through its embedded cognitive learning process.
- Cognitive mechanisms that support the driver/user's full understanding of the capabilities and limitations towards the in-vehicle available levels of autonomy, as well as the driver/user's awareness of the on-board operator system's current state, could yield safety benefits. On this way, real-time critical situations during the driving task can be reinforced appropriately by 'i-ALS' approach.
- Driver/user's profile data and personal preferences towards driving automation should be managed appropriately, i.e. preferences towards a mind-on / feet-off / hands-on / eyes-on approach. As such, driver/user's preferences need to be assessed in real-time. On this way, 'i-ALS' functionality aims to exploit driver/user's preferences between different modes of driving automation, by proposing the

most suitable LoA to be implemented in order to enhance the driving experience within AVs.

- Cross-border driving scenarios between countries with differences in the legal framework and regulations for AD should be taken into consideration. As such, 'i-ALS' functionality contributes to the selection of the most suitable LoA that a driver/user should follow for his road journey, taking into account the local legal regulations towards vehicles with driving automation capabilities.
- Training and educational purposes related to AD technologies can be supported by 'i-ALS' functionality. Since complicate human-machine interactions could be demonstrated between drivers/users and AVs to the real-world, the proposed functionality could be applied to simulation environments (i.e. driving simulators or field tests) by increasing the driving experience with different levels of autonomy and maximizing drivers' intention to accept/use AVs.
- Car pooling services by sharing an AV towards a common destination can be reinforced by 'i-ALS' approach, i.e. where passenger's preferences might lean towards lower levels of autonomy. As such, 'i-ALS' functionality aims to identify and propose optimum matches, taking into account the passenger's request, the available real-time information towards vehicle's driving environment, the passenger's profile data and personal preferences, and the associated policies.

5.2.2 Business case

The present subsection aims at exemplifying the context in which the proposed 'i-ALS' cognitive management functionality is envisaged to operate, through a business case.

To this point, 'i-ALS' functionality begins to operate as soon as a request arrives by the driver/user. As such, a business case assumes that an individual driver/user desires to make a certain journey with his/her AV. The driver/user logs on 'i-ALS' functionality and its Graphical User Interface (GUI), which may form part of a complete on-board ICT-based system. In case it is the first time that the driver/user enters 'i-ALS', he/she is prompted to complete a form regarding his/her profile data and specific preferences, as well as the importance he/she attributes to the parameters, in the form of weights.

In the case the driver/user is already registered, he/she can immediately make a request by placing the desired destination point. In this respect, 'i-ALS' recognizes the driver/user and has access to his profile information, personal preferences, importance of each preference, and history. This information on each driver/user, his/her preferences, and the past activity on the system (history) are kept in log files, in appropriately formed databases. At the same time, 'i-ALS' is aware of the on-board vehicle levels of autonomy and it is in position to converge fast and export reliable decisions on the optimal LoA to be implemented during the AV's ride. Moreover, knowing the driver/user's past activity on 'i-ALS' functionality, the evaluations and feedback that the driver/user has done and received, respectively, and the previous selections he/she has expected towards levels of driving autonomy, 'i-ALS' can avoid or prefer certain directives.

5.2.3 High-level description

The business case previously mentioned, regardless of its evolution, raises four fundamental requirements for 'i-ALS':

- **Personalization**: This ensures the provision of accurate matching solutions in a twofold manner, tailored to driver/user needs and vehicle's driving environment.
- **Adaptability**: This ensures the efficient interaction with the in-vehicle available levels of autonomy and exploitation of the drivers'/users' preferences.
- **Knowledge aggregation**: This enables the utilization of information extracted from past interactions and to accelerate and make more efficient future decisions.
- **Scalability**: This enables the ad-hoc selection of a more distributed or a more centralized mode of operation, depending on the particular contextual needs.

In the light of those requirements, the whole framework, in which the proposed 'i-ALS' platform operates, is shown in Fig. 5.1. This framework reflects an approach that disposes certain inputs and outputs, described below, whereas its description has been influenced by related research attempts with regards to decision making (Dimitrakopoulos et al., 2013).

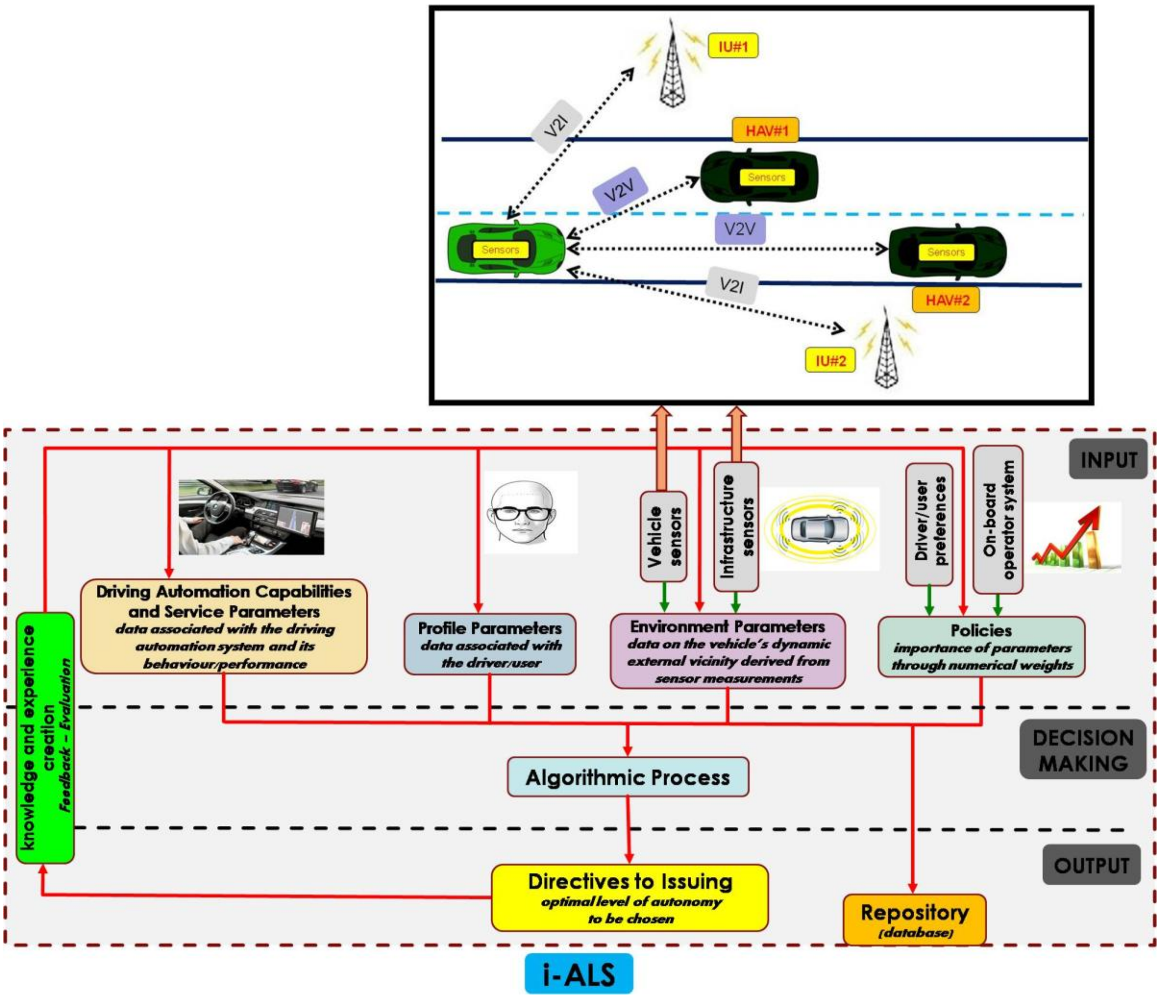


Fig. 5.1 High-level architecture of 'i-ALS' functionality.

In a more detailed analysis, 'i-ALS' cognitive management functionality combines three different types of input information:

(i) **driving automation capabilities and service parameters**, i.e., data associated with the on-board operator system and its behavior/performance (e.g., fail-operational safety, driver-automation interaction, driver workload, driving pleasure, etc.),

(ii) **profile parameters**, i.e., data that are specific to the driver/user of the vehicle (e.g., age, gender, education level, driving experience, driving style, etc.), and

(iii) **external environment parameters**, i.e., real-time information associated with the vehicle's dynamic vicinity aspects obtained from vehicle's and infrastructure's sensors through V2V/V2I/I2V communication technologies (e.g., road condition, weather condition, road network type, vehicle congestion level, etc.). On this stage, it should be noted that sensor measurements provide 'i-ALS' platform with input information very often, so as to cater for timely delivery of crucial information to the on-board operator system. Last, information transferred to 'i-ALS' includes time-stamps for considering also transmission delays, whereas propagation delays are of minor importance to the present Ph.D. dissertation, because of the presupposition of the reliable operation of sensors, vehicular networks and communication technologies.

Furthermore, two sets of overarching policies towards the importance of associated parameters are also included as input data, which aim at maximizing the performance, safety, reliability and stability of the decisions taken by 'i-ALS' cognitive management functionality, from an end-to-end perspective. The first set of policies reflects driver/user's personal preferences towards a set of predefined driving automation capabilities and services. On this way, even non-technology expert drivers/users can provide 'i-ALS', through the interface system, with feedback on their preferences. To do so, driver/user needs to specify the importance he/she attributes to each of those parameters. This is achieved by attributing each one of the predefined driving automation capabilities and service parameters with a certain weight value between 0 and 1, with 0 implying that the parameter has the lowest importance for the driver/user and 1 pointing at the highest importance. Of course, it is possible that some driving automation capabilities and service parameters could have the same weight value for the driver/user. For instance, a driver/user may consider fail-operational safety and driving pleasure equally important. The aforementioned weight values are set by the driver/user just for one time.

In addition, the second set of policies, which are associated with the vehicle's dynamic driving environment, is established by the on-board operator system, based on real-time information extracted from vehicle’s and infrastructure’s sensors through V2V/V2I/I2V communication technologies. In a similar way like previously, the in-vehicle operator system attributes each of the external environment parameters with a certain weight value between 0 and 1. The value 0 implies that the external environment parameter has the lowest importance for the in-vehicle operator system, whereas the value 1 pointing at the highest importance. As external environment parameters can change rapidly from time to time during the AV’s ride, the on-board operator system may need to adapt frequently, in-real time, their respective weight values.

Moreover, it should be noted that ‘i-ALS’ functionality uses as input a knowledge-based learning scheme, which is further enhanced by two well-established evaluation procedures, so as to infer experience to the functionality. The first evaluation process is associated with the driving automation capabilities and service parameters and is made by drivers/users after the completion of their road journeys with the use of the embedded ‘i-ALS’ cognitive management functionality in AVs. In addition, the information acquired towards external environment parameters is processed and appropriately interpreted by the on-board operator system, through a second evaluation process, so as to infer knowledge to ‘i-ALS’. More in detail, this process is associated with the ability of each LoA (among the set of available in-vehicle levels of autonomy) in tackling the vehicle’s dynamic environment situations.

Based on the aforementioned input information (including driving automation capabilities and service parameters, profile parameters, external environment parameters, policies, knowledge-based learning scheme) and the applied decision-making algorithmic process, ‘i-ALS’ output aims at issuing commands (directives) to vehicle’s central operator system, through the reconsideration of the vehicle’s LoA, as well as notifying the driver/user accordingly. As will be described below, ‘i-ALS’ utilizes a heuristic that can exploit the contextual input data in terms of optimizing an objective function (OF) towards the optimal LoA to be chosen.

Furthermore, all combinations of contextual input data and related decisions are kept in an appropriately structured database. On this way, the aforementioned mixed knowledge-based acquisition captures the following aspects:

(a) It keeps track of certain contextual situations (recurrent or emergencies) and the way they have been confronted is retained, so as to serve for future decisions.

(b) It tries to estimate what constitutes a dangerous contextual situation, in terms of improving the specification of certain values of parameters that would be more "subjective" than others, such as the road condition and the weather condition.

(c) It tries to estimate the importance of each parameter, judging from previous situations encountered and decisions taken, so as to gradually learn and improve the specification of contextual parameters' weight values.

In particular, whenever a specific input situation is encountered, 'i-ALS' performs an initial search in the appropriate parts of the (classified) database, so as to check whether a similar situation has been encountered also in the past and how it has been tackled (through an optimal or suboptimal solution). In affirmative, 'i-ALS' functionality proposed herein does not need to run its algorithm and the previous decision, through the exploitation of knowledge and experience, is applied again. Otherwise, 'i-ALS' functionality needs to run its algorithm and reach a decision, through the process described in the following. For example, since vehicle's or/and infrastructure's sensors provide continuously the 'i-ALS' functionality with real-time surrounding environment information, the algorithm needs to run only when something changes, i.e., when the present contextual input situation has not been addressed before. In this respect, parameter changes are adapted fast and successfully, valuable time is saved and the overall complexity is reduced.

As a whole, the functionality 'i-ALS' presented comprises cognitive management mechanisms for dynamically selecting the best available LoA of an AV, by taking into account driver/user preferences and requirements, vehicle's driving environment characteristics, policies, and knowledge established through machine learning scheme. In this direction, LoA selection process is an optimization procedure that takes into account a predefined set of input parameters and decides on the most appropriate LoA through which an application can be obtained by a driver/user when he/she desires to have a certain road journey with his/her AV.

5.3 Cognitive selection of music genre

5.3.1 Motivation and challenges

As mentioned previously in Chapter 2, in the last few decades, the automotive world is witnessing a trend related to the extensive use of newly introduced IVI systems, attributing vehicles with intelligence, which aim to improve either the drivers/passengers' safety, or the drivers/passengers' quality of driving through entertainment, or both (Dimitrakopoulos et al., 2013; Dimitrakopoulos & Demestichas, 2010). The big challenge of IVI systems is not only on how to collect and model large volumes of information but how to develop innovative services and safety applications in real-time for better support the driving task (Kephart & Chess, 2003; Tang & Li, 2014; Cao, 2015].

In most of cases, IVI systems involve a complex multimodal interaction to perform a task. As such, unsafe situations can be created for drivers/users on the road by increasing the time they spend with their eyes and attention off the road and hands off the wheel (Harbluk et al., 2007; Toledo et al., 2008). For example, to select a music option, a driver/user might push a button on the steering wheel, issue a voice-based command, view the options presented on an LCD screen and select a soundtrack via touch using the screen display. The larger number of controls being introduced to select a music option is becoming an additional source of distraction to the driver from the important task of driving (Schneiderman, 2012).

In order to further facilitate the design, development and integration of novel services and safety applications inside AVs, cognitive features should be added to their IVI systems by using advances in artificial intelligence-supported technology. As such, IVI systems will be capable of reconfiguring their operating parameters by offering more extensive navigation assistance while driving, managing audio/visual entertainment content, delivering rear-seat entertainment, as well as connectivity with smart phones for hands free experience with the help of voice commands (Guo et al., 2017). In this respect, infotainment options should create a safer in-car experience helping drivers/users keep their eyes on the road and their hands on the wheel (Sonnenberg, 2010).

With the vision to build on the aforementioned approach, the present Ph.D. dissertation aims to specify and design the architecture of such a novel driver-oriented IVI cognitive functionality, as well as the development of the software entities required. This functionality aims to be capable in proposing the optimal MG when an individual drive/user wishes to make a certain journey with his/her AV, by taking into consideration a predefined set of attributes/parameters (driver/user personality features, driver/user current situation, driver/user personal preferences, real-time information associated with the vehicle's driving environment), as well as the policies, and previous knowledge turned into experience. It should be noted that this operation will be autonomous and driver/user's intervention will not be required. At the same time this operation will be designed in order to be human-centric by satisfying driver/user's preferences and requirements.

According to what mentioned above, it is necessary that such an IVI cognitive functionality will be able to monitor the driving environment and driver/user's preferences and requirements, and operate each time in the most suitable MG, using previous knowledge and experience. The platform that incorporates such functionality is named 'i-M' (intelligent-Music) and its architecture and specifications will be specified in the following. In particular, 'i-M' functionality aims to contribute in improving driving experience and interaction with AVs, as well as to avoid driver's distraction from the important task of driving, through the exploitation of a dynamic, real-time, automatic selection of MG, among a set of the in-vehicle available music options, during road journey. This is justified as follows:

- Intelligence embedded in AVs towards the effective communication, through soundtrack entertainment, between the vehicle and its driver/user is still at a low level. As such, ‘i-M’ contributes to a significant increase in vehicle’s intelligence, through its valuable entertainment support that provides to the driver/user a priori.

- Changes are involved continuously in vehicle’s external environment, and this means that, in principle, on-board intelligent infotainment functionalities should be implemented for improving quality of traveling. In this context, ‘i-M’ aims to adapt to vehicle’s external environment changes, fast and successfully, through its embedded learning and adaptation process.
- Driver/user’s current situation and preferences need to be assessed in real-time and should be managed appropriately, i.e. his/her preferences towards the sound of quality, his/her current mental mood, etc. On this way, ‘i-M’ functionality aims to exploit driver/user’s current situation and preferences between different music options, by proposing the most suitable MG to be implemented.
- Car pooling services can be reinforced by ‘i-M’ functionality, i.e. where user’s preferences might lean towards pop music. As such, ‘i-M’ approach aims to identify and propose optimal decisions, by taking into account the destination, the available information towards vehicle’s external environment, the user’s profile data, the user’s current situation, the user’s personal preferences, and the associated policies.

5.3.2 Business case

The present subsection aims at exemplifying the context in which the proposed ‘i-M’ cognitive IVI functionality is envisaged to operate, through a business case.

To this point, it should be noted that ‘i-M’ functionality can operate as soon as a request arrives by the driver/user. As such, a business case assumes an individual driver/user who desires to make a certain journey with his/her AV, as well as a set of on-board available music options. The driver/user logs on ‘i-M’ functionality, which may form part of a complete on-board IVI system that utilizes a Graphical User Interface (GUI). In case it is the first time that the driver/user enters ‘i-M’, he/she is prompted to complete a form regarding his/her profile and current situation data (age, gender, mental mood, etc.), as well as his/her specific preferences towards all the input parameters, in the form of weight values.

In the case the driver/user is already registered, he/she can immediately make a request by placing the desired destination point. In this respect, 'i-M' recognizes the driver/user and has access to his profile information, personal preferences, importance of each preference, and history. This information on each driver/user, his/her preferences, and the past activity on the system (history) is kept in log files, in appropriately formed databases. At the same time, 'i-M' is aware of all the candidate music genres and it is in position to converge fast and export reliable decisions on the optimal MG to be implemented during the AV's ride. Moreover, knowing the driver/user's past activity on 'i-M' functionality, the evaluations and feedback that the driver/user has done and received, respectively, and the previous selections he/she has expected towards music selections, 'i-M' can avoid or prefer certain directives.

5.3.3 High-level description

In the light of the above business case, the whole framework, in which the proposed 'i-M' platform operates, is shown in Fig. 5.2. In a more detailed analysis, 'i-M' cognitive management functionality combines three different types of input information:

i. **quality of service (QoS) parameters**, i.e., data associated with the on-board infotainment functionality and its behavior/performance (e.g., sound quality, driver-system interaction, ease to use, driving pleasure, etc.),

ii. **profile and current situation parameters**, i.e., data that are specific to the driver/user of the vehicle and its current psychological situation (e.g., driving style, driving experience, mental mood, etc.), and

iii. **external environment parameters**, i.e., data associated with the vehicle's environment aspects (e.g., weather condition, time of day, vehicle congestion level, road condition, etc.). It should be noted that the external environment information is acquired mainly from the wireless sensors placed on the vehicle and on specific parts of the transportation infrastructure. As such, useful real-time information exchange transformed into collective intelligence to 'i-M' infotainment functionality.

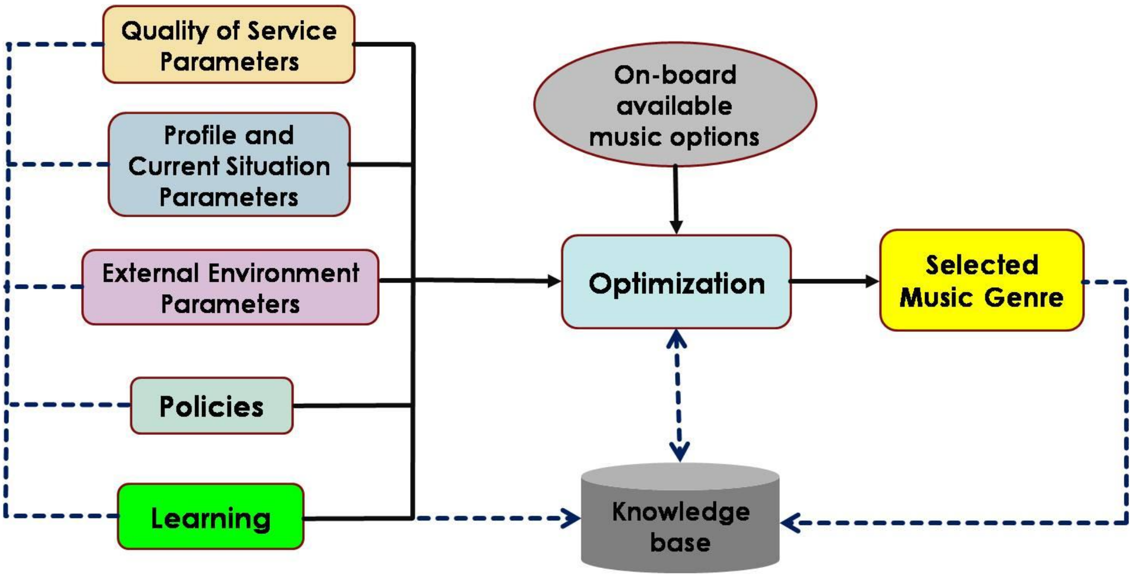


Fig. 5.2 High-level architecture of 'i-M' functionality.

Furthermore, 'i-M' functionality uses as input a set of overarching policies, which reflects driver/user preferences attributed to the aforementioned parameters. On this way, even non-technology expert drivers/users can provide 'i-M', through its interface system, with feedback on their preferences. To do so, driver/user needs to specify the importance he/she attributes to each of those parameters. This is achieved by attributing each one of the above parameters with a certain weight value between 0 and 1. Value 0 implies that the associated parameter has the lowest importance for the driver/user and value 1 pointing at the highest importance. Of course, it is possible that some input parameters could have the same weight value for the driver/user. For instance, a driver/user may consider weather condition and sound of quality equally important.

Moreover, it should be noted that 'i-M' uses as input a knowledge-based learning scheme, which is further enhanced by a well-established evaluation procedure, so as to infer experience to the functionality. The aforementioned evaluation process is made by users (drivers and/or passengers) after the completion of their road journeys with the use of 'i-M' functionality.

Based on the aforementioned input information (including QoS parameters, profile and current situation parameters, external environment parameters, policies, learning scheme) and the applied decision-making algorithmic process, 'i-M' output aims at issuing commands (directives) and notifying the driver/users, accordingly, through the reconsideration of the vehicle's on board MG. As will be described below, 'i-M' utilizes a heuristic that can exploit the input data in terms of optimizing an objective function (OF) towards the optimal music genre to be chosen.

Furthermore, all combinations of input data and related decisions are kept in an appropriately structured database. On this way, the aforementioned mixed knowledge-based acquisition captures the following aspects:

(a) It keeps track of certain situations and the way they have been confronted is retained, so as to serve for future decisions.

(b) It tries to estimate the importance of each parameter, judging from previous situations encountered and decisions taken, so as to gradually learn and improve the specification of parameters' weight values.

In particular, whenever a specific contextual input situation is encountered, 'i-M' performs an initial search in the appropriate parts of the (classified) database, so as to check whether a similar situation has been encountered also in the past and how it has been tackled (through an optimal or suboptimal solution). In affirmative, 'i-M' functionality proposed herein does not need to run its algorithm and the previous decision, through the exploitation of knowledge and experience, is applied again. Otherwise, 'i-M' functionality needs to run its algorithm and reach a decision, through the process described in the following. For example, since vehicle's sensors provide the on-board 'i-M' functionality with input real-time surrounding environment information, the algorithm needs to run only when something changes, i.e., when the present input situation has not been addressed before. In this respect, parameter changes are adapted fast and successfully, valuable time is saved and the overall complexity is reduced.

5.4 Utilization and adaptation of Bayesian Networks theory

5.4.1 Overview

In the present dissertation, and for simulating the aforementioned proposed functionalities (‘i-ALS’ and ‘i-M’, respectively), probabilistic context-aware models are applied for enabling proactive decision makings and selection processes (Al-Sultan et al., 2013). Since proactive decision methods provide a recommendation about the optimal time of applying an action, the values of the contextual input elements at the time when the system recommends the implementation of the action is subjected in high uncertainty.

Probabilistic context-aware models are treated with the use of a machine learning technique in order to effectively deal with uncertainty in a future context. Future context is not known in advance for two reasons: First, the conditions under which the system examined will function cannot be predicted with certainty. Second, the proactive decision model is triggered after the context-aware model, and therefore, the recommended times of actions implementation are not known before the context prediction.

In order to tackle this challenge, the relative algorithms for simulating the context-aware cognitive management functionalities ‘i-ALS’ and ‘i-M’ have been constructed according to the Bayesian Networks (BNs) theory (Russell et al., 2010; Neapolitan, 2003). BNs theory is a well-established probabilistic graphical model used in artificial intelligence for the development of cognitive management systems by means of analysing decision strategies for diverse problems of varying size and complexity, where uncertainties are inherent in the examined systems. Causal networks, belief networks, probabilistic networks are other names for BNs.

BNs have many advantages such as structural learning possibility, combination of different sources of knowledge, explicit treatment of uncertainty and support for decision analysis, and fast responses. They have since proven to be applicable to a wide range of problems in the fields of engineering and IT (Feng et al., 2014). However, BNs have steadily begun to be particularly useful in medicine, due to their ability to be used in aiding diagnosis (Flávio et al., 2014). Other areas where BNs have been developed and have found a use include military applications, space shuttle propulsion systems, and applications in Microsoft Office (e.g. software troubleshooting, 'the paper clip'), biological and ecological applications, financial market analysis, risk assessments of nuclear power plants, pattern analysis and robotics (Sharma & Kulkarni, 2016). Moreover, BNs have begun to be adopted in the field of modeling new transportation modes like car pooling, car sharing, automated vehicles, etc. (Li et al., 2019).

The strong point of BNs is that real life problems can be transformed to simpler problems by focusing on specific variables of interest. In addition, BNs have a number of other appealing properties that make them particularly useful for data analysis and decision-making processes. In addition to their simple causal graphical structure: they can be readily extended and modified; they can readily incorporate missing data through the application of Bayes' theorem; they are able to be understood without much mathematical background; they have been shown to have good predictive accuracy with small sample sizes; they can be used to forecast the likely values of system states given differing future scenarios; they can integrate different sub-models, even if these operate on different scales; and they can be easily combined with decision analytic tools to aid management decision-making for optimising a desired outcome (Kontkanen et al., 1997).

5.4.2 Bayesian Networks classical model

BNs fundaments come from the Reverend Thomas Bayes' (1702-1761) theorem on conditional probability. Since the knowledge represented in the net is mostly **subjective**, **uncertain** and **incomplete**, it comes natural to interpret the data (reasoning) in them from probability theory. Network topology depends on data of the study area. It can be created from databases, expert knowledge, document or situation analysis (Mitchell, 1997).

From machine learning point of view, BNs' learning is referred to construct a network automatically from direct observations avoiding human intervention in the knowledge acquisition process. Formally a BN models the causal-reasoning relationships between a set of variables. A BN contains two key aspects. The first is a graphical representation of the dependencies between variables. A Directed Acyclic Graph (DAG) is used to represent this (Pearl, 2000). Each variable is represented by a single node within the graph. Direct causal dependencies are represented by a directed arc from the "causing" node to the node that is affected. The second aspect of a BN is the collection of Conditional Probability Tables (CPTs) which represents the probabilities of each state of a node occurring given the states its parents may take. The strengths of relationships represented by directed arcs can be modelled in the probability values stored within the CPTs associated with each node. These values are used to infer the posterior probabilities of each variable given those of its parents.

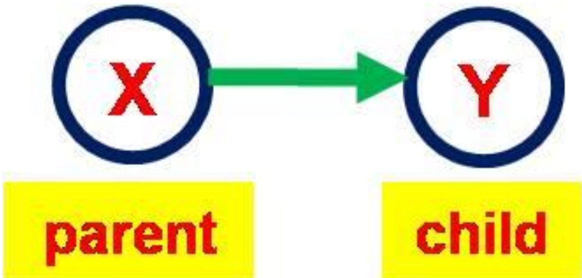


Fig. 5.3 Basic causal structure of a BN.

In this respect, as depicted in Fig. 5.3, a simple BN is designed as a causal structure, where node X affects node Y, and therefore, X is referred to as a parent of Y, with Y being referred to as a child of X. Each arc in BN is directed from a parent to a child, so all nodes with connections to a given node constitute its set of parents. Each variable (X, Y) is associated with a value domain and a Conditional Probability Distribution (CPD) on parent's values. The variables can take discrete or continuous values. Hence, it is possible to have hybrid BNs.

5.4.3 Naïve-Bayes classifier

According to the above, BNs are used in order to represent mainly state-space models. A state-space model is applied in order to make someone able not only to represent the problem space but also to predict its future state based on past input. The past input may be collected for offline or online analysis. In an online analysis the goal is to predict the future state of a system using the observations up to the current time.

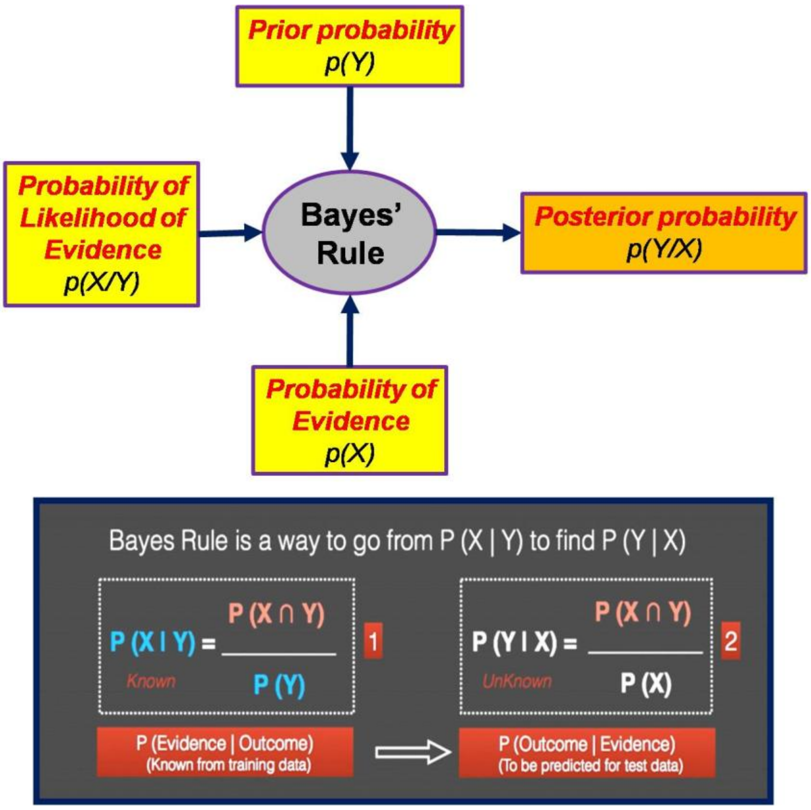


Fig. 5.4 Bayes' theorem characteristics.

BNs use Bayes' theorem to update or revise the beliefs of the probabilities of system states taking certain values, in light of new evidence (referred to as a posteriori) (Mas-Colell, 1995). More in detail, in Bayes' theorem, a prior (unconditional) probability represents the likelihood that the target parameter will be in a particular state; the conditional probability calculates the likelihood of the state of a parameter given the states of input parameters affecting it; and the posterior probability is the likelihood that parameter will be in a particular state, given the input parameters, the conditional probabilities, and the rules governing how the probabilities combine. In this respect, the Bayes rule is a way of going from *P(X|Y)*, known from a training dataset, to find P(Y|X), as depicted in Fig. 5.4, according to the formula:

$$P(Y/X) = \frac{P(X/Y) \bullet P(Y)}{P(X)} \tag{1}$$

For observations in test or scoring data, the *X* would be known while *Y* is unknown. Furthermore, *P(Y)* is the prior distribution of target parameter *Y*; *P(Y|X)* is the posterior distribution, i.e. the probability of *Y* given new data *X*; and *P(X|Y)* the likelihood function, i.e. the probability of *X* given existing data *Y*.

But, in real-world situations, we typically have multiple *X* variables. As such, Bayes' rule can be extended to what is called Naïve-Bayes (NB) classifier. It is called 'Naive' because of the naive assumption that the *X*'s are independent of each other. Consequently, given a *n*-dimensional observation vector ***X*** *= (X1, X2, … , Xn)* and the class *k* of the variable *Y*, the class-conditional probability function of eq.(1) can be rewritten as:

$$P(Y = k/X1, \ldots, Xn) = \frac{P(X1, \ldots, Xn/Y = k) \bullet P(Y = k)}{P(X1, \ldots, Xn)} \tag{2}$$

In technical jargon, the left-hand-side of eq.(2) is understood as the posterior probability or simply the posterior. The right-hand-side of eq.(2) has two terms in the numerator. The first term is called the "probability of likelihood of evidence". It is nothing but the conditional probability of each *X*'s given *Y* is of particular class '*k*'. The second term is called the "prior probability" which is the overall probability of *Y = k*, where '*k*' is a class of *Y*.

On the other hand, in the denominator, since all the *X*'s are assumed to be independent of each other, you can just multiply the likelihoods of all the *X*'s and called it the "probability of likelihood of evidence". It should be noted that the denominator of eq.(2) is the same for all possible values of the class variable *Y*, so it's optional to compute. As such, according to NB classifier, the probabilities of given set of the input *n*-dimensional observation vector $\boldsymbol{X} = (X1, X2, \dots, Xn)$ for all possible values of the class variable *Y* are computed, and therefore the output with maximum probability is picked up.

There are two major advantages of the NB classifier. First, the naive assumption of feature independence reduces the number of probabilities that need to be calculated. This, in turn, reduces the requirement on the size of training set. As an example, the number of features is considered to be 10. Without the naive independence assumption, $2^{10} = 1024$ probabilities for each class should be calculated. With the independent features assumption, the number of probabilities to be calculated per class reduces to 10. In addition, another advantage of NB classifier is that it is still possible to perform classification even if one or more features are missing; in such situations the terms for missing features are simply omitted from calculations.

5.4.4 General formulation

As mentioned previously, BNs can be used to explore and display causal relationships between key factors and final outcomes of a system in a straightforward and understandable manner. As BNs are causal, they can also be used to calculate the effectiveness of interventions, such as alternative management decisions or policies, and system changes, such as those predicted for changes in AV's LoA and MG, respectively. Importantly, the uncertainties associated with these causal relationships can also be explored at the same time.

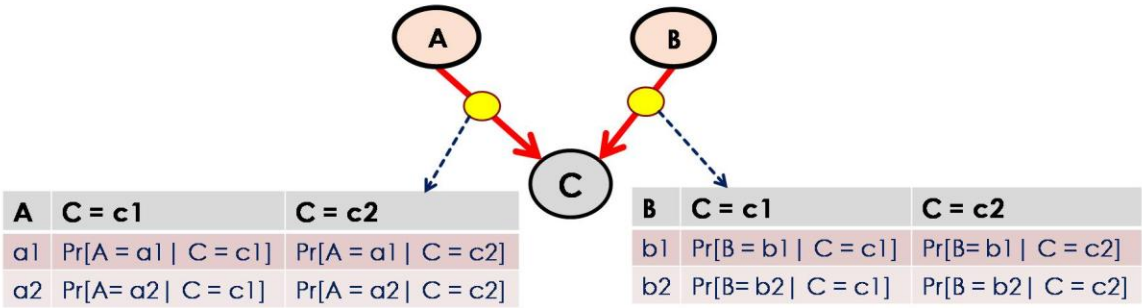


Fig. 5.5 Simple 3-node BN showing conditional dependence of C on A and B.

To do so, the DAG that is used in Fig. 5.5 shows a simple 3-node BN, where random variables A and B (parent nodes) represent the causal factors of random variable C (child node), and edges represent conditional dependences. In this respect, node C is in a converging connection, while nodes A and B are known. As such, not knowing C makes A and B independent (common effect), whereas C is conditionally dependent on both A and B. In order to transform the above DAG into a BN, the marginal probability distributions P(A) and P(B), as well as the conditional probability P(C|A,B) (read as "the probability of C given A and B"), need to be estimated.

To simplify estimating and using these quantities in the BN, the variables are discretized into distinct states allowing one to characterize the continuous probability distributions through a discretized CPT. Discretization of variables is not a requirement of BNs in general but is a convention used here to ease computation, elicitation of probabilities from experts and communication of results to stakeholders. The practical reason is concerned with the fact that BNs face some constraints when dealing with continuous variables (Jensen, 2007). The first constraint is that the BN can handle only conditional Gaussian distributions. The second constraint is that a continuous variable is not allowed to have a discrete child. On the other hand a main disadvantage of discretization is in the potential loss of information; however, it can be particularly useful in the case of variables with a distinct breakpoint significant to management.

The relationship between a child node and all its parents is described by a CPT, which describes the probability of child node being within a state, given a combination of values of parent states. Consequently, the size of the CPT for each variable is the product of the numbers of states of the child node and of all its parent nodes.

Figure 5.5 provides two independent CPTs, which are defined for variables of interest A and B. Each column of the CPTs refers to a specific value of C. Assuming there are two available discrete values of C, the CPTs include 2 columns. Each line of the CPTs corresponds to a certain state of variables A and B. For example $\alpha 1$ and $\alpha 2$ comprise the set from which random variable A can take values. Without loss of generality, enumeration can be done in ascending order ($\alpha 1 < \alpha 2$). Each cell in CPTs provides the value of conditional probabilities, i.e. *Pr[A = a1 | C = c1]* expresses the probability that state *a1* regarding the variable A will be achieved, given that a certain value c1 of the variable C occurs. In this respect, given a certain value c1, the most probable achievable *a1* value is the one that is associated with the maximum conditional probability in the respective column.

It should be noted that the probabilities in the CPTs are updated every time new values regarding the parameters A and B arrive. As such, BN's learning process relies on the constant update and maintenance of conditional probability values, of the form *Pr[A, B | C = ci] (i= 1, 2)*. BN's learning process is further simplified by assuming that the target attributes A and B are conditionally independent, according to the NB classifier, as described in subsection 5.4.3. It has been demonstrated, theoretically and practically, that this independence assumption performs very well, as compared to more sophisticated (but also more complex) classifiers (Friedman et al., 1997; Domingos & Pazzani, 1997). This latter statement holds even if strong dependencies among target features exist.

On this way, the first term in the numerator of eq.(2) can easily be rewritten by using the joint probability formula:

$$Pr[A,B|C=c_i] = Pr[A|C=c_i] \bullet Pr[B|C=c_i] \tag{3}$$

In this respect, eq.(1) can be rewritten as:

$$Pr[C=c_i/A,\ B] = \frac{Pr[A|C=c_i] \bullet Pr[B|C=c_i] \bullet Pr[C=c_i]}{Pr(A,\ B)} \tag{4}$$

5.5 Overall cognitive process

5.5.1 General

In summary, the overall BN's learning process evolves as follows. Data towards input parameters are collected through the training data sets (through measurements or/and evaluations from other users in the past), as described previously in subsections 5.2.3

and 5.3.3. Based on these data, the conditional probabilities are updated, which provide an estimation of how probable it is that a specific feature-parameter (parent node) will reach a certain state, given a certain state of the child node. The next step is the update of the probability density function values. The probability density function offers a more aggregate estimation regarding the probability to achieve a certain combination of input features-parameters, given a certain child node state. These probabilities are exploited by the knowledge-based selection scheme described in subsection 5.5.4.

5.5.2 Fundamental elements leading to knowledge

As already stated, the mechanisms leading to knowledge are influenced by Bayesian networking concepts. Therefore, they rely on random variables, conditional probabilities and a probability density function, which expresses and quantifies the knowledge on the parameters associated with the available states of the child node.

Random variables: The features-parameters (parent nodes) associated with the available states of the child node can be changing with time, in a random manner. It should be noted that parameters' capabilities are determined by the context of operation and by the policies, as mentioned previously in subsections 5.2.3 and 5.3.3. Therefore, random variables C and V_j can be defined for representing a specific state of the child node C and a value of the j-th parameter ($j = 1, \dots , M$), respectively. Random variable C can take values from 1 to AC (corresponding set of available values of node C). Each variable V_j is associated with a set of reference states RV_{ij} ($i \in AC, j = 1, \dots , M$). Specifically, variable V_j can take a value among those in the set of reference states RV_{ij}, when the state i of variable C is considered.

From the sets of reference states, a set of vectors XR_i can be defined for each state i of variable C ($i \in AC$). Such a set of vectors, XR_i, derives as the Cartesian product of the various RV_{ij} sets, i.e., $XR_i = RV_{i1} \times RV_{i2} \times \dots \times RV_{iM}$. Therefore, a XR_i set provides all the potential reference states for the parameters associated with a specific value $i \in AC$. Each vector $xr_i \in XR_i$ has the form $xr_i = \{rv_{i1}^k, \dots , rv_{iM}^k\}$, where $rv_{ij}^k \in RV_{ij}$ $(j = 1, \dots ,M)$

denotes the k-th reference value for the j-th parameter when state i is considered. Therefore, each vector $xr_i \in XR_i$ is one of the options regarding the parameters of a certain state $i \in AC$.

Conditional probabilities: The fundamental elements on which the knowledge on the associated parameters can be based, are conditional probabilities that have the form $Pr[V_j = rv_{ij}^k \mid C = i]$, where r_{ij}^k denotes the k-th reference value for the j-th parameter when state i of variable C is considered. These conditional probabilities express the likelihood that the j-th parameter will be equal to the reference value r_{ij}^k, given state i. Figure 5.6 depicts the organization of information, for an arbitrary value $i \in AC$. As mentioned previously, in order to make the problem simpler, the different reference states that can be achieved for each parameter are considered as discrete.

Parameters	Reference Values				
1	r_{i1}^1	…	r_{i1}^k	…	…
	$Pr[V_1 = r_{i1}^1 \mid C = i]$	…	$Pr[V_1 = r_{i1}^k \mid C = i]$	…	…
…	…	…	…	…	…
	…	…	…	…	…
j	r_{ij}^1	…	r_{ij}^k	…	…
	$Pr[V_j = r_{ij}^1 \mid C = i]$	…	$Pr[V_j = r_{ij}^k \mid C = i]$	…	…
…	…	…	…	…	…
	…	…	…	…	…
M	r_{iM}^1	…	r_{iM}^k	…	…
	$Pr[V_M = r_{iM}^1 \mid C = i]$	…	$Pr[V_M = r_{iM}^k \mid C = i]$	…	…

Fig. 5.6 Organization of the basic information elements (for arbitrary state i of variable C) on which the knowledge-based mechanism is based.

Probability density function: A probability density function value quantifies the knowledge regarding context. The probability density function offers a more aggregate estimation regarding the probability to achieve a certain combination of associated parameters, which corresponds to a specific input contextual level, given a certain state of C. In other words, the values of the density function express the knowledge on how probable a particular (state of C, domain characteristics, input contextual level) triplet is, compared to all other possible triplets. The update of these values constitutes the learning process.

To do so, the following probability density function can be defined for each value *i*, based on the numerator of eq.(4):

$$f\left(x_i\right) = Pr[C = i].\prod_{j=1}^{M} Pr[V_j = rv_{ij}^k \,|\, C = i] \qquad (5)$$

The *Pr[C = i]* probabilities show the volume of information existing for state *i* of variable *C*. The sum of the *Pr[C = i]* quantities, over all *i* ϵ *AC*, is 1. The higher the value of the probability density function $f(x_i)$, the more information exists for this specific value of C, and consequently, the more reliable the existing information is.

Knowledge: As mentioned above, the values of the probability density function $f(x_i)$ express in an aggregate manner the knowledge on how probable it is that state *i* will achieve the level (combination of parameters) indicated by the vector x_i. Therefore, the $f(x_i)$ values contribute to increasing the reliability of the selections, since decision making can take into account the knowledge expressed through the probability associated with the x_i vector.

5.5.3 Update of the conditional probabilities

The goal of this process is to identify the most probable parameter values. To do so, the conditional probabilities $Pr[V_j = rv_{ij}^k \mid C = i]$ in the right end of eq.(5) need to be updated.

For this purpose, it is assumed that a BN collects data for each state *i* in the available states set *AC*, through the training data sets described in subsections 5.2.3 and 5.3.3. So, the prior probabilities *Pr[C = i]* of eq.(5) can be taken equal to the number of collections for a specific state *i*, i.e. *count[C = i]*, divided by the total number of collections for all the *N* available states of *C*:

$$Pr[C=i] = \frac{count[C=i]}{count[C=1]+...+count[C=N]} \quad (6)$$

In the present analysis, the update of the conditional probabilities $Pr[V_j = rv_{ij}^k \mid C = i]$ takes into account the "distance" (absolute difference) of the mean collected data values v_{ij}^{coll} from the reference values rv_{ij}^k. Let dif_{ij} be the difference between the maximum and the minimum reference value in the set of reference states RV_{ij}. Then, for each reference value $rv_{ij}^k \in RV_{ij}$ the following correction factor cf_{ij}^k can be computed:

$$cf_{ij}^k = 1 - \frac{\left| rv_{ij}^k - v_{ij}^{coll} \right|}{dif_{ij}} \quad (7)$$

where $0 \le cf_{ij}^k \le 1$. A correction value close to one means that the corresponding reference value rv_{ij}^k and the mean collected value v_{ij}^{coll} are close, and thus, the corresponding conditional probability value should be reinforced accordingly. The opposite stands if cf_{ij}^k is close to zero.

Given a candidate state *i* of *C*, the new value of a conditional probability, $Pr[V_j = rv_{ij}^k \mid C = i]$, can be obtained as the product of the old value, the correction factor cf_{ij}^k and a normalization factor L_{ij}:

$$Pr[V_j = rv_{ij}^k \mid C=i]_{new} = L_{ij} \cdot cf_{ij}^k \cdot Pr[V_j = rv_{ij}^k \mid C=i]_{old} \quad (8)$$

The normalization factor L_{ij} is used to ensure that the updated values of all conditional probabilities for a certain input contextual level will sum up to one, when a specific state of variable *C* is considered. It can be computed through the following relation:

$$L_{ij} \cdot \sum_{j=1}^{M} cf_{ij}^k \cdot Pr[V_j = rv_{ij}^k \mid C=i]_{old} = 1 \quad (9)$$

Based on the above, it can be defined that the proposed update supervised machine learning strategy converges when the corresponding conditional probability of the reference value, which is closest to the mean collected data value, becomes the highest. At this point, the conditional probabilities that correspond to the other (candidate) reference values are either being reduced or reinforced less.

Moreover, in order to ensure adaptability to new conditions, the conditional probabilities can be prohibited from falling below a certain probability threshold Pr_{min}.

In summary, the update machine learning strategy includes:

(i) collection of measurements through training data sets;

(ii) computation of the correction factors through eq.(7), of the normalization factor through eq.(9), and of the new values of conditional probabilities through eq.(8);

(iii) the Q probabilities that may fall below Pr_{min} are set equal to the threshold;

(iv) the remaining probabilities that have not fallen below the Pr_{min} threshold are equally reduced so as to sum to $(1 - Q{\cdot}Pr_{min})$.

After the update of the conditional probabilities values, the update of $f(x_i)$ values follows. This is realised through the use of eq.(5). These latter values are utilized by the knowledge-based selection scheme described in the following subsection.

5.5.4 Knowledge-based selection scheme

This subsection describes the selection scheme that can be supported by exploiting the knowledge that is acquired. The input comprises the set of in-vehicle available states of the child node C, the importance of each parameter and the knowledge regarding the parameter capabilities. The output is again the specific value of C, among the available set of states AC that should be selected.

The scheme bases the selection of states of C on their probabilities of achieving the parameter states. For each value of C there is a parameters' input contextual level that it is more likely to achieve. The selection then relies on how desired these, most probable, parameter levels are, with respect to the policy information, expressed through weights for each parameter. In a sense, the states of C are ordered into a priority list and the one with the highest value can be selected.

To do so, the computation of a so called appropriateness value av_i for all the available states $i \in AC$, is needed. The computation can be split into two main phases, namely normalization and appropriateness value computation.

Normalization: The first phase is required for facilitating the comparison of the input parameter capabilities of the various states of C. The phase can be split into two steps. The first step is to find the worst, wv_j, and best, bv_j, values for each parameter j ($j = 1, \ldots, M$). These derive from the comparison of the rv_{ij} ($i \in AC$) values. The second step is to normalize the rv_{ij} values. Each normalized value nrv_{ij} ($j = 1, \ldots, M$) can be provided by the formula:

$$nrv_{ij} = 1 - \frac{\left|rv_{ij} - wv_j\right|}{\left|bv_j - wv_j\right|} \tag{10}$$

In case the worst, wv_j, and best, bv_j, values are equal, the normalized value nrv_{ij} can be equal to one.

Appropriateness value computation: After normalization, the appropriateness value av_i of a certain state i can be computed through the following formula:

$$av_i = \sum_{j=1}^{M} w_j nrv_{ij} \tag{11}$$

where $i \in AC$, $j = 1, \ldots, M$, and w_j provides the importance of the j-th parameter.

Knowledge-based objective function value computation: These values are computed for each state $i \in AC$ and are derived from the most probable parameter capabilities, through the probability density function values $f(x_i)$, eq.(5). In other words, the knowledge-based objective function value OF_i is calculated as a product of the probability density function value $f(x_i)$ (knowledge) and the appropriateness value av_i:

$$OF_i = f\left(x_i\right) \cdot av_i \tag{12}$$

Knowledge-based selection: The state of *C* with the highest OF_i value is selected based on the knowledge, as obtained from the aforementioned process. Finally, the decision is implemented.

Figure 5.7 depicts an overview of the overall process for learning the capabilities of candidate states of child node *C* and exploiting the acquired knowledge in order to select the most appropriate state. Table 5.1 provides an overview of all the symbols used, listed in alphabetical order.

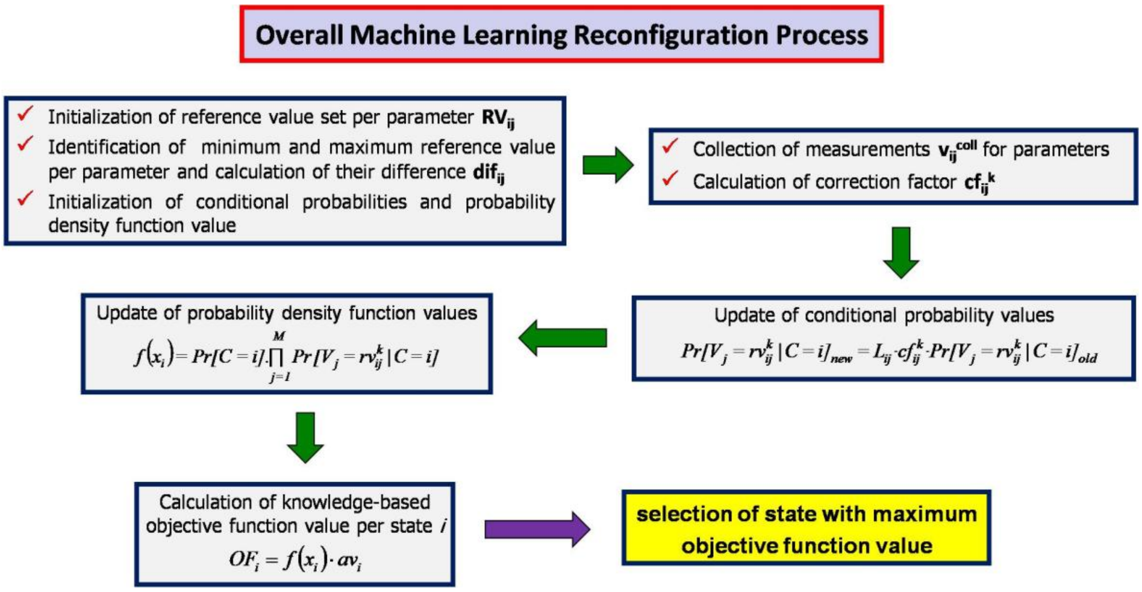


Fig. 5.7 Overview of machine learning and knowledge-based selection process.

5.6 i–ALS simulation results

5.6.1 General aspects – simulation setup

This section describes the main aspects of the simulation process and a short description of the indicative driving scenarios that were used for deriving the results on the behavior and performance of i-ALS's cognitive mechanism and knowledge-based selection scheme. To do so, an appropriate BN is designed in modeling 'i-ALS' functionality for the prediction of the vehicle's LoA.

Domain Analysis: It concerns the determination of all variables that characterize the domain of interest and the individuation of all the possible states associated with each variable of the BN. Each random variable represents a node of the BN.

Table 5.25 Overview of symbols used for the formulation of the knowledge-based selection scheme.

Symbol	Meaning
C	*Random variable representing the child node*
AC	*Set of the available states of the child node*
V_j	*Random variable representing the value for the j-th parameter*
w_j	*Weight value indicating the importance of the j-th parameter*
RV_{ij}	*Set of reference values that can be taken by random variable V_j when a state i ϵ AC is considered*
rv_{ij}^k	*k-th reference value for parameter j (j = 1, 2, …, M) when state i ϵ AC is considered*
v_{ij}^{coll}	*Collected value (through measurements or/and evaluations from other users in the past) of j-th parameter of i-th candidate state*
$Pr[V_j = rv_{ij}^k \mid C = i]$	*Probability that the value of the j-th parameter will equal the k-th reference value for this parameter, given that the state of the child node is i.*
L_{ij}	*Normalization factor*
Pr_{min}	*Threshold for value of conditional probabilities*
dif_{ij}	*Difference between the maximum and the minimum reference value of RV_{ij}*
cf_{ij}^k	*Correction factor for the k-th reference value of the parameter j regarding state i.*
$f(x_i)$	*Probability density function value indicating the probability that a certain combination of input parameter values can be provided by state i*
bv_j	*Best value for of the j-th parameter*
wv_j	*Worst value for of the j-th parameter*
nrv_{ij}	*Normalization factor for rv_{ij} values*
av_i	*Appropriateness value for state i*
OF_i	*Knowledge-based objective function value for state i*

Predictor Selection: In the present analysis, 'i-ALS' functionality aims to predict the appropriate in-vehicle LoA. Assuming an AV has three on-board available levels of autonomy within its operator computer system, the random variable-feature LoA (child node) can take the values 2 (partial automation), 3 (conditional automation), and 4 (high automation), according to the corresponding SAE levels of autonomy, as described in Chapter 2.

Parent Node Set Determination: The features for AV's level of autonomy prediction can be classified into three types:

(1) features related to driving automation capabilities and service issues,

(2) features related to driver/user's profile, and

(3) features related to external environment

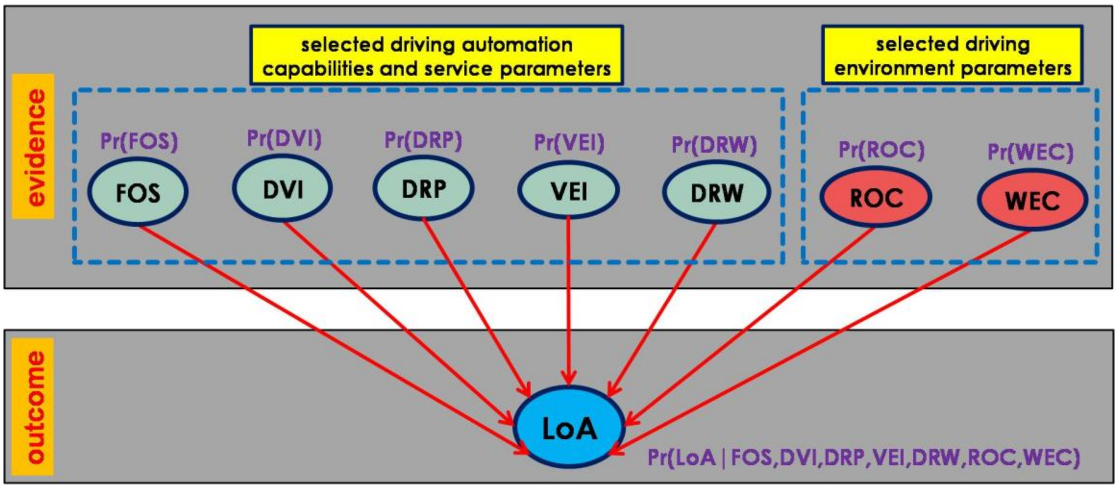


Fig. 5.8 Structure of the proposed BN for LoA prediction in AVs.

In order to be comprehensive, and, at the same time, try to minimize the complexity and facilitate the reader in understanding the potentials of the proposed 'i-ALS' cognitive functionality, a set of seven random variables-parameters (parent nodes) is considered, as depicted in Fig. 5.8:

A. two external environment parameters, such as **road condition (ROC)** and **weather condition (WEC)**

B. five parameters related to driving automation capabilities and service issues, like **fail-operational safety (FOS)**, **driver-vehicle interaction (DVI)**, **driving pleasure (DRP)**, **vehicle-environment interaction (VEI)** and **driver workload (DRW)**

In this manner, input variables ROC, WEC, FOS, DVI, DRP, VEI and DRW cause the random variable LoA and are assumed to be statistically independent. Although simulation process with seven input causes is assumed herewith, i-ALS's functionality algorithmic process is highly scalable, in that it can be readily generalized to include more causes-parameters, as well as to be easily adapted / changed so as to utilize a different list of input features.

In addition, since no large-scale public AVs exist today, parameters selection related to driving automation capabilities and service issues were inspired by the results in Chapter 3, which provides insight into the factors affecting potential users' intension to adopt and drive/use AVs, as well as by a large number of similar studies in the published literature (Payre et al., 2014; Kyriakidis et al., 2017; Haboucha et al., 2017; Bansal et al., 2016; Zmud & Sener, 2017; Piao et.al., 2016; Panagiotopoulos & Dimitrakopoulos, 2018a). Please note that features which are specific to the driver/user of the vehicle (profile parameters) have not been considered in the present analysis.

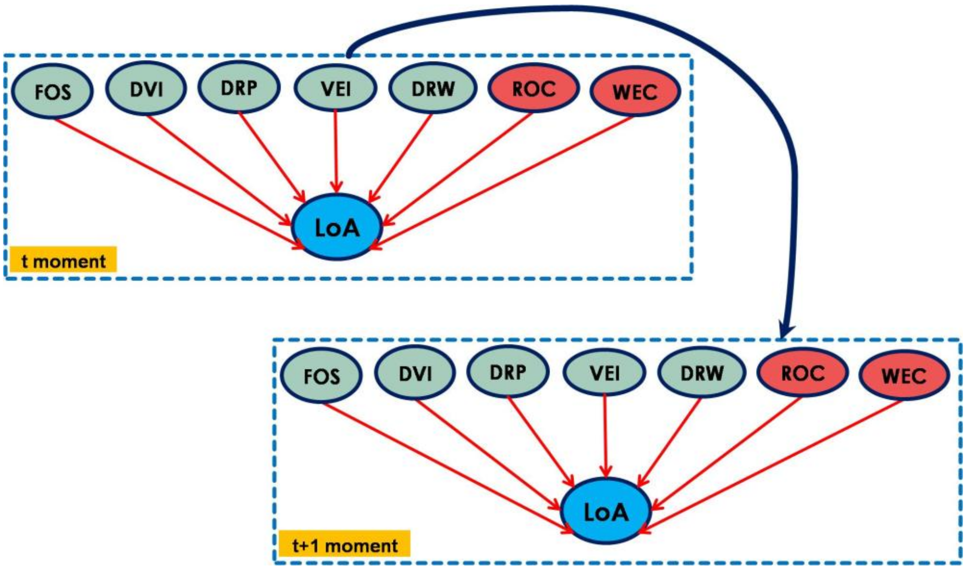


Fig. 5.9 BN structure for LoA prediction in AVs between two adjacent time slices.

Based on the above, the complete BN node set is:

Parent node set (predictands) = {ROC, WEC, FOS, DVI, DRP, VEI, DRW}

Child node set (predictor) = {LoA}

The definition of causality is the premise to express the transfer rules between different nodes. Based on the network nodes, the following causality is defined:

$$Pr[\,ROC, WEC, FOS, DVI, DRP, VEI, DRW \mid LoA\,]$$

$$Pr[\,LoA(t+1) \mid LoA(t)\,]$$

Figure 5.9 shows the BN topology structure for LoA prediction in AVs between two adjacent time slices (t, t+1), including the initial network and transition network.

Table 5.26 Description of variables in proposed BN for LoA prediction in AVs.

Variables	Number of Reference States	Short Description
Child node		
LoA	3	2. partial
		3. conditional
		4. high
Parent nodes		
ROC, WEC	5	1. "extremely low response"
		2. "quite low response"
		3. "average response"
		4. "quite high response"
		5. "extremely high response"
FOS, DVI, DRP, VEI, DRW	5	1. "not at all satisfied"
		2. "low satisfied"
		3. "average satisfied"
		4. "high satisfied"
		5. "completely satisfied"

Determination of Node Reference States: In order to make the simulation analysis simpler, the different states that can be achieved by the aforementioned input parameters are considered as discrete; this fact minimizes the complexity of the problem. In the present analysis, a grid of five discrete reference states is applied as following (Table 5.2):

- Driving automation capabilities and service parameters FOS, DVI, DRP, VEI and DRW can take the discrete reference states "not at all satisfied" (rs_1 = 1), "low satisfied" (rs_2 = 2), "average satisfied" (rs_3 = 3), "high satisfied" (rs_4 = 4) and "completely satisfied" (rs_5 = 5)
- Driving environment parameters ROC and WEC can take the discrete reference states "extremely low response" (rs_1 = 1), "quite low response" (rs_2 = 2), "average response" (rs_3 = 3), "quite high response" (rs_4 = 4) and "extremely high response" (rs_5 = 5)

On this way, the values that are associated with the seven input variables ROC, WEC, FOS, DVI, DRP, VEI and DRW, are denoted as V_{ROC}, V_{WEC}, V_{FOS}, V_{DVI}, V_{DRP}, V_{VEI} and V_{DRW}, respectively. For brevity, the set of reference states {rs_1, rs_2, rs_3, rs_4, rs_5} or {1, 2, 3, 4, 5} for the "driving pleasure (DRP)" parameter is depicted, via the corresponding CPT, in Fig. 5.10, for the three available levels of autonomy (LoA = 2, 3, 4). Each time, random variable V_{DRP} can take a value from the above set of reference states.

DRP *(driving pleasure)*	**LoA = 2** *(partial)*	**LoA = 3** *(conditional)*	**LoA = 4** *(high)*
rs_1 = 1 *(not at all satisfied)*	$Pr[V_{DRP} = 1 \mid LoA= 2]$	$Pr[V_{DRP} = 1 \mid LoA= 3]$	$Pr[V_{DRP} = 1 \mid LoA= 4]$
rs_2 = 2 *(low satisfied)*	$Pr[V_{DRP} = 2 \mid LoA= 2]$	$Pr[V_{DRP} = 2 \mid LoA= 3]$	$Pr[V_{DRP} = 2 \mid LoA= 4]$
rs_3 = 3 *(average satisfied)*	$Pr[V_{DRP} = 3 \mid LoA= 2]$	$Pr[V_{DRP} = 3 \mid LoA= 3]$	$Pr[V_{DRP} = 3 \mid LoA= 4]$
rs_4 = 4 *(high satisfied)*	$Pr[V_{DRP} = 4 \mid LoA= 2]$	$Pr[V_{DRP} = 4 \mid LoA= 3]$	$Pr[V_{DRP} = 4 \mid LoA= 4]$
rs_5 = 5 *(completely satisfied)*	$Pr[V_{DRP} = 5 \mid LoA= 2]$	$Pr[V_{DRP} = 5 \mid LoA= 3]$	$Pr[V_{DRP} = 5 \mid LoA= 4]$

Fig. 5.10 Structure of the CPT for the "driving pleasure (DRP)" parameter.

Importance of Input Parameters: In the following, the impact of these weights on the behavior of the knowledge-based selection scheme is presented through specific results according to the experimental datasets.

Parameter Learning: Learning of the CPTs that truly reflect the causality among variables forms a crucial part of the reconfiguration and adaptation machine learning algorithm, as described in section 5.5. Since the structure of the proposed BN for LoA selection in AVs is determined, the conditional independencies for the family of LoA and its parent nodes can be learned from the experimental datasets.

In this manner, datasets associated with driving automation capabilities and service parameters (FOS, DVI, DRP, VEI and DRW), are based on a well-established evaluation process, which is made by drivers/users towards the three available on-board levels of autonomy (LoA = 2, 3 and 4), after the completion of their road journeys with AVs and 'i-ALS' functionality. As mentioned in Table 5.2, a 5-point integer scale, i.e. from "1" to "5", is used for the ranking of the available driving automation capabilities and service parameters towards the experience of the drivers/users with a certain in-vehicle LoA, with "1" standing for "not at all satisfied" and "5" standing for "completely satisfied".

Additionally, datasets associated with external environment parameters (ROC, WEC), are based on a second well-established evaluation process, which is made by the on-board operator system towards the ability of the three available levels of autonomy (LoA = 2, 3 and 4) in tackling dynamic environment situations. A similar 5-point scale from "1" to "5", as mentioned in Table 5.2, is followed for the nodes ROC and WEC, with "1" standing for "extremely low response" and "5" standing for "extremely high response".

The above reconfiguration and adaptation machine learning algorithm starts with the developed structure for a single time slice and then proceeds to learn the temporal dependencies which exist between time slices. In the present analysis, it is assumed that the aforementioned datasets used for learning parameters contained only complete data.

The above process enables AVs to operate each time in the best available LoA. On this way, the optimal LoA is the one that satisfies the criteria already specified. In any case, even after the proposal made by ‘i-ALS’ functionality, the driver/user is free to decide whether he/she will move on with the implementation of the itinerary.

Case Studies: In the present thesis, four discrete-event simulations have been constructed, as more realistic as possible, where ‘i-ALS’ machine learning process is being implemented with the aid of SimEvents (an add-on to MATLAB). The goal of these simulations is to show how fast ‘i-ALS’ functionality can converge and find the optimum LoA during the AV’s ride. More in detail, simulation results derive from the inputs of the scheme, namely, the driving environment information, profile data, driving automation capabilities and service features, as well as policies which yield the importance of the aforementioned parameters. It should be noted that the work and the results presented hereafter regarding ‘i-ALS’ cognitive management functionality can be generic and adaptable to the requirements of several driving simulations with respect to AVs.

In this direction, the first simulation is a "regular" case, which aims at showing the gradual development of knowledge in identifying the most probable parameter values, as fast as possible, and thus proposes the most appropriate LoA. The second simulation provides evidence on ‘i-ALS’ functionality’s fast adaptation when comparatively high importance is attributed to a specific driving automation capability/service parameter (e.g., FOS). The third simulation is a typical car-sharing case study, which investigates how the embedded ‘i-ALS’ functionality and its knowledge-based selection scheme are appropriately adjusted, as fast as possible, when the driver/user changes (e.g., in the case of a family when someone else wants to drive the same AV), and thus identifies the most appropriate LoA that on-board operator system should follow for the "new" driver/user. The last (fourth) simulation aims at testing i-ALS’s adaptation to a situation that changes, i.e., when the WEC external environment parameter changes during the road journey with the AV.

In order to simulate the above case studies, it is assumed that ‘i-ALS’ functionality enables the driver/user to input and specify the importance (weights) given to the five selected driving automation capabilities and service parameters (FOS, DVI, DRW, VEI and DRP), as well as to properly visualise the outcomes of the algorithm. In addition, the implementation enables the on-board operator system to input and specify the importance (weights) given to the two selected external environment parameters (ROC, WEC).

5.6.2 Scenario A1: "regular" case

This discrete-event simulation represents a "regular" case, which aims to demonstrate evidence of i-ALS's efficiency, by providing the most appropriate LoA to an individual driver/user who wishes to have a road journey with his AV. For this purpose, driver/user John, a 55-years old man, is considered who wishes to travel with his AV, from SP-1 (starting point-1) to DP-1 (destination point-1), an itinerary of 40 kilometers (km), on a well-maintained highway, during a sunny day, with clear visibility.

Table 5.27 Scenario A1: Collected evaluation values and respective weights for the available input parameters.

Driving automation capabilities and service parameters	Weight values according to driver's/user's preferences	Collected values through the evaluation procedure from other drivers/users		
		LoA = 2	LoA = 3	LoA = 4
FOS	*0.25*	*4*	*3*	*4*
DVI	*0.25*	*3*	*4*	*4*
DRW	*0.133*	*4*	*4*	*3*
VEI	*0.133*	*3*	*3.5*	*4*
DRP	*0.133*	*3.5*	*3.5*	*3*
Driving environment parameters	Weight values according to on-board operator system	Collected values through the evaluation procedure from the on-board operator system		
		LoA = 2	LoA = 3	LoA = 4
ROC	*0.05*	*5*	*5*	*5*
WEC	*0.05*	*5*	*5*	*5*

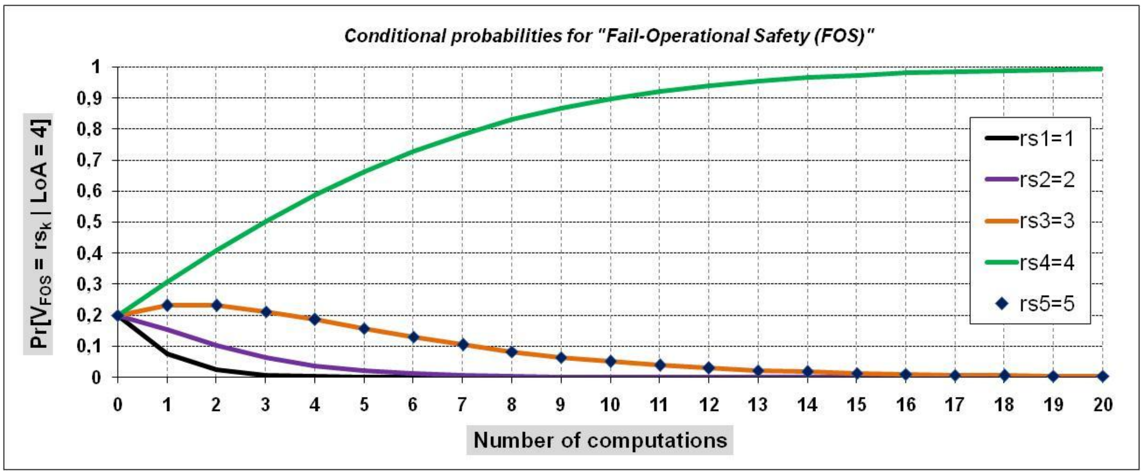
Driver/user John has already registered on 'i-ALS' functionality in the past by filling his profile data and stating his personal preferences (weight values) towards the importance he attributes to each one of the pre-defined driving automation capabilities and service features (FOS, DVI, DRW, VEI and DRP). Based on the data depicted in Table 5.3, FOS and DVI parameters have a high importance (weight value 0.25) for the driver/user John, while he has equal interest (weight value 0.133) in DRW, VEI and DRP parameters. As such, driver/user John disposes a unique identity for on-board 'i-ALS' functionality.

On the other hand, as shown in Table 5.3, the on-board operator system of the AV gives a low importance (weight value 0.05) to the pre-defined external environment parameters (ROC and WEC) due to extremely good road (well-maintained highway) and weather (sunny day with clear visibility) conditions. In that framework, and having in mind that there are seven input contextual parameters in total, the sum of all weight values is equal to 1.

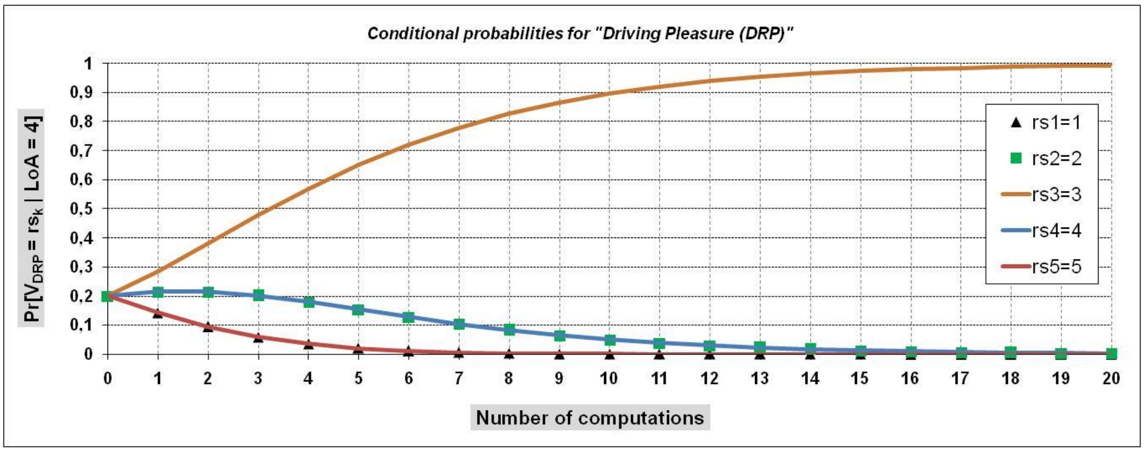
Additionally, collected values based on datasets associated with the evaluation procedures from other drivers/users and the vehicle's on-board operator system towards the contextual parameters FOS, DVI, DRW, VEI, DRP, ROC and WEC, are demonstrated in Table 5.3. These values have been executed for each one of the three available on-board levels of autonomy (LoA = 2, 3 and 4) per contextual parameter.

Initially, the conditional probabilities of the form $Pr[V_j = rs_k \mid LoA = i]$ regarding each input contextual parameter j (FOS, DVI, DRW, VEI, DRP, ROC, WEC), where rs_k can take values among the set of reference states {rs_1, rs_2, rs_3, rs_4, rs_5} or {1, 2, 3, 4, 5} and i = 2, 3, 4, are equal to 0.2, due to the fact that no previous knowledge is available to 'i-ALS' management functionality. Moreover, regarding the amount of information available for each LoA, it is assumed that prior probabilities Pr[LoA = 2] = Pr[LoA = 3] = Pr[LoA = 4] = 0.333, i.e., equal amount of information exists for each LoA.

Behavior of cognitive mechanism – evolution of conditional probabilities: As mentioned previously, the conditional probabilities represent the estimation on how probable it is that a certain reference value for a contextual parameter can be achieved, given a specified LoA. In this framework, Fig. 5.11(a) and 5.11(b) present results related to the efficiency of the machine learning process by analysing the evolution over time of conditional probabilities for two driving automation capabilities and service features (FOS, DRP) that can be achieved by the high level of autonomy (LoA = 4). More in detail, in each graph of Fig. 5.11, the x-axis denotes the discrete number of computations during which 'i-ALS' cognitive functionality conducts and provides calculations for feeding our method, whereas the y-axis shows the values of conditional probabilities in the form $Pr[V_{FOS} = rs_k \mid LoA = 4]$ and $Pr[V_{DRP} = rs_k \mid LoA = 4]$, respectively. The above cognitive process is applied in 20 time slices of runs (discrete computations).



(a)



(b)

Fig. 5.11 Scenario A1: High level of autonomy (LoA = 4) and conditional probabilities curves for the driving automation capabilities and service parameters (a) FOS and (b) DRP.

The graphs show that 'i-ALS' cognitive functionality readily learns the capabilities of the FOS and DRP contextual parameters to reach certain values, and thus converges to the collected values indicated by the datasets associated with the evaluation records (from other drivers/users) towards the high level of autonomy (LoA = 4). In this respect, regarding, e.g., the FOS parameter (Fig. 5.11(a)), the conditional probability $Pr[V_{FOS} = 4 \mid LoA = 4]$ immediately becomes significant (equals to 0.504 and 0.898 after three and ten discrete runs, respectively), and soon is much higher than the rest, e.g. the probabilities for the "neighboring" reference values $Pr[V_{FOS} = 5 \mid LoA = 4]$ and $Pr[V_{FOS} = 3 \mid LoA = 4]$ equal to 0.212 and 0.051 after three and ten simulation steps, respectively.

It should be noted that, initially, the probabilities for the reference values $rs_3 = 3$ and $rs_5 = 5$ are slightly increased, then they remain at a certain level for almost three runs, and after they start being reduced. Moreover, as expected in this case, from the beginning, there is a slight diminishment for $Pr[V_{FOS} = 2 \mid LoA = 4]$ and a severe degradation for $Pr[V_{FOS} = 1 \mid LoA = 4]$. Taking into account the above remarks, it is obvious that after almost 18 simulation steps, the most probable value regarding FOS parameter reaches the collected value ($rv_4 = 4$) for the high level of autonomy (LoA = 4), as depicted in Table 5.3.

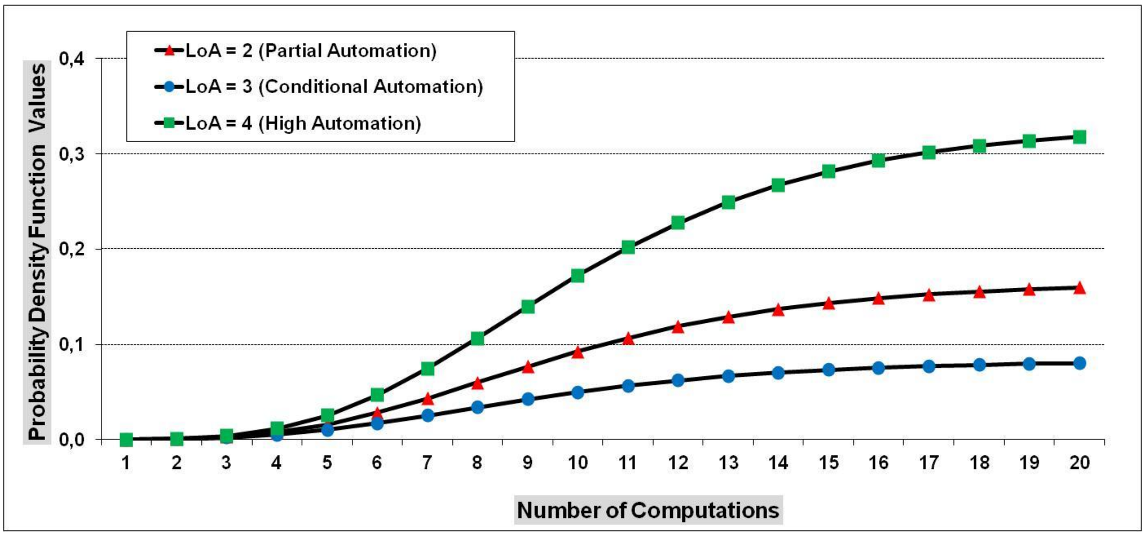


Fig. 5.12 Scenario A1: Probability Density Function values for the three on-board available levels of autonomy (LoA = 2, 3 and 4).

Similar notes can be stated about the most probable value regarding the DRP contextual parameter, where 'i-ALS' converges fast and successful to the collected value (rv_3 = 3) after almost 18 computations, as indicated in Table 5.3, regarding the high level of autonomy (LoA = 4). Identical curves can also be created for the other levels of autonomy (LoA = 2 and 3), which are omitted for brevity reasons.

Changes in the conditional probabilities entail that the values of the probability density function $f(x_i)$ in eq.(5) and, therefore, our knowledge regarding the capabilities of the driving automation levels (in terms of achieving certain parameter values) will also be changing. The $f(x_i)$ values for the three levels of autonomy (LoA = 2, 3 and 4), are shown in Fig. 5.12. It can be observed that the gradual acquisition of knowledge is easier in the case of the high level of autonomy (LoA = 4), since it becomes significant after only a few computations (five to six). In contrast to this, the acquisition of knowledge in the case of the conditional level of autonomy (LoA = 3) is more difficult since there is a significant delay in its increase. On the other hand, the partial level of autonomy (LoA = 2) is somewhere between LoA = 3 and LoA = 4 options.

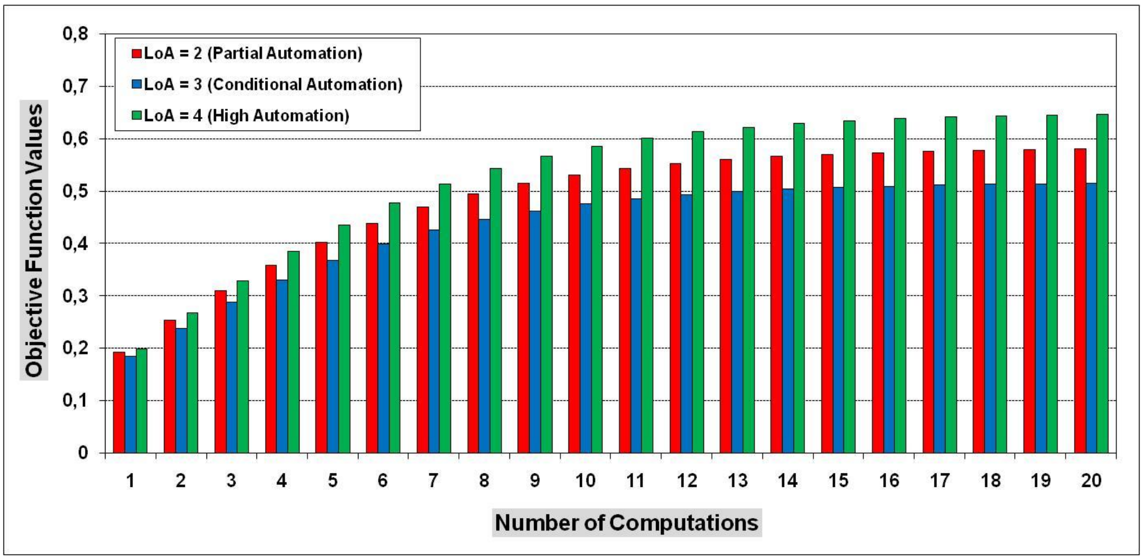


Fig. 5.13 Scenario A1: Knowledge-based objective function (OF) values for the on-board available levels of autonomy (LoA = 2, 3 and 4).

Behavior of knowledge-based selection scheme: This section presents results on the impact of the values of the weights (importance) of input contextual parameters on the decision-making phase, and thus the behavior of the knowledge-based selection scheme. To do so, the knowledge-based objective function (OF) values for the three on-board available levels of autonomy are calculated using eq.(12) and depicted in Fig. 5.13. It can be stated, that the knowledge-based selection scheme of 'i-ALS' functionality decides on LoA = 4 (high level of autonomy) as the most appropriate LoA to be implemented for John's road journey with his AV, by taking into account seven specified contextual parameters and their input values, as well as the relative policy information, according to Table 5.3.

The above simulation results about Scenario A1 show, in general, that a small number of discrete computations is required for 'i-ALS' functionality in obtaining knowledge and reliable decisions towards the optimal level of autonomy (LoA = 4). Regarding vehicle's LoA selection (LoA = 4), i-ALS functionality informs John, through the interface system, with the following message: *"the on-board operator system of your AV has decided to follow the high level of autonomy for your journey. As such, your AV can itself perform all aspects of dynamic driving task towards your destination point and you will have a reasonable amount of transition time before you must take the control of the vehicle (mind-on / feet-off / hands-off / eyes-off approach)"*. John is free to decide whether he will move on with the implementation of the indicated level of autonomy (LoA = 4) during his road journey, even after the proposal made by 'i-ALS' functionality.

5.6.3 Scenario A2: "safety-driven" case

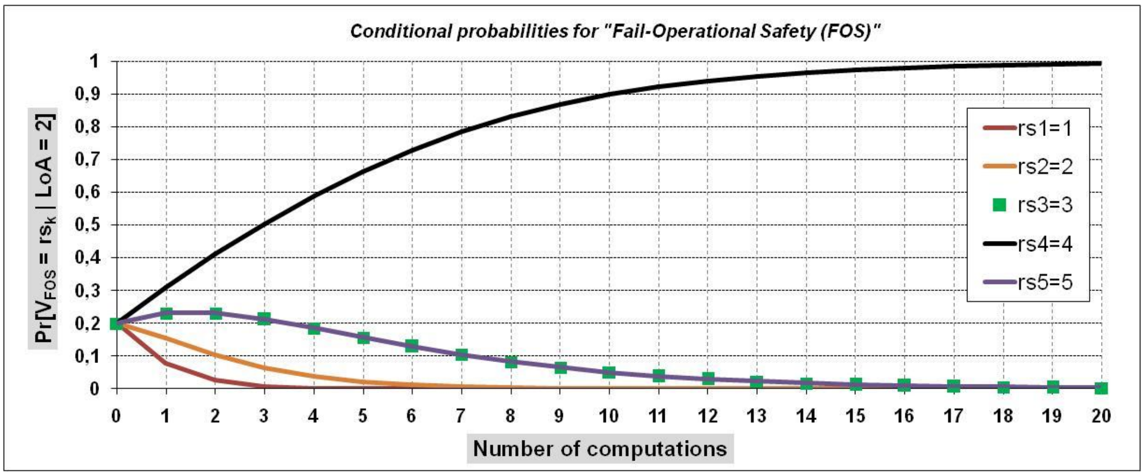
The goal of the present discrete-event simulation is to demonstrate the performance of 'i-ALS' in a case where a candidate driver/user values extremely high a certain driving automation capability and service feature (the fail-operational safety FOS, in our case). In this scenario, driver/user Mary, a 40-years old woman, wishes to travel with her (owned) AV from SP-2 (starting point-2) to DP-2 (destination point-2), an itinerary of 40 kilometers (km), on a wet/slippery highway, in early morning, with average visibility.

Driver/user Mary has already registered on i-ALS functionality in the past by filling her profile data and stating her personal preferences (weight values) towards the importance she attributes to each one of the pre-defined driving automation capabilities and service features (FOS, DVI, DRW, VEI and DRP). Based on the weight values depicted in Table 5.4, FOS parameter is of very high importance for the driver/user Mary (weight value 0.6), while she has equal interest (weight value 0.05) in DVI, DRW, VEI and DRP parameters. As such, driver/user Mary disposes a unique identity for on-board i-ALS functionality. On the other hand, as shown in Table 5.4, the on-board operator system of the AV gives a higher importance (weight value 0.1) to the pre-defined external environment parameters (ROC and WEC) due to external road (wet/slippery highway) and weather (early morning with average visibility) conditions. In that framework, and having in mind that there are seven input contextual parameters in total, the sum of all weight values is equal to 1.

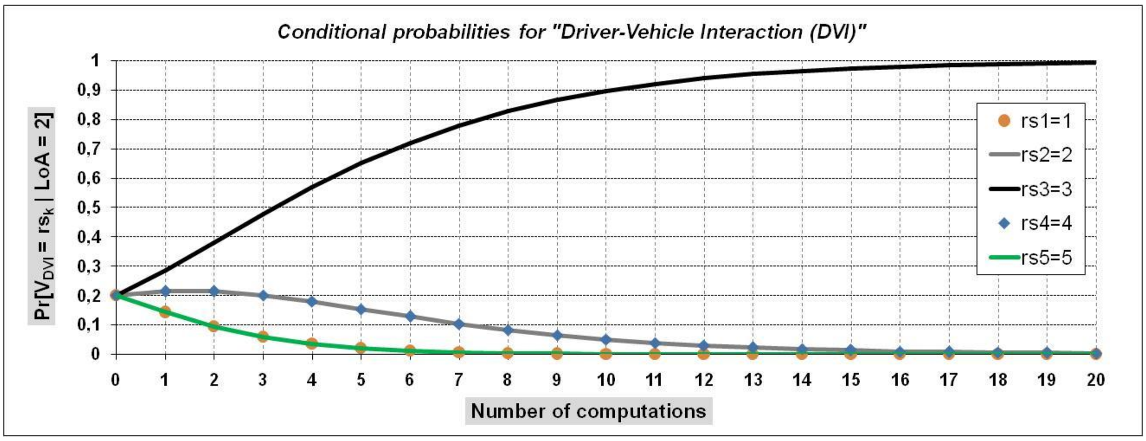
Table 5.28 Scenario A2: Collected evaluation values and respective weights for the available input parameters.

Driving automation capabilities and service parameters	Weight values according to driver's/user's preferences	Collected values through the evaluation procedure from other drivers/users		
		LoA = 2	LoA = 3	LoA = 4
FOS	*0.6*	*4*	*3.5*	*3.5*
DVI	*0.05*	*3*	*4*	*4.5*
DRW	*0.05*	*3*	*3.5*	*3*
VEI	*0.05*	*4*	*3*	*4*
DRP	*0.05*	*4*	*3*	*2.5*
Driving environment parameters	Weight values according to on-board operator system	Collected values through the evaluation procedure from the on-board operator system		
		LoA = 2	LoA = 3	LoA = 4
ROC	*0.1*	*4.5*	*4*	*4*
WEC	*0.1*	*4.5*	*4*	*4*

Additionally, collected values based on large-scale datasets associated with the evaluation procedures from other drivers/users and the vehicle's on-board operator system towards the input parameters FOS, DVI, DRW, VEI, DRP, ROC and WEC, are demonstrated also in Table 5.4. These values have been executed for each one of the three available on-board levels of autonomy (LoA = 2, 3 and 4) per input parameter.



(a)



(b)

Fig. 5.14 Scenario A2: Partial level of autonomy (LoA = 2) and conditional probabilities curves for the driving automation capabilities and service parameters (a) FOS and (b) DVI.

The overall cognitive process is applied again in 20 series of computations. Figures 5.14(a) and 5.14(b) indicatively show the distribution of conditional probabilities for two driving automation capabilities and service parameters (FOS, DVI) that can be achieved by the partial level of autonomy (LoA = 2). The graphs show that 'i-ALS' functionality quickly learns the capabilities of the aforementioned parameters (to reach a certain value, i.e. $rs_3 = 3$, when it comes to DVI parameter regarding the partial LoA, and converges to the collected evaluation value, as depicted in Table 5.4.

Considering the FOS parameter, which is of interest in Scenario A2 due to its high importance (weight), the conditional probability $Pr[V_{FOS} = 4 \mid LoA = 2]$ immediately becomes dominant, in contrast to the probabilities regarding the reference values $rs_1 = 1$, $rs_2 = 2$, $rs_3 = 3$, and $rs_5 = 5$, which suffer a degradation, which is justified by the fact that the values collected from the evaluation records are far higher. Again, the predominant probability $Pr[V_{FOS} = 4 \mid LoA = 2]$ is reinforced from the beginning and is not significantly affected after a small number of computations.

Similar notes can be stated about the most probable values regarding the DVI parameter where the reference value $rs_3 = 3$ is reached after almost 18 discrete runs. Identical curves can also be envisaged for the other levels of autonomy (LoA = 3 and 4), and they are omitted for brevity. In all cases, 'i-ALS' reconfiguration machine learning process exhibits fast and successful adaptations to the collected values. Furthermore, probability density function analysis and relative graphical depictions regarding the Scenario A2 are omitted for brevity.

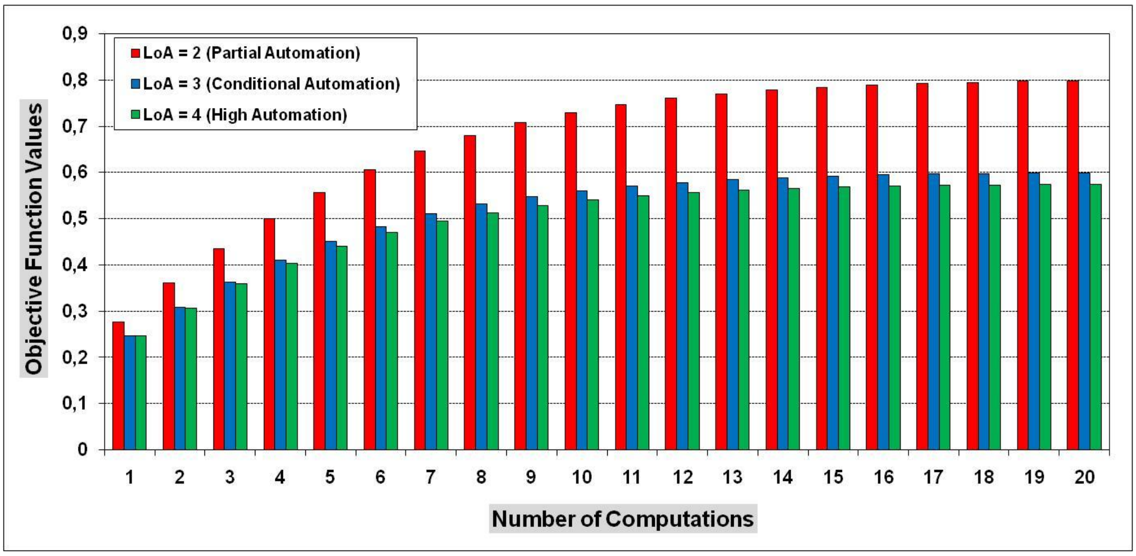


Fig. 5.15 Scenario A2: Knowledge-based objective function (OF) values for the three in-vehicle levels of autonomy (LoA = 2, 3 and 4).

In addition, the knowledge-based objective function (OF) values for the three in-vehicle levels of autonomy (LoA = 2, 3 and 4) are depicted in Fig. 5.15. In fact, the OF values regarding LoA = 2 (partial level of autonomy) becomes high immediately. This reveals i-ALS's ability to efficiently consider policies (preferences depicted on weights), since the importance attributed to the FOS parameter, is very high. On this way, LoA = 2 seems to be the most safety-driven level of autonomy to be implemented for Mary's road journey. To do so, 'i-ALS' functionality informs Mary, through the interface system, with the following message: *"the on-board operator system of your AV has decided to follow the partial level of autonomy for your journey. As such, you must remain engaged with the driving task and you should monitor the driving environment at all times towards your destination point (mind-on / feet-off / hands-on / eyes-on approach)"*.

5.6.4 Scenario A3: "car sharing" case

Car sharing is the shared use of a vehicle that enables drivers/users to have short-term access to desired destinations on an "as-needed" basis. Car sharing services has experienced a significant boom in recent years as an alternative transportation mode against vehicle ownership. On this way, the advent of AVs could boost the adoption of car sharing as more inexpensive and convenient on-demand services could be achieved by shared automated vehicles (Fagnant & Kockelman, 2014; Chen et al., 2016).

The main aim of car sharing services is to provide individuals with a mobility solution that requires lower responsibilities and smaller associated costs than vehicle ownership As such, the adoption of AVs would result in more car sharing demand as the barriers of standard car sharing such as lack of dedicated parking slots and the cost (i.e., time, availability and distance) to access the shared car can be addressed by AVs (Krueger et al., 2016; Agapitou et al., 2014; Fagnant & Kockelman, 2015).

Based on the above, the goal of the present discrete-event simulation is to demonstrate the performance of 'i-ALS' in a "car-sharing" case where the same AV of

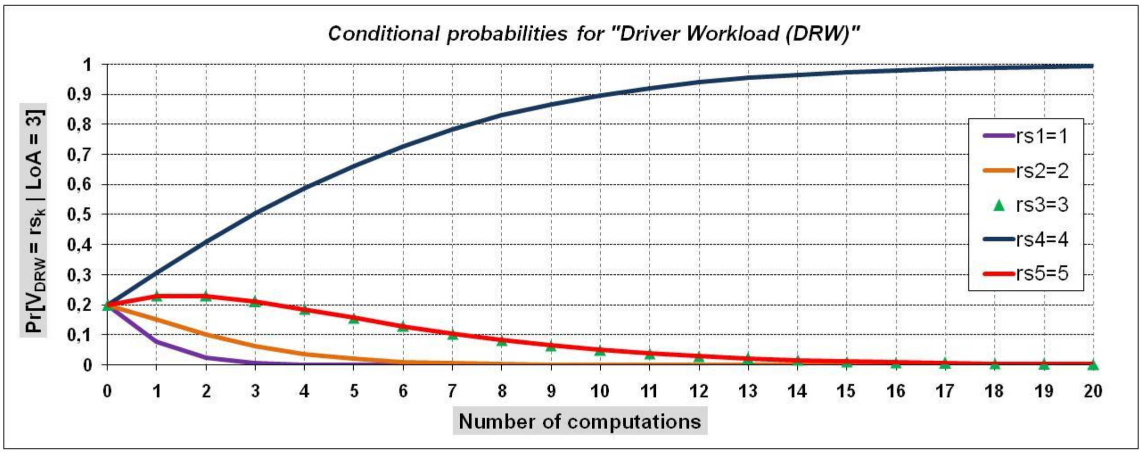
John, as described before in Scenario A1, is going to be used by his son Marcus, a 25-years old man. Marcus wishes to travel at midday, from SP-3 (starting point-3) to DP-3 (destination point-3), an itinerary of 40 kilometers (km), on a well-maintained small road with two directions with a cloudy sky leading to low–intensity rain.

Table 5.29 Scenario A3: Collected evaluation values and respective weights for the available input parameters.

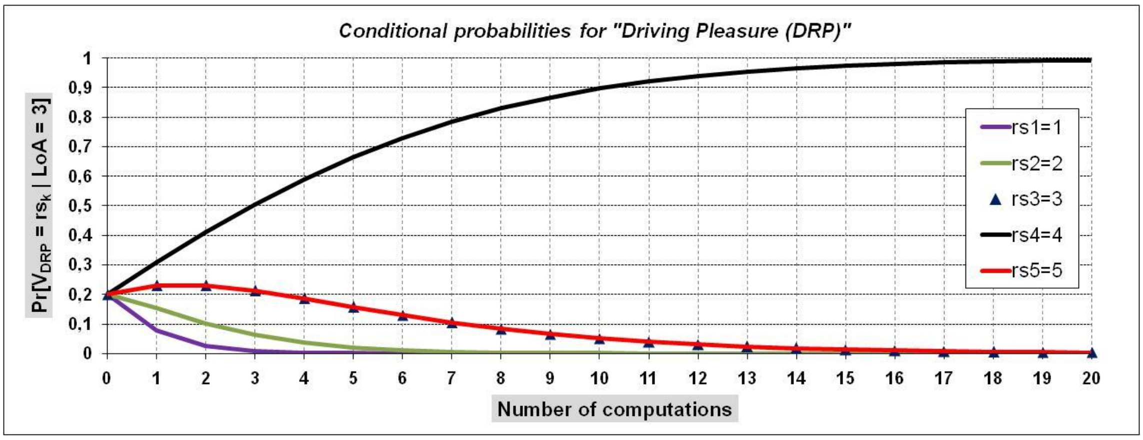
Driving automation capabilities and service parameters	Weight values according to driver's/user's preferences	Collected values through the evaluation procedure from other drivers/users		
		LoA = 2	LoA = 3	LoA = 4
FOS	*0.05*	*4*	*4.5*	*4*
DVI	*0.05*	*3*	*3.5*	*3*
DRP	*0.3*	*3.5*	*4*	*2.5*
VEI	*0.05*	*3.5*	*3.5*	*4*
DRW	*0.3*	*2.5*	*4*	*3.5*
Driving environment parameters	Weight values according to on-board operator system	Collected values through the evaluation procedure from the on-board operator system		
		LoA = 2	LoA = 3	LoA = 4
ROC	*0.1*	*4*	*4.5*	*4.5*
WEC	*0.15*	*3*	*4*	*4*

Driver/user Marcus has already registered on 'i-ALS' functionality in the past by filling his personal profile data and stating the weight values of parameters according to his personal preferences on driving automation capabilities and service issues (FOS, DVI, DRW, VEI and DRP). Based on the data depicted in Table 5.5, young driver Marcus wishes to enjoy the driving and gives high importance (weight value 0.3) to the parameter DRP. Moreover, driver Marcus wants to have more choices for comfortable and productive driving during his road journey, so he also gives high importance (weight value 0.3) to the parameter DRW, while the weight value of the remaining driving automation capabilities and service features (FOS, DVI, and VEI) is set to 0.05.

On this way, driver/user Marcus disposes a unique identity for on-board 'i-ALS' functionality.



(a)



(b)

Fig. 5.16 Scenario A3: Conditional level of autonomy (LoA = 3) and conditional probabilities curves for the driving automation capabilities and service parameters (a) DRW and (b) DRP.

On the other hand, as shown in Table 5.5, the on-board operator system of the AV gives high importance (weight values 0.1 and 0.15) to the pre-defined external environment parameters ROC and WEC, respectively, due to observable driving conditions (small road with two directions in low-intensity rain). It should be stated again that the sum of all weight values towards the seven input contextual parameters is equal to 1. In addition, collected values based on large-scale data records associated with the evaluation procedures from other drivers/users and the in-vehicle's operator system towards the contextual parameters FOS, DVI, DRW, VEI, DRP, ROC and WEC, are demonstrated in Table 5.5 for each one of the three available on-board levels of autonomy (LoA = 2, 3 and 4).

As mentioned previously, the overall machine learning reconfiguration process is applied in 20 series of computations. Figures 5.16(a) and 5.16(b) indicatively show the distribution of conditional probabilities for two driving automation capabilities and service parameters (DRW, DRP) due to their high importance (weights). The above graphs show that 'i-ALS' functionality quickly learns the capabilities of the aforementioned parameters (to reach a certain value, i.e. $rs_4 = 4$) and converges to the collected evaluation data regarding the conditional level of autonomy (LoA = 3), as depicted in Table 5.5. In a more detailed analysis, it should be noted that the conditional probabilities $Pr[V_{DRW} = 4 \mid LoA = 3]$ and $Pr[V_{DRP} = 4 \mid LoA = 3]$ immediately becomes dominant, in contrast to the probabilities towards the reference values rs_1 = 1, rs_2 = 2, rs_3 = 3 and rs_5 = 5, which suffer a degradation. Again, the predominant probabilities $Pr[V_{DRW} = 4 \mid LoA = 3]$ and $Pr[V_{DRP} = 4 \mid LoA = 3]$ are reinforced from the beginning and is not significantly affected after a small discrete number of computations.

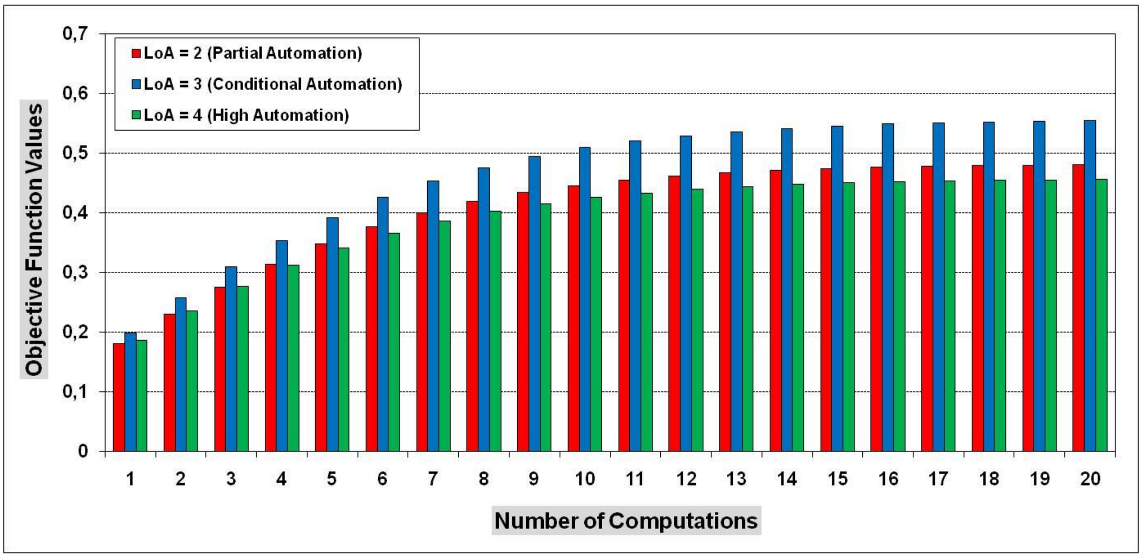


Fig. 5.17 Scenario A3: Knowledge-based objective function (OF) values for the three on-board levels of autonomy (LoA = 2, 3 and 4).

Furthermore, the knowledge-based objective function (OF) values for the three levels of autonomy (LoA = 2, 3 and 4) are depicted in Fig. 5.17. In fact, the OF values regarding the conditional level of autonomy (LoA = 3) becomes significant immediately. This reveals i-ALS's ability to efficiently consider policies (Marcus's preferences depicted on weight values), since the importance attributed to the driving automation capabilities and service parameters DRW and DRP are quite high.

Therefore, LoA = 3 seems to be the most suitable level of autonomy to be applied for Marcus's road journey. To do so, 'i-ALS' functionality informs Marcus, through the interface system, with the following message: *"the on-board operator system of your AV has decided to follow the conditional level of autonomy for your journey. As such, you are expected to be takeover-ready to take control of your AV at all times towards your destination point, when the on-board operator system may request it (mind-on / feet-off / hands-off / eyes-on approach)"*.

5.6.5 Scenario A4: impact of weather condition

The present discrete-event simulation aims at testing how fast 'i-ALS' cognitive management functionality can adapt to a parameter that changes, i.e., when the WEC parameter changes during the road journey. To do so, the same driver/user John is considered, as mentioned previously in Scenario A1. John wishes to travel with his AV from SP-4 (starting point-4) to DP-4 (destination point-4), an itinerary of 40 kilometers (km), on a well-maintained highway. Initially and for almost 20 km, there is a cloudy sky with clear visibility. After that, climatic conditions change rapidly leading to heavy–intensity rain for almost 5 km, while a low-intensity rain is existed for the remaining 15 km of the itinerary.

Table 5.6 shows the collected values from the evaluation records, as well as the respective importance (weight values), regarding the available set of input parameters. It should be noted that the external parameter ROC has a low importance (0.05) for the on-board operator system due to extremely good road condition (well-maintained highway), whereas it gives high importance (0.3) to the external parameter WEC due to changes in weather condition (cloudy sky with clear visibility, heavy–intensity rain, and low-intensity rain, respectively). Furthermore, with respect to the importance (weights) of driving automation capabilities and service parameters, FOS and DVI have a high importance (0.25) for the driver/user John, while he has equal interest (0.05) in DRW, VEI and DRP, respectively. In that framework, and having in mind that there are seven input parameters in total, the sum of all weight values is equal to 1.

Table 5.30 Scenario A4: Collected evaluation values and respective weights for the available input parameters.

Driving automation capabilities and service parameters	Weight values according to driver's/user's preferences	Collected values through the evaluation procedure from other drivers/users								
		LoA = 2			LoA = 3			LoA = 4		
		1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
FOS	*0.25*	*4*	*4*	*4*	*3*	*3*	*3*	*4*	*4*	*4*
DVI	*0.25*	*3*	*3*	*3*	*4*	*4*	*4*	*4*	*4*	*4*
DRP	*0.05*	*4*	*4*	*4*	*4*	*4*	*4*	*3*	*3*	*3*
VEI	*0.05*	*3*	*3*	*3*	*3.5*	*3.5*	*3.5*	*4*	*4*	*4*
DRW	*0.05*	*3.5*	*3.5*	*3.5*	*3.5*	*3.5*	*3.5*	*3*	*3*	*3*
Driving environment parameters	Weight values according to on-board operator system	Collected values through the evaluation procedure from the on-board operator system								
		LoA = 2			LoA = 3			LoA = 4		
		1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
ROC	*0.05*	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*5*
WEC	*0.3*	*5*	*3*	*4*	*5*	*4*	*4.5*	*5*	*3.5*	*4.5*

In order to facilitate the algorithmic process on catching the WEC changes, it is assumed that 30 discrete computations can be separated in three phases (1st, 2nd, and 3rd). Each one of the three phases corresponds to the three different weather conditions, i.e., cloudy sky with clear visibility, heavy–intensity rain, and low-intensity rain, respectively. More in detail, in the first phase (cloudy sky with clear visibility), which comprises of the first ten computations, all the available levels of autonomy appear to be able to respond at the highest level (parameter WEC takes the value 5). In addition, in the remaining twenty computations corresponding to the second (heavy–intensity rain) and third (low-intensity rain) phases, the three available levels of autonomy (LoA = 2, 3 and 4) appear to be able to respond at a lower level, i.e., the parameter WEC takes the values (3, 4, 3.5) and (4, 4.5, 4.5), respectively. All the aforementioned collected values regarding WEC parameter are depicted analytically in Fig. 5.18.

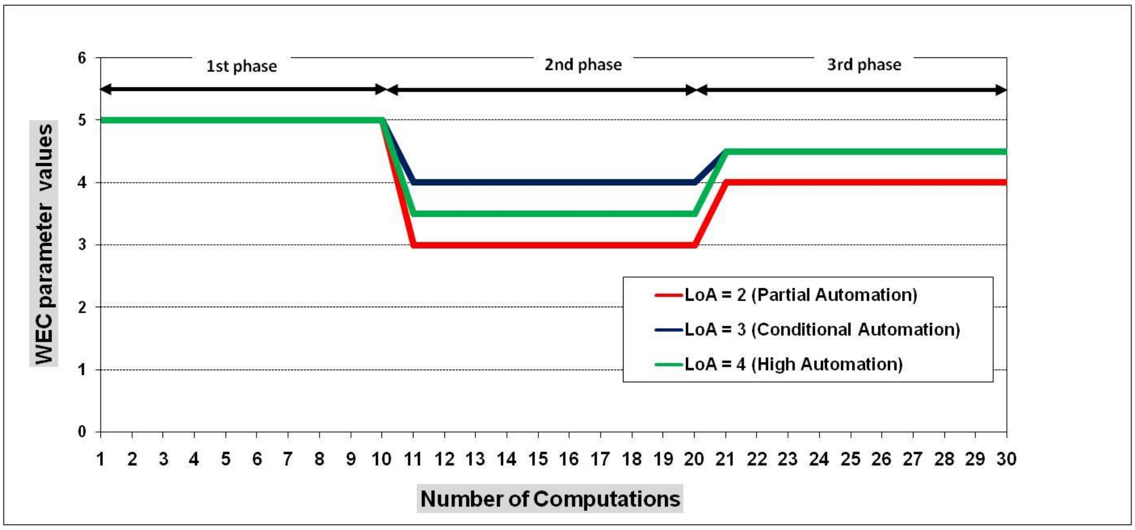


Fig. 5.18 Scenario A4: Values collected through the evaluation records for the WEC parameter regarding the three levels of autonomy split in three phases (1st, 2nd, 3rd).

In Fig. 5.19 the conditional probabilities towards WEC parameter, which can be achieved by the partial level of autonomy (LoA = 2), separated into three phases, are depicted. In the first phase (computations 1–10), the conditional probability $Pr[V_{WEC} = 5 \mid LoA = 2]$ appears to be the dominant one. Then, in the second (2nd) phase and for computations 11–17, the conditional probability $Pr[V_{WEC} = 5 \mid LoA = 2]$ takes again higher values, while the values of the conditional probabilities $Pr[V_{WEC} = 4 \mid LoA = 2]$ and $Pr[V_{WEC} = 3 \mid LoA = 2]$ are gradually increasing, with a parallel reduction of the remaining conditional probabilities. During the remaining computations 18-20 of the second (2nd) phase, as well as in the whole third (3rd) phase (computations 21–30), the most likely reference value to be achieved is $rs_4 = 4$, and thus, $Pr[V_{WEC} = 4 \mid LoA = 2]$ gradually becomes the prevalent one.

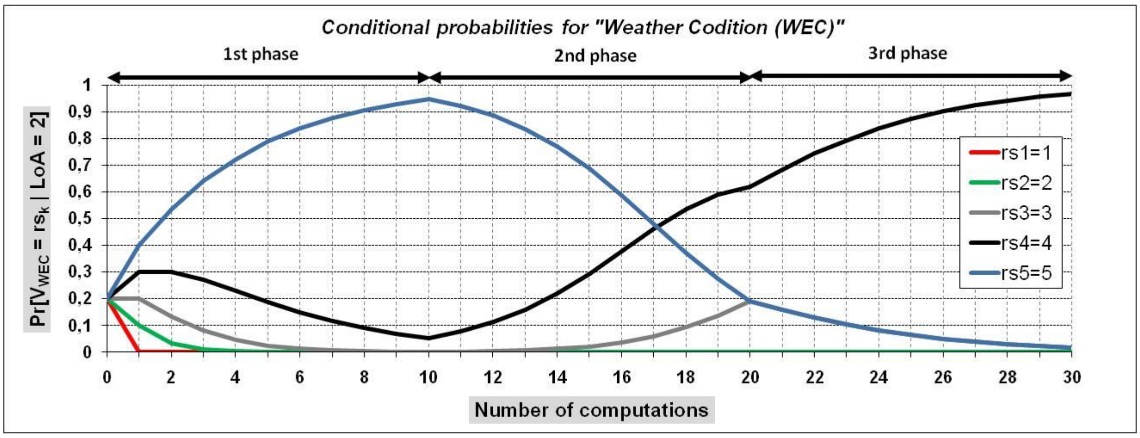


Fig. 5.19 Scenario A4: Conditional probabilities for WEC parameter towards partial level of autonomy (LoA = 2) in three phases (1st, 2nd, 3rd).

Based on the above, there is a characteristic point (computation 17), where a false decision may be taken. However, ‘i-ALS’ cognitive management functionality quickly “recovers” in terms of achieving the new capabilities of the WEC parameter towards the partial level of autonomy (LoA = 2), as depicted in Table 5.6. As such, a small amount of computational time is required for ‘i-ALS’ functionality to catch the change in weather condition, thus enabling fast adaptations.

With respect to the knowledge-based objective function (OF) values, the partial level of autonomy (LoA = 2) reaches the highest possible values after almost 25 computations on average, whereas high automation level (LoA = 4) was the dominant one for the first 18 computations, as depicted in Fig. 5.20. In the case where ‘i-ALS’ functionality proposes high level of autonomy (LoA = 4), as the most appropriate to be followed by driver/user John during the first 20 km of his pre-defined road journey (cloudy sky with clear visibility), the following message is demonstrated: *"the on-board operator system of your AV has decided to follow the high level of autonomy. As such, your AV can itself perform all aspects of dynamic driving task towards your destination point and you will have a reasonable amount of transition time before you must take the control of the* *vehicle (mind-on / feet-off / hands-off / eyes-off approach)"*. On the other hand, when 'i-ALS' functionality proposes partial level of autonomy (LoA = 2), as the most appropriate to be followed by driver/user John during the last 20 km of his itinerary (heavy–intensity rain, low-intensity rain), the following message is depicted: *"due to changes in weather conditions during your journey, the on-board operator system of your AV has decided to follow the partial level of autonomy. Please be aware of remaining engaged with the driving task and monitoring the driving environment at all times towards your final destination point (mind-on / feet-off / hands-on / eyes-on approach)"*.

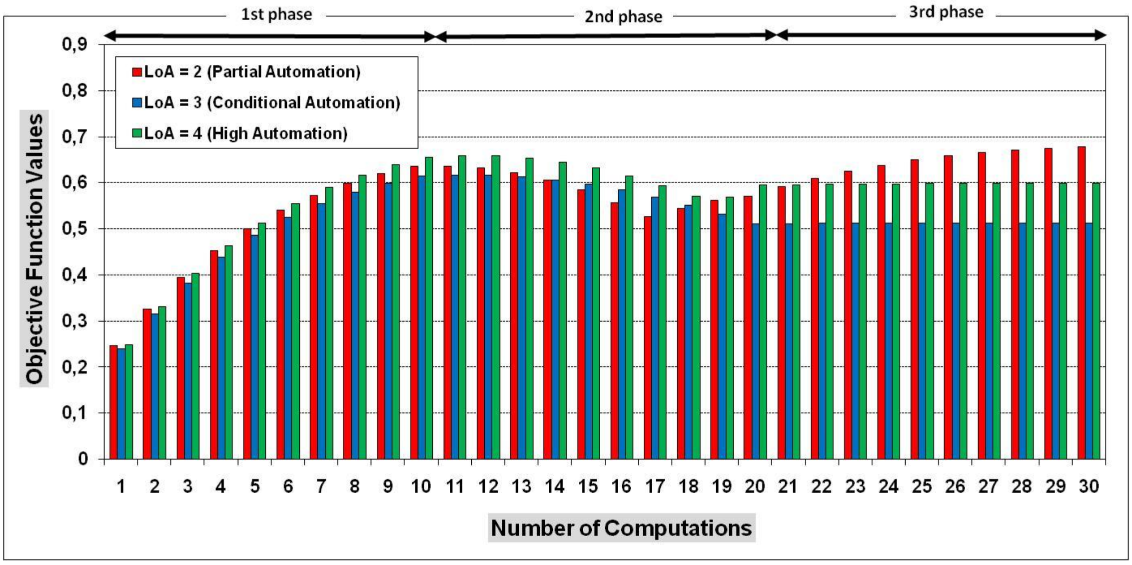


Fig. 5.20 Scenario A4: Knowledge-based objective function (OF) values for the three levels of autonomy (LoA = 2, 3 and 4) in the three phases.

Based on the above statements, it should be noted that the proposed 'i-ALS' cognitive management functionality is tested in demanding situations, due to the fact that the WEC parameter changes during the road journey. According to the aforementioned simulation results, a small computational effort is required to acquire the knowledge, and therefore minimizing the transition (downgrading) from the high level of autonomy (LoA = 4) to the partial level of autonomy (LoA = 2). This reveals i-ALS's ability to efficiently provide appropriate adaptations about the most suitable LoA, since the in-vehicle operator system gives high importance to the external parameter WEC, as its value changes during road journey. This is highly desirable, as 'i-ALS' can catch changes in climatic conditions, even at a nonpermanent basis.

5.7 i-M simulation results

5.7.1 General aspects – simulation setup

This section describes the main aspects of the simulation process and a short description of the indicative discrete-event simulations that were used for deriving the results on the behavior and performance of i-M's cognitive mechanism and knowledge-based selection scheme. To do so, an appropriate BN is designed in modeling 'i-M' functionality for the prediction of the on-board MG.

Domain Analysis: It concerns the determination of all variables that characterize the domain of interest and the individuation of all the possible states associated with each variable of the BN. Each random variable represents a node of the BN.

Predictor Selection: In the present analysis, 'i-M' functionality aims to predict the "optimal" MG, as the soundtrack to a certain route. It is assumed that the music library of an IVI system includes information on the genre of every track within the library. Furthermore, the system is capable of playing music of a certain genre. For the running proposed Bayesian framework, we consider there are only three genres within the system: pop, rock and jazz music. As such, the random variable-feature MG (child node) can take the values 1, 2 or 3, corresponding to the pop, rock and jazz music style, respectively.

Parent Node Set Determination: As mentioned previously, features for in-vehicle's MG prediction can be classified into three types:

(1) features related to quality of service (QoS),

(2) features related to driver/user's profile and current situation, and

(3) features related to vehicle's external environment

In order to be comprehensive, and, at the same time, try to minimize the complexity and facilitate the reader in understanding the potentials of the proposed 'i-M' cognitive functionality, a set of six random variables-parameters (parent nodes) is considered, as depicted in Fig. 5.21:

A. two external environment parameters, such as **weather condition (WEC)** and **time of day (TID)**

B. two parameters related to quality of service (QoS), like **sound quality (SOQ)** and **driving pleasure (DRP)**

C. two parameters related to driver/user's profile and current situation, like **kind of passenger (KPA)** and **mental mood (MEM)**

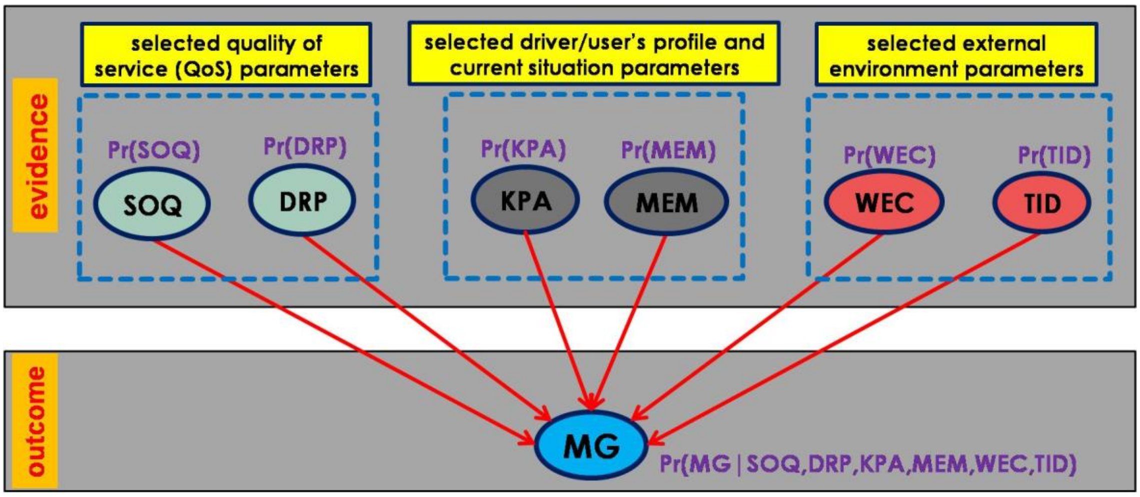


Fig. 5.21 Structure of the proposed BN for in-vehicle's MG prediction.

In this manner, input variables WEC, TID, SOQ, DRP, KPA and MEM cause the random variable MG and are assumed to be statistically independent. Although simulation process with six input causes is assumed herewith, i-M's algorithmic process is highly scalable, in that it can be readily generalized to include more causes-parameters, as well as to be easily adapted / changed so as to utilize a different list of input features.

Based on the above, the complete BN node set is:

Parent node set (predictands) = {SOQ, DRP, KPA, MEM, WEC, TID}

Child node set (predictor) = {MG}

The definition of causality is the premise to express the transfer rules between different nodes. Based on the network nodes, the following causality is defined:

$$Pr[SOQ, DRP, KPA, MEM, WEC, TID \mid MG]$$

$$Pr[MG(t+1) \mid MG(t)]$$

Figure 5.22 shows the BN topology structure for in-vehicle's MG prediction between two adjacent time slices (t, t+1), including the initial network and transition network.

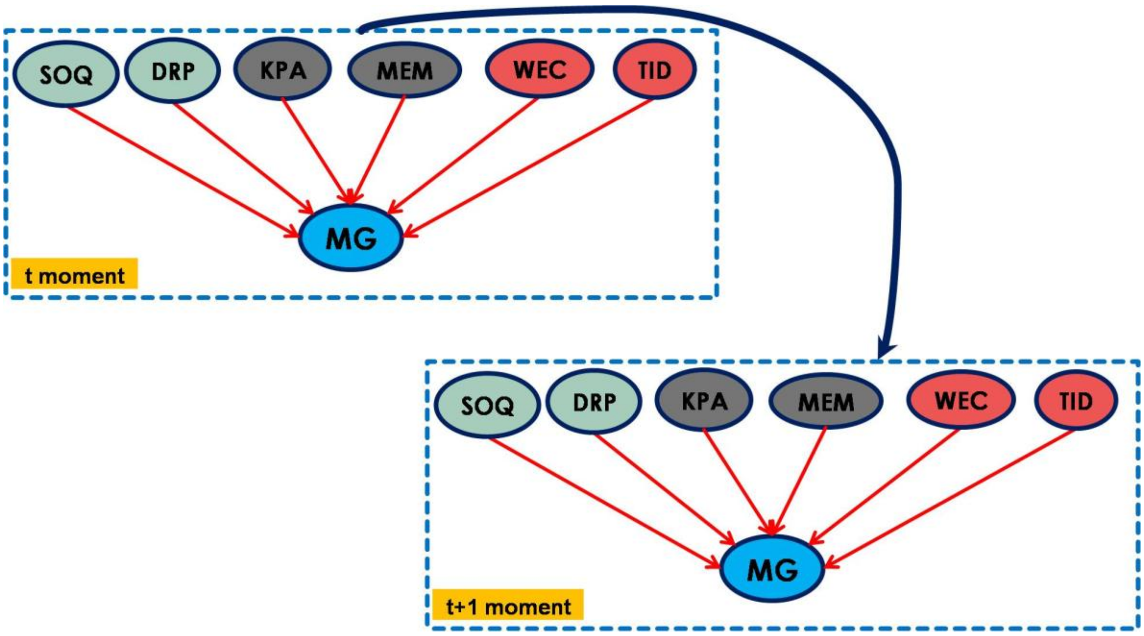


Fig. 5.22 BN structure for in-vehicle's MG prediction between two adjacent time slices.

Determination of Node Reference States: In order to make the simulation analysis simpler, the different states that can be achieved by the aforementioned input parameters are considered as discrete; this fact minimizes the complexity of the problem. In the present analysis, a grid of five discrete reference states is applied as following (Table 5.7):

- Quality of Service (QoS) parameters FOS and DRP can take the discrete reference states "not at all satisfied" ($rv_1 = 1$), "low satisfied" ($rv_2 = 2$), "average satisfied" ($rv_3 = 3$), "high satisfied" ($rv_4 = 4$) and "completely satisfied" ($rv_5 = 5$)

- External environment parameter WEC can take the discrete reference states "snowy" (rv_1 = 1), "windy" (rv_2 = 2), "rainy" (rv_3 = 3), "cloudy" (rv_4 = 4) and "sunny" (rv_5 = 5)
- External environment parameter TID can take the discrete reference states "(00:00-06:00)" (rv_1 = 1), "(06:00-10:00)" (rv_2 = 2), "(10:00-15:00)" (rv_3 = 3), "(15:00-20:00)" (rv_4 = 4) and "(20:00-00:00)" (rv_5 = 5)

Table 5.31 Description of variables in proposed BN for in-vehicle's MG prediction.

Variables	Number of Reference Values	Short Description
Child node		
MG	3	1. pop 2. rock 3. jazz
Parent nodes		
FOS, DRP	5	1. "not at all satisfied" 2. "low satisfied" 3. "average satisfied" 4. "high satisfied" 5. "completely satisfied"
WEC	5	1. "snowy" 2. "windy" 3. "rainy" 4. "cloudy" 5. "sunny"
TID	5	1. "(00:00-06:00)" 2. "(06:00-10:00)" 3. "(10:00-15:00)" 4. "(15:00-20:00)" 5. "(20:00-00:00)"
KPA	5	1. "none" 2. "friend" 3. "girlfriend/wife" 4. "children" 5. "family (girlfriend/wife + children)"
KPA	5	1. "extremely bad" 2. "quite bad" 3. "average" 4. "quite good" 5. "extremely good"

- Driver/user's profile and current situation parameter KPA can take the discrete reference states "none" (rv_1 = 1), "friend" (rv_2 = 2), "girlfriend/wife" (rv_3 = 3), "children" (rv_4 = 4) and "family (girlfriend/wife + children)" (rv_5 = 5)
- Driver/user's profile and current situation parameter MEM can take the discrete reference states "extremely bad" (rv_1 = 1), "quite bad" (rv_2 = 2), "average" (rv_3 = 3), "quite good" (rv_4 = 4) and "extremely good" (rv_5 = 5)

SOQ *(sound quality)*	**MG = 1** *(pop)*	**MG = 2** *(rock)*	**MG = 3** *(jazz)*
rv_1 = 1 *(not at all satisfied)*	$Pr[V_{SOQ} = 1 \mid MG = 1]$	$Pr[V_{SOQ} = 1 \mid MG = 2]$	$Pr[V_{SOQ} = 1 \mid MG = 3]$
rv_2 = 2 *(low satisfied)*	$Pr[V_{SOQ} = 2 \mid MG = 1]$	$Pr[V_{SOQ} = 2 \mid MG = 2]$	$Pr[V_{SOQ} = 2 \mid MG = 3]$
rv_3 = 3 *(average satisfied)*	$Pr[V_{SOQ} = 3 \mid MG = 1]$	$Pr[V_{SOQ} = 3 \mid MG = 2]$	$Pr[V_{SOQ} = 3 \mid MG = 3]$
rv_4 = 4 *(high satisfied)*	$Pr[V_{SOQ} = 4 \mid MG = 1]$	$Pr[V_{SOQ} = 4 \mid MG = 2]$	$Pr[V_{SOQ} = 4 \mid MG = 3]$
rv_5 = 5 *(completely satisfied)*	$Pr[V_{SOQ} = 5 \mid MG = 1]$	$Pr[V_{SOQ} = 5 \mid MG = 2]$	$Pr[V_{SOQ} = 5 \mid MG = 3]$

Fig. 5.23 Structure of the CPT for the "sound quality (SOQ)" parameter.

On this way, the random variables that correspond to the six input parameters SOQ, DRP, KPA, MEM, WEC and TID, are denoted as V_{SOQ}, V_{DRP}, V_{KPA}, V_{MEM}, V_{WEC} and V_{TID}, respectively. For brevity, the set of reference states {rv_1, rv_2, rv_3, rv_4, rv_5} or {1, 2, 3, 4, 5} for the "sound quality (SOQ)" parameter is depicted, via the corresponding CPT, in Fig. 5.23, for the three available music genres (MG = 1, 2, 3). Each time, random variable V_{SOQ} can take a value from the above set of reference states.

Importance of the Input Parameters: In the following, the impact of these weights on the behavior of the knowledge-based selection scheme is presented through specific results according to input datasets and input values.

Parameter Learning: Learning of the CPTs that truly reflects the causality among variables forms a crucial part of the reconfiguration and adaptation machine learning algorithm described in section 5.5. Since the structure of the proposed BN for in-vehicle MG selection is determined, the conditional independencies for the family of MG and its parent nodes towards the QoS parameters FOS and DRP can be learned from the experimental datasets. Such datasets are based on a well-established evaluation process, which is made by users (drivers or/and passengers) towards the three available in-vehicle music options (MG = 1, 2 and 3), after the completion of their road journeys with intelligent AVs and ‘i-M’ functionality. As mentioned previously in section 5.3.3, a 5-point scale from "1" to "5" is used by the users (drivers or/and passengers) for the ranking of their experience with a certain in-vehicle MG, with "1" standing for "not at all satisfied" and "5" standing for "completely satisfied". In this case, utility volumes express the level of satisfaction of each user (driver and/or passenger) with the recommendation of ‘i-M’ towards music genre selections.

In addition, input values for the external environment parameters WEC and TID are based on the real-time observable sensor information, whereas input values for the PAS and MEM parameters are inserted by the driver when he/she logs on to the ‘i-M’ infotainment functionality.

The above reconfiguration and adaptation machine learning algorithm starts with the developed structure for a single time slice and then proceeds to learn the temporal dependencies which exist between time slices. In the present analysis, it is assumed that the datasets used for learning FOS and DRP parameters contained only complete data.

The above process enables intelligent AVs to operate each time in the best available MG. On this way, the optimal MG is the one that satisfies the criteria already specified. In any case, even after the proposal made by ‘i-M’ functionality, the driver/user is free to decide whether he/she will move on with the implementation of the demonstrated MG selection within his/her road journey.

Case Studies: In the present thesis, two discrete-event simulations have been constructed, as more realistic as possible, where ‘i-M’ functionality is being implemented with the aid of SimEvents (an add-on to MATLAB). The goal of these simulations is to showcase how fast ‘i-M’ functionality can converge and find the optimum MG during the vehicle’s ride. More in detail, simulation results derive from the inputs of the scheme, namely, the external environment information, profile and current situation data, quality of service features, as well as policies which yield the importance of the aforementioned parameters. It should be noted that the work and the results presented hereafter regarding 'i-M' cognitive management functionality can be generic and adaptable to the requirements of several driving scenarios with respect to intelligent AVs.

In this direction, the first scenario represents a "regular" case, which aims at identifying the most probable input parameter values, as fast as possible, and thus proposes the most appropriate MG. The second scenario provides evidence on 'i-M' functionality's fast adaptation to a parameter that changes, i.e., when the external environment feature WEC is modified during the road journey. It should be stated that for the first scenario the simulation process is applied in 20 series of discrete events (iterations) every 0.1 seconds, whereas the simulation process for the second scenario is implemented in 30 series of discrete events (computations) every 0.1 seconds.

Moreover, as the above discrete-event simulation models the operation of 'i-M' infotainment functionality as a (discrete) sequence of events in time, each event occurs at a particular instant in time and marks a change of state in 'i-M', based on the input values of the six specified input parameters (WEC, TID, KPA, MEM, SOQ and DRP). In order to simulate the above driving scenarios, it is assumed that 'i-M' functionality enables the driver/user to easily input and specify the importance (weights) given to the aforementioned six specified input parameters, as well as to properly visualise the outcomes of the algorithm. Although simulation analysis with six features is assumed herewith, 'i-M' infotainment functionality's process is highly scalable, in that it can be easily adapted / changed so as to utilize a different list of contextual parameters.

5.7.2 Scenario B1: "regular" case

This discrete-event simulation represents a "regular" case, which aims at identifying the most probable input parameter values, as fast as possible, and thus proposes the most appropriate MG, among those in the music library of IVI system (pop, rock and jazz). In particular, the present case study assumes that driver/user George, a 45-years old man, wishes to have a road journey with his girlfriend Mary from SP-A (starting point – A) to DP-B (destination point – B), by using his owned car, during a sunny day with clear visibility, in the early evening, as depicted in Fig. 5.24.

George logs on to the on-board 'i-M' infotainment functionality and he is prompted to complete a form by filling the input values associated with KPA and MEM parameters and stating the weight values for all the input parameters (WEC, TID, KPA, MEM, SOQ, DRP) according to his personal preferences. Therefore, George disposes a unique identity for 'i-M' functionality.

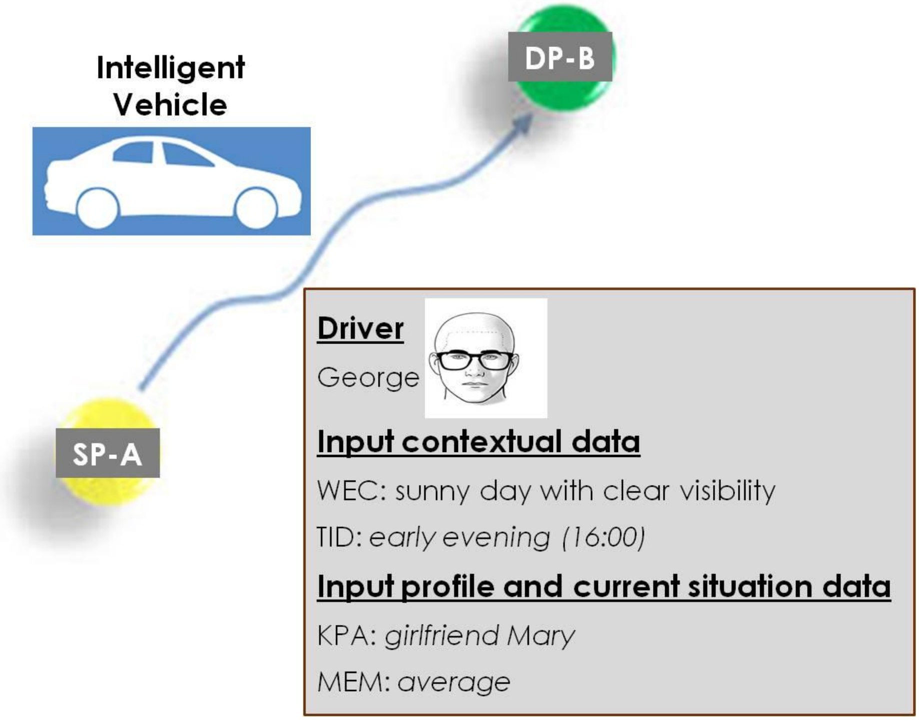


Fig. 5.24 Scenario B1: "regular" case.

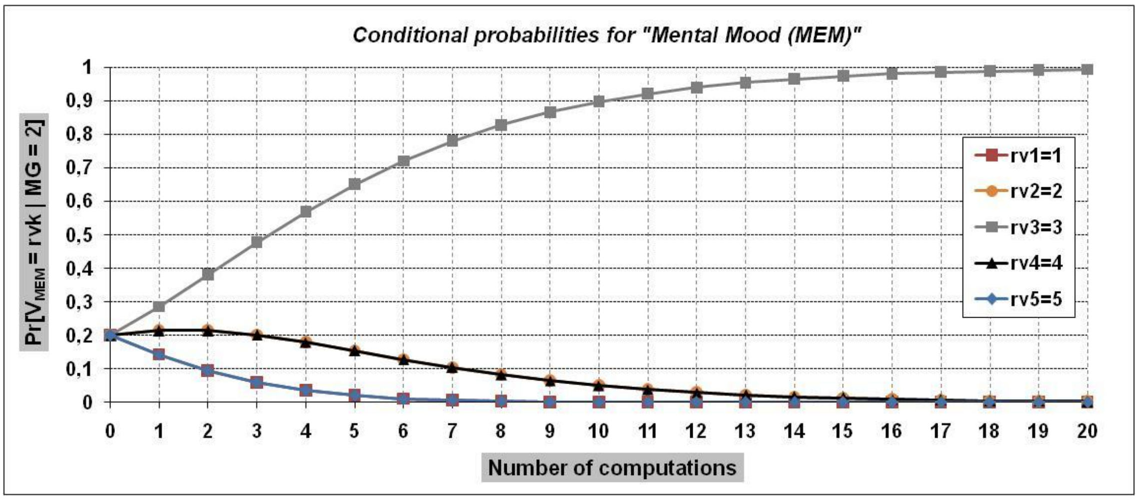
The set of parameters, their input values (obtained either through sensors or inserted by the driver or collected through the evaluation process) and their respective weights are depicted in Table 5.8. It should be noted that with respect to the importance (weights) of parameters, KPA and MEM have a high importance (0.25) for the driver/user George, while he has less interest to the other input parameters WEC, TID, SOQ and DRP. In that framework, and having in mind that there are six input parameters in total, the sum of all weights is equal to 1.

Additionally, input values obtained either through sensors (WEC, TID) or inserted by the driver/user (KPA, MEM) or collected through the datasets associated with the evaluation procedure from other users (drivers or/and passengers) towards SOQ and DRP parameters, are demonstrated in Table 5.8. These values have been executed for each one of the three available on-board music genres (MG = 1, 2 and 3) per input parameter.

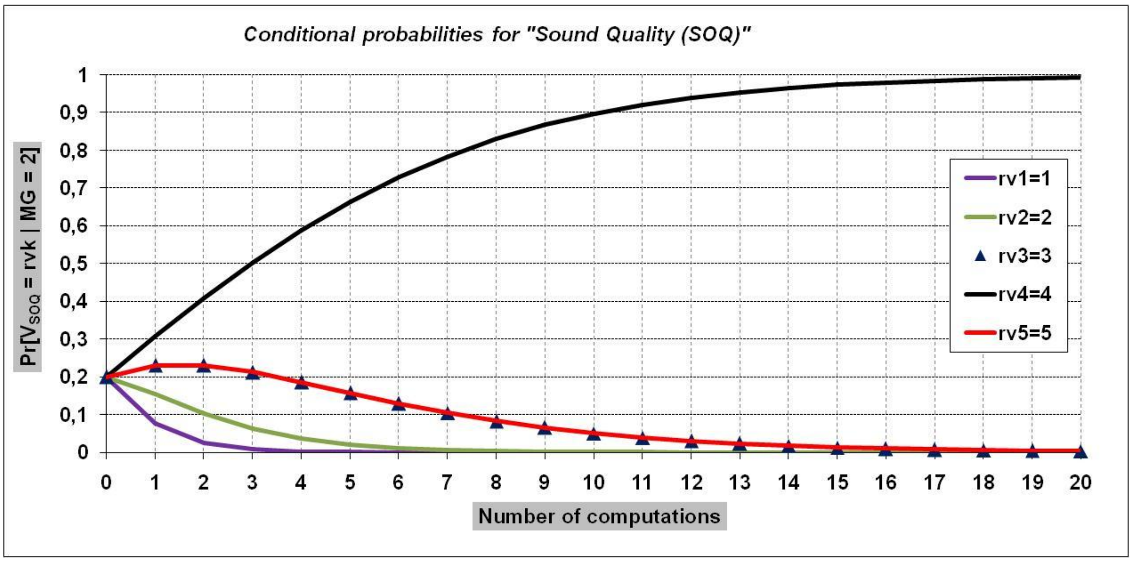
Table 5.32 Scenario B1: Collected evaluation values and respective weights for the available input parameters.

Quality of service parameters	Weight values according to driver/user's preferences	Collected values through the evaluation procedure from other users		
		MG = 1	MG = 2	MG = 3
SOQ	*0.2*	*3.5*	*4*	*3.5*
DRP	*0.1*	*3.5*	*4*	*3*
External environment parameters	Weight values according to driver/user's preferences	Collected values obtained through sensors		
		MG = 1	MG = 2	MG = 3
WEC	*0.1*	*5*	*5*	*5*
TID	*0.1*	*4*	*4*	*4*
Profile and current situation parameters	Weight values according to driver/user's preferences	Collected values inserted by the driver/user		
		MG = 1	MG = 2	MG = 3
KPA	*0.25*	*3*	*3*	*3*
MEM	*0.25*	*3*	*3*	*3*

Initially, the conditional probabilities of the form $Pr[V_j = rv_k \mid MG = i]$ regarding each input parameter j (WEC, TID, KPA, MEM, SOQ, DRP), where rv_k can take values among the set of reference states {rv1, rv2, rv3, rv4, rv5} or {1, 2, 3, 4, 5} and i = 1, 2, 3, are equal to 0.2, due to the fact that no previous knowledge is available to 'i-M' cognitive management functionality. Moreover, regarding the amount of information available for each MG, it is assumed that prior probabilities Pr[MG = 1] = Pr[MG = 2] = Pr[MG = 3] = 0.333, i.e., equal amount of information exists for each MG.



(a)



(b)

Fig. 5.25 Scenario B1: Rock music genre (MG = 2) and conditional probabilities curves for the parameters (a) MEM and (b) SOQ.

Behavior of cognitive mechanisms – evolution of conditional probabilities: As mentioned previously, the conditional probabilities represent the estimation on how probable it is that a certain reference state for an input parameter can be achieved, given a specified MG. In this framework, Fig. 5.25(a) and 5.25(b) present results related to the efficiency of 'i-M' functionality by analyzing the evolution over time of conditional probabilities for MEM and SOQ parameters towards the rock music style (MG = 2). More in detail, in each graph of Fig. 5.25, the x-axis denotes the discrete number of simulation steps (computations) during which 'i-M' cognitive functionality conducts and provides calculations for feeding our method, whereas the y-axis shows the values of conditional probabilities in the form $Pr[V_{SOQ} = rv_k \mid MG = 2]$ and $Pr[V_{MEM} = rv_k \mid MG = 2]$, respectively.

The graphs show that 'i-M' cognitive functionality can easily learns the capabilities of the aforementioned input parameters MEM and SOQ to take certain values, and thus converges to the collected values ($rv_3 = 3$ and $rv_4 = 4$, respectively) towards the rock music genre (MG = 2), as depicted in Table 5.8. On this way, regarding, e.g., the SOQ parameter (Fig. 5.25(b)), the conditional probability $Pr[V_{SOQ} = 4 \mid MG = 2]$ immediately becomes significant, and very soon is much higher than the rest, e.g. the probabilities for the "neighboring" reference states $Pr[V_{SOQ} = 3 \mid MG = 2]$ and $Pr[V_{SOQ} = 5 \mid MG = 2]$.

In this respect, initially, the probabilities for the reference states $rv_3 = 3$ and $rv_5 = 5$ are slightly increased, then they remain at a certain level for almost three computational steps, and after they start being reduced. Moreover, as expected in this case, from the beginning, there is a slight diminishment for $Pr[V_{SOQ} = 2 \mid MG = 2]$ and a severe degradation for $Pr[V_{SOQ} = 1 \mid MG = 2]$. Taking into account the above remarks, it is obvious that after almost 18 simulation steps, the most probable value regarding SOQ parameter reaches the collected value ($rv_4 = 4$) for the rock music genre (MG = 2), as depicted in Table 5.8.

Similar notes can be stated about the most probable value regarding the MEM parameter, where the reference value $rv_3 = 3$ is reached after almost 18 simulation steps. Similar curves can also be created for the other options of music (MG = 1 and 3), and they are omitted for brevity reasons. In all cases, 'i-M' converges fast and successful to the collected values.

Behavior of knowledge-based selection scheme: This section presents results on the impact of the values of the weights (importance) of input parameters on the decision-making phase, and thus the behavior of the knowledge-based selection scheme. To do so, the knowledge-based objective function (OF) values for the three in-vehicle available music genres are calculated using eq.(12) and depicted in Fig. 5.26. It can be stated, that the option MG = 2 (rock music) becomes significant very soon, is further reinforced and reaches much higher values than the other music genres (MG = 1 and MG = 3). As such, knowledge-based selection scheme of 'i-M' functionality decides on MG = 2 (rock music genre) as the most appropriate music option to the driver/user George and his girlfriend Mary (passenger), by taking into account six specified input parameters and their reference values, as well as the relative policy information, according to Table 5.8.

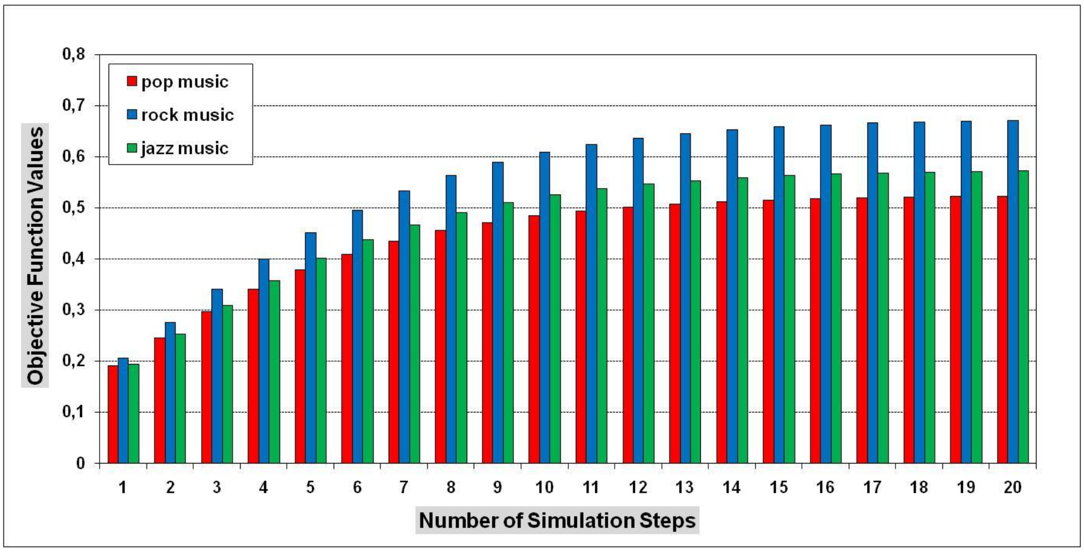


Fig. 5.26 Scenario B1: Knowledge-based objective function (OF) values for the in-vehicle available music genres (MG = 1, 2 and 3).

The above results about Scenario B1 show, in general, that a small number of computations is required for 'i-M' functionality in obtaining knowledge and reliable decisions towards the optimal recommendation music genre (MG = 2). 'i-M' functionality informs the driver/user George to decide whether he/she will move on with the implementation of the indicated soundtrack for his road journey, even after the proposal made by the decision-making algorithm. Driver/user George is free to confirm this recommendation by a single interaction. In addition, after the completion of the road journey with the use of 'i-M' functionality, George and his girlfriend Mary are prompted to evaluate their satisfaction with the proposed music soundtrack (MG = 2).

5.7.3 Scenario B2: impact of weather condition

The present discrete-event simulation aims at testing how fast 'i-M' cognitive management functionality can adapt to a parameter that changes, i.e., when the external environment parameter WEC is modified during the road journey. In particular, the second (2nd) scenario assumes that driver Maria, a 25-years old woman, is considered. Maria wishes to have a road journey (alone) with her owned car, at the early morning, from SP-C (starting point – C) to DP-D (destination point – D), an itinerary of 50 kilometers (km), on a well-maintained highway. With respect to the weather condition, initially and for almost 20 km (up to point C), there is a cloudy sky with clear visibility. After point C, and for the remaining 30 km of the itinerary, the weather condition changes rapidly leading to low–intensity rain, as depicted in Fig. 5.27.

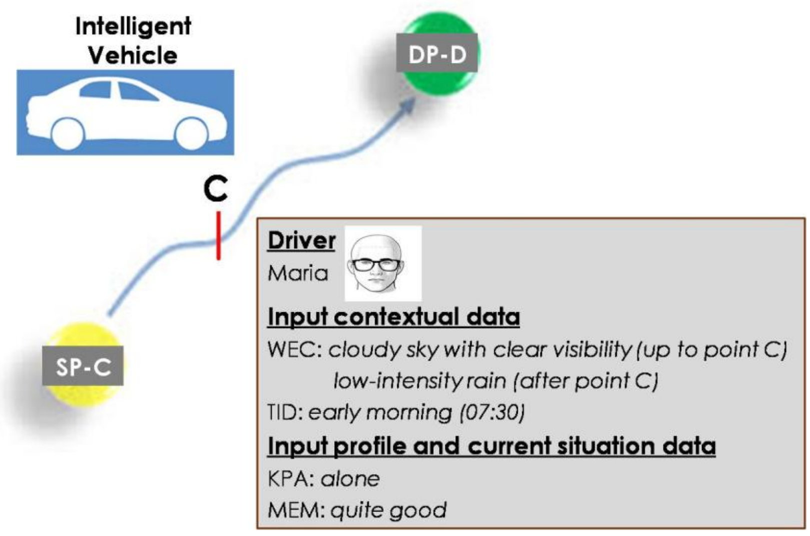


Fig. 5.27 Scenario B2: impact of weather condition.

When Maria enters her vehicle, she has an initial interface with 'i-M' functionality in its central IVI console. After the login process has been successfully executed, Maria specifies the input values for the parameters KPA and MEM and fills the weight values of all the input parameters (WEC, TID, KPA, MEM, SOQ, DRP) according to her personal preferences. As such, Maria disposes a unique identity for 'i-M' functionality.

Table 5.33 Scenario B2: Collected evaluation values and respective weights for the available input parameters.

Quality of service parameters	Weight values according to driver/user's preferences	Collected values through the evaluation procedure from other users					
		MG=1		MG=2		MG=3	
		1st	2nd	1st	2nd	1st	2nd
SOQ	*0.2*	*4.4*	*4.4*	*3.25*	*3.25*	*3.5*	*3.5*
DRP	*0.2*	*4.6*	*4.6*	*3.5*	*3.5*	*4.4*	*4.4*
External environment parameters	Weight values according to driver/user's preferences	Collected values obtained through sensors					
		MG=1		MG=2		MG=3	
		1st	2nd	1st	2nd	1st	2nd
WEC	*0.2*	*4*	*3*	*4*	*3*	*4*	*3*
TID	*0.2*	*2*	*2*	*2*	*2*	*2*	*2*
Profile and current situation parameters	Weight values according to driver/user's preferences	Collected values inserted by the driver/user					
		MG=1		MG=2		MG=3	
		1st	2nd	1st	2nd	1st	2nd
KPA	*0.05*	*1*	*1*	*1*	*1*	*1*	*1*
MEM	*0.15*	*4*	*4*	*4*	*4*	*4*	*4*

Table 5.9 shows the set of parameters and their respective importance (weights), as well as their input collected values. It should be noted that with respect to the importance (weights) of input parameters, SOQ, DRP, WEC and TID have a high importance (0.2) for the driver/user Maria, while she has less interest to the other input parameters KPA and MEM. Having in mind that there are six input parameters in

total, the sum of all weights is equal to 1. Additionally, input values obtained either through sensors (WEC, TID) or inserted by the driver/user (KPA, MEM) or collected through large-scale datasets associated with the evaluation procedure from other users (drivers or/and passengers) towards SOQ and DRP quality of service parameters. These values have been executed for each one of the three available on-board music genres (MG = 1, 2 and 3) per input parameter.

In order to facilitate the algorithmic process on catching the WEC changes, it is assumed that 30 computations can be separated in two phases (1st and 2nd). Each one of the two phases corresponds to different weather condition (cloudy sky with clear visibility and low-intensity rain, respectively). As such, in Fig. 5.28 the conditional probabilities towards WEC parameter, which can be achieved by the pop music genre (MG = 1), separated into two phases, are depicted. In the first phase (simulation steps 1–10), the conditional probability *Pr[*V_{WEC} *= 4 | MG = 1]* appears to be the dominant one. Then, in the second (2nd) phase and for simulation steps 11–20, the conditional probability *Pr[*V_{WEC} *= 4 | MG = 1]* takes again higher values, while the values of the conditional probability *Pr[*V_{WEC} *= 3 | MG = 1]* are gradually increasing, with a parallel reduction of the remaining conditional probabilities.

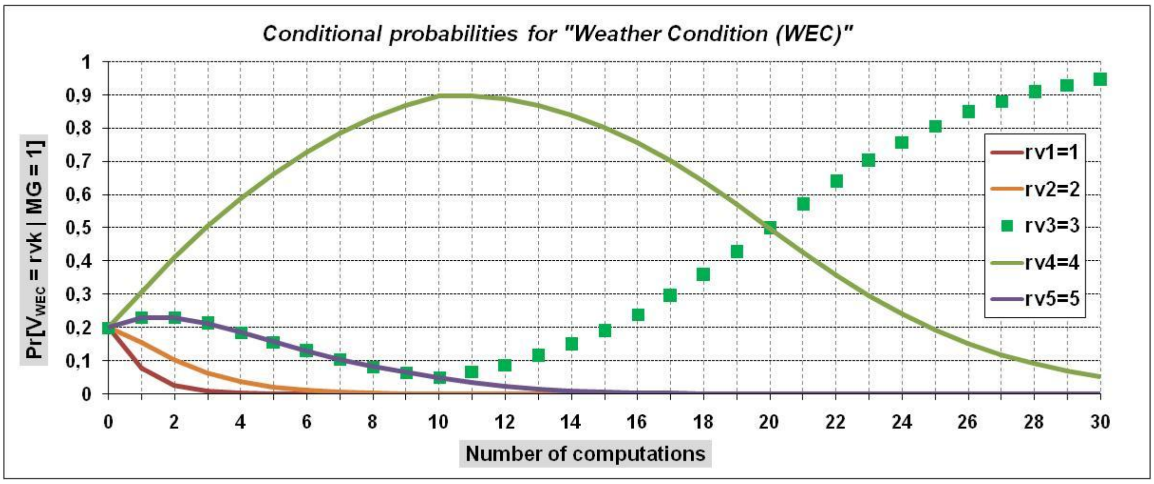


Fig. 5.28 Scenario B2: Conditional probabilities of WEC parameter in the two phases (1st and 2nd).

During the last simulation steps 21-30 of the second phase, the conditional probability *Pr[V_{WEC} = 3 | MG = 1]* gradually becomes the prevalent one, where the most likely reference value reaches the collected value (rv_3 = 3), as depicted in Table 5.9. As such, there is a characteristic point (simulation step 20), where 'i-M' functionality quickly "recovers", in terms of achieving the new capabilities of the WEC parameter.

Furthermore, the knowledge-based objective function (OF) values for the pop music genre (MG = 1) reach the highest possible values from the beginning, as depicted in Fig. 5.29. As such, 'i-M' infotainment functionality decides on MG = 1 (pop music) as the most appropriate music option to the driver Maria. Based on the above, it should be stated that the proposed 'i-M' cognitive management functionality is tested in demanding situations, due to the fact that the WEC parameter changes during the journey and affects the input collected values. The above show, in general, that a small amount of computational time is required for 'i-M' machine learning process to catch the change in WEC, thus enabling fast adaptations. After the completion of the road journey with the use of 'i-M' functionality, Maria is prompted to evaluate her satisfaction with the proposed music soundtrack (MG = 1).

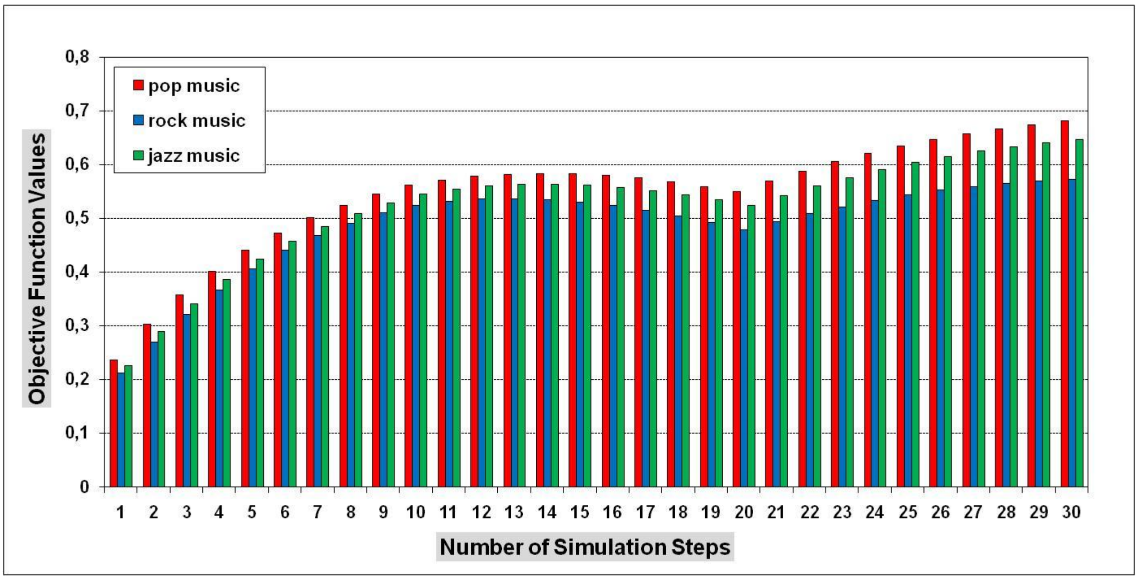


Fig. 5.29 Scenario B2: Knowledge-based objective function (OF) values for the three music genres (MG = 1, 2 and 3) in the two phases.

5.8 Summary

This chapter presented the related work that has been conducted in the area of AI inside vehicles with the deployment of cognitive management systems and implementation of appropriate machine learning techniques for enhancing the efficiency of autonomous driving, and therefore, increasing the acceptance of AVs in terms of the road safety and driving experience factors. More in detail, two on-board intelligent functionalities, namely 'i-ALS' and 'i-M', that comprises mechanisms for dynamically selecting the optimal LoA and optimal MG in AVs, respectively, are presented, taking into account a set of input contextual features-parameters, as well as a predefined set of policies. Challenges associated with the aforementioned functionalities, as well as architectural components and classical business cases are depicted in detail.

Moreover, the exploitation of an appropriate reconfiguration and adaptation algorithmic process, based on Bayesian networking principles parallel with the NB classifier, is described, which helps functionalities gradually obtain knowledge, regarding the probabilities that the proposed mechanisms can achieve certain states, which lead to higher reliability of the final decisions. The goal of such a machine learning technique is to maintain a certain level of simplicity (computationally intensive operations are undesirable in a real-time optimization system), without however compromising the effectiveness and extendibility of the proposed solutions.

Furthermore, extensive discrete-event simulations – case studies have been considered, as more realistic as possible, to reflect the proposed 'i-ALS' and 'i-M' application potentials, concerning specific criteria. The focus was mainly to showcase the efficiency of their embedded learning algorithm, in terms of accuracy and speed of convergence, the knowledge developed and acquired in various situations, the corresponding computational effort required, and the LoA and MG selections conducted. Although simulations with a pre-defined set of input variables have been conducted each time, the proposed reconfiguration and adaptation learning process is highly scalable, in that it can be easily adapted / changed so as to utilize a different list of input parameters.

Results show that minimal computational effort is required for the acquisition of context information and the associated learning. Moreover, it is shown that the proposed knowledge-based selection scheme (combined with the cognitive mechanism) increases the reliability of the selections. Therefore, it contributes to the decreasing of frequent changes that could be triggered by sudden, temporary changes in the input parameters. As such, 'i-ALS' and 'i-M' can propose enhanced decision-making selections, as well as fast and successful adaptations towards dynamic changes of input parameters. In this sense, the proposed functionalities contributes to making service provision more seamless and stable to drivers/passengers when using AVs for their road journeys. As such, 'i-ALS' and 'i-M' attribute intelligence to AVs and enhance the acceptance of AVs in terms of the road safety and driving experience, operating as in-car intelligent personal assistants for the drivers/users.

Finally, it should be stated that part of the aforementioned work towards the implementation of on-board intelligent management functionalities for LoA and MG selections have been accepted for publication in the IEEE Transactions on Intelligent Transportation Systems (Dimitrakopoulos & Panagiotopoulos, 2020) and in the IET Intelligent Transport Systems Journal (Panagiotopoulos & Dimitrakopoulos, 2019a), as well as in the proceedings of the 26th Intelligent Transportation Systems World Congress, which was held in Singapore, from 21 October to 25 October 2019 (Panagiotopoulos & Dimitrakopoulos, 2019b) and in the proceedings of the 10th International Conference on Information, Intelligence, Systems and Applications, which was held in Patras, Greece, from 15 July to 17 July 2019 (Panagiotopoulos & Dimitrakopoulos, 2019c).

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

Contents

6.1 Overall contribution

While the technological progress regarding AVs seems to have accelerated throughout the last years, there are open issues that should be covered by the automotive industry, academia and researchers. Such vehicles will operate in complex dynamic environments, and therefore, they require methods that generalize to unpredictable situations and reason in a timely manner in order to reach human-level reliability and react safely even in complex urban situations. With the ever-increasing popularity of machine learning techniques and complex planning and decision-making methods, verification and guaranteed performance of the autonomous driving pipeline have become challenges still to be addressed. Besides technical issues and legal, economic and security-relevant implications, societal aspects also play a crucial role for the possible implementation of AVs in the future international market.

In the light of the above, the main contribution of this thesis to the existing state-of-the-art is outlined as follows:

I. **It improves the knowledge on factors that potentially influence the user acceptance of AVs.**
At the moment, AVs are only used on some prototypes by the automotive industry and they are tested in some specific zones where the relative companies have been regulated to work. Since AVs are currently being developed by major car

manufacturers planning to be available in market diffusion the next years, the present Ph.D. dissertation (Chapter 3) proposes two adapted versions of the original well-established social-psychological frameworks – Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) – to investigate in what extent consumers intend to drive/use AVs in the future, by identifying the factors that affect the uptake of such vehicles.

The implications of the present analysis show that driving enjoyment plays a big part in consumers' desire to drive/use AVs for their travels. In this context, it is obvious that consumers will still want to enjoy the driving/usage of vehicles equipped with autonomous driving technology. Furthermore, the trust in automation technology and the perceived usefulness appear to be important deciding factors. Therefore it is hoped that in order to maximize AVs uptake, designers and developers in the automotive field can consider the above issues when implementing more permanent versions of private transportation choices like vehicles with autonomous driving technology.

In addition, it seems that demographic variables such as age and gender do not significantly impact on people's intentions towards AVs, suggesting that broader societal acceptance is more important than targeting specific groups. However, more research is required to understand the impact of other demographic variables such as income or education, as these first mile/last mile solutions are likely to be targeted at marginalised groups who are not catered for by current public transport provisions.

II. **It proposes an authenticated communication protocol for enhancing the security and privacy levels of vehicular communications**.

Since perceived trust/reliability plays a significant role in consumers' intension to accept and drive/use AVs, the present Ph.D. thesis (Chapter 4) develops a novel mechanism to guarantee the primary security requirements (authentication, integrity, non-repudiation, etc.) for reliable deployment of Internet of Vehicles (IoV) technology in the transport area.

The proposed approach is based on Diffie–Hellman key agreement scheme, where the concepts of vehicle identity process, cryptography process and data communication process were extensively presented and identified throughout the design and operation scheme. Such a protocol enhances the efficiency of vehicular interactions and improves the acceptance of AVs regarding trust/reliability in terms of security protection and data privacy issues.

In particular, the presented protocol utilizes IUs that have higher computation power than OBUs to disseminate authenticated messages about the observed phenomena by vehicles within an IUs’ transmission range. Moreover, in the proposed approach, the IUs have the ability to verify the authenticity of the sender and the integrity of the message before disseminating it to the other vehicles. In this respect, the anonymity of the senders is preserved, whereas message integrity, source authentication, fast verification and efficient dissemination of messages are achieved.

III. It proposes novel on-board cognitive management techniques for enhancing the acceptance of AVs in terms of road safety and driving experience.

Since cognitive management systems are a well promising area of research interest, the present Ph.D. thesis (Chapter 5) presents frameworks for two newly introduced cognitive management functionalities, i.e. i-ALS (intelligent Autonomous Level Selection) and i-M (intelligent Music), their definitions and characteristics, as well as their generic conceptual architectures. These functionalities are based on the approach for context-awareness in proactive data-driven decision making, by utilizing machine learning techniques and real-time prediction/prognostic algorithms for level of autonomy and music genre management schemes.

An appropriate reconfiguration and adaptation algorithmic process, based on Bayesian networking principles parallel with the Naïve-Bayes classifier, was developed in helping functionalities gradually obtain knowledge, regarding the probabilities that their embedded mechanisms can achieve certain states, which lead to higher reliability of the final decisions.

Furthermore, extensive discrete-event simulations – case studies have been considered, as more realistic as possible, to reflect the proposed ‘i-ALS’ and ‘i-M’ application potentials, concerning specific criteria in terms of accuracy and speed of convergence, the knowledge developed and acquired in various situations, the corresponding computational effort required, and the LoA and MG selections conducted.

Results show that minimal computational effort is required for the acquisition of context information and the associated learning. Moreover, it is shown that the proposed knowledge-based selection scheme (combined with the cognitive mechanism) increases the reliability of the selections. Therefore, it contributes to the decreasing of frequent changes that could be triggered by sudden, temporary changes in the input parameters. As such, ‘i-ALS’ and ‘i-M’ can propose enhanced decision-making selections, as well as fast and successful adaptations towards dynamic changes of input parameters. In this sense, the proposed functionalities contributes to making service provision more seamless and stable to drivers/passengers when using AVs for their road journeys.

In this sense, ‘i-ALS’ and ‘i-M’ functionalities attribute intelligence to the vehicles and enhance the acceptance of AVs in terms of road safety and driving experience, operating as in-car intelligent personal assistants for the drivers/users. Moreover, the aforementioned architectures can be seen as a blueprint for the design, development and integration of a larger on-board management platform in supporting all the novel services and applications towards in-vehicle intelligence.

6.2 Recommendations for future research

The work presented in this Ph.D. thesis serves actually as a basis for enhancing driving/usage of AVs. This work may be extended in the following aspects:

I. User acceptance.

Like any other studies, this Ph.D. thesis has some limitations that should be considered in future research studies. In this manner, the presented implications need to be evaluated in light of the quite futuristic character of AVs at the time of the survey. AVs are not yet launched on mass consumer markets. Hence, the our respondents in both web-based questionnaire surveys (Chapter 3) did not have any hands-on experience with autonomous car passenger vehicles and could only state their guesses based on our description provided at the beginning of the questionnaires as well as on information they might have gathered on their own. Also, majority of our sample individuals in both surveys were relatively young (under 40 years old). Hence, differences might be found for other age groups. In addition, our surveys were conducted via online means of communication (i.e. e-mail lists, websites, social media) and, hence, excluded people that do not use the Internet.

Furthermore, due to the ever-changing technology in the areas of transportation and mobility, the hypothetical antecedents of privately-owned AVs' adoption tested in the proposed TAM-extended and UTAUT-extended models might not include the whole spectrum of influential factors. In this case, further adoption factors/moderators and their effects on consumer intentions towards the driving/usage of AVs need to be explored in future work. For instance, it would be interesting to investigate consumer attitudes toward AVs for private use considering perceived anxiety and appropriateness of automation technology, as additional predictor variables on consumer preferences towards AVs, as well as the moderating effect of automation capabilities knowledge in car vehicles. Furthermore, since only European people were surveyed, our results might not hold true for non-European people as consumers' opinions and preferences also vary among nations and countries. In this way, future research studies can be conducted on different countries including data from end users with different background and experience. Finally, although the presented user acceptance studies were based on a quantitative research approach and the relative aims of the Ph.D. thesis were met, it would have enhanced our findings if a mix-method approach could be implemented.

II. Communication protocols for vehicular interactions.

The proposed analysis in Chapter 4 could also be extended to hybrid vehicular network architectures combining both V2V and V2I/I2V communications in the same scenario. In these schemes AVs can interact with the roadside equipments either in a single hop or multi-hop fashions, depending on the distances, i.e., if they can or not access directly the roadside IUs or other vehicles that are far away.

As future activities in this area one could consider the proposed protocols to be implemented and verified in sufficiently large and realistic V2V and V2I/I2V communication field tests. Depending on the results of these field trials, conclusions could be derived on which of the existing security specifications are covered or could be further improved. Moreover, as different vehicular network protocols, mechanisms and applications are based on different architectures and assumptions, a common evaluation framework is needed to compare different security research contributions.

III. On-board cognitive management techniques.

The presented analysis in Chapter 5 could be extended to a series of exciting research areas. Indicatively, the possibility of testing the responses of the proposed on-board management functionalities (‘i-ALS’ and ‘i-M’) by changing the importance (weights) attributed to the pre-defined contextual parameters could be explored. Additionally, what could also be investigated is the potential to expand our learning scheme so as to consider and investigate Bayesian Networks with more input contextual variables (causes) related to vehicle’s external environment and user's profile and current situation, and then test the response of 'i-ALS' and 'i-M'.

Moreover, 'i-ALS' and 'i-M' functionalities could also operate, in cooperation with other electronic components inside the vehicle, as part of a larger management system towards in-vehicle intelligence, such as issuing directives to the drivers/users in tackling emergency and unexpected situations (on-road object detection, surrounding obstacles' locations, etc.) by taking other useful decisions during vehicle's ride and informing appropriately the drivers/passengers. In addition, due to the fact that the proposed 'i-ALS' and 'i-M' functionalities involve high-level human-machine interactions, simulation environments approaching to the real-world (i.e. driving simulators or field tests) should be applied to fully demonstrate the effectiveness of the proposed intelligent platforms.

In addition, cognitive intelligence and non-causal decision-making enables autonomous driving systems to process information locally and respond quickly to situations. As such, driving decisions are time-sensitive, and in certain circumstances (inclement weather, complex terrain, transient environmental disturbances) latencies could prove fatal. On this way, human inspired AI systems could be designed for enabling innovative human-inspired control of intelligent AVs. These will be built upon highly safe, reliable control architectures based on high-performance domain units, linked via high-speed networks for fast data exchange.

6.3 Thesis publications

The published work emerges as part of this Ph.D. thesis consists of five (5) papers in international journals and nine (9) publications in international conferences.

In Scientific Journals

[jp1] Dimitrakopoulos, G., **Panagiotopoulos, I.** *"In-Vehicle Infotainment Systems: Using Bayesian Networks to Model Cognitive Selection of Music Genres",* IEEE

Transactions on Intelligent Transportation Systems, **2020**, doi: 10.1109/TITS.2020.2997003

[jp2] **Panagiotopoulos, I.**, Dimitrakopoulos, G. *"Investigating the Acceptance on the Road to Connected-Autonomous Vehicles",* International Journal of Transportation Systems, Vol. 4, pp. 56–61, **2019**

[jp3] **Panagiotopoulos, I.**, Dimitrakopoulos, G. "Cognitive Intelligence of Highly Automated Vehicles in a Car Sharing Context", IET Intelligent Transport Systems Journal, Vol. 13, Issue 11, pp. 1604–1612, **2019**

[jp4] **Panagiotopoulos, I.,** Dimitrakopoulos, G. *"An empirical Investigation on Consumers' Intentions Towards Autonomous Driving"*, Elsevier Transportation Research Part C: Emerging Technologies, Vol. 95, pp. 773–784, **2018**

[jp5] **Panagiotopoulos, I.,** Dimitrakopoulos, G. *"Diffie–Hellman Process and its Use in Secure and Authenticated VC Networks"*, IET Intelligent Transport Systems Journal, Vol. 12, Issue 9, pp. 1082 –1087, **2018**

<u>In Conference Proceedings</u>

[cp1] **Panagiotopoulos, I.**, Dimitrakopoulos, G., Keraitė G., Steikuniene, U. *"Are Consumers Ready to Adopt Highly Automated Passenger Vehicles? Results from a Cross-National Survey in Europe"*, in Proc. 6th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2020), 2– 4 May **2020**, ON-LINE STREAMING EVENT.

[cp2] Dimitrakopoulos, G., **Panagiotopoulos, I.** "*Hybrid Cognitive Computing for Enabling Automated Driving*", in Proc. 6th Annual International Conference on Computational Science and Computational Intelligence (CSCI), 5-7 December **2019**, Las Vegas, NV, USA, pp. 1236-1242.

[cp3] **Panagiotopoulos, I.**, Dimitrakopoulos, G. *"On-Board Intelligent Management Functionality for Improving the Driving of Highly Automated Vehicles"*, in Proc. 26th Intelligent Transport Systems (ITS) World Congress, 21-25 October **2019**, SINGAPORE (**<u>BEST SCIENTIFIC PAPER AWARD</u>**)

[cp4] **Panagiotopoulos, I.,** Dimitrakopoulos, G. *"Cognitive Infotainment Systems for Intelligent Vehicles"*, in Proc. 10th International Conference on Information, Intelligence, Systems and Applications, 15-17 July **2019**, Patras, GREECE

[cp5] **Panagiotopoulos, I.,** Dimitrakopoulos, G. *"Analysis of a Consumer Survey on Highly Automated Vehicles"*, in Proc. 13th Intelligent Transport Systems (ITS) European Congress, 3-6 June **2019**, Eindhoven, NETHERLANDS

[cp6] **Panagiotopoulos, I.,** Dimitrakopoulos, G. *"Behavioral Intention to Use Autonomous and Connected Vehicles: A Focus-Based Questionnaire Survey on University Students"*, in Proc. 25th Intelligent Transport Systems (ITS) World Congress, 17-21 September **2018**, Copenhagen, DENMARK.

[cp7] **Panagiotopoulos, I.,** Dimitrakopoulos, G. *"Diffie-Hellman Process for Enhancing Security in Vehicular Communication Networks"*, in Proc. 1st IEEE International Conference on Industrial Cyber-Physical Systems (ICPS), 15–18 May **2018**, Saint Petersburg, RUSSIA, pp. 409-416.

[cp8] **Panagiotopoulos, I.,** Dimitrakopoulos, G. *"On reliability Assessment Approaches in Vehicular Communications"*, in Proc. 24th Intelligent Transport Systems (ITS) World Congress, 29 October – 2 November **2017**, Montreal, CANADA.

[cp9] **Panagiotopoulos, I.,** Dimitrakopoulos, G., Anagnostopoulos, D. *"Data Privacy and Security in Vehicular Communications: Research Achievements and Challenges"*, in Proc. 16th Annual Wireless Telecommunications Symposium (WTS), 26-28 April **2017**, Chicago, USA.

APPENDIXES

Contents

APPENDIX A

A.1 Survey#1 general information

This survey is part of a doctoral dissertation in the Department of Informatics and Telematics / School of Digital Technology / Harokopio University of Athens (HUA). The main aim of this survey is to predict and investigate the factors related to the intention to accept and drive/use Autonomous Vehicles (AVs).

The completion of the questionnaire is anonymous and you will need at about five (5) minutes to complete it. Aside from your time, there are no costs for taking part in the study.

Please be advised that for the research purposes of the above survey, all your answers will remain completely confidential.

A.2 Survey#1 topic introduction

The purpose of this survey is to examine the factors that might influence people's future use of AVs and how high levels of vehicle automation could affect the ways in which people will choose to travel in the future.

In this direction, you may be able to buy an AV from major manufacturers or access one through a car-sharing service within the next ten (10) years. An AV is a motor vehicle equipped with devices to communicate with other surrounding vehicles or the road infrastructure via internet and capable to perform all driving functions in certain or/and all traffic, road and weather conditions.

Therefore, while AVs is expected to have great potential improving safety and efficiency of road transportation, many challenges are yet to be addressed. One of the biggest threats that society will face as transportation transforms in the coming years is vehicle data protection and security. Security becomes an even bigger concern with AVs in which software and connectivity plays a much bigger and more critical role for their safe driving.

A.3 Questionnaire survey#1

FIRST PART: Demographic and general attributes

Q1. What is your gender?

- *Male*
- *Female*
- *Other*

Q2. What is your age?

- *18-30*
- *31-40*
- *41-50*
- *51-60*
- *More than 60*

Q3. What is the highest degree or level of school you have completed?

- *Grade 12 or less*
- *High school graduate*
- *Associate's degree or some college*
- *Bachelor's degree (B.Sc.)*
- *After Bachelor's degree (M.Sc., Ph.D.)*

Q4. What is your current level of employment?

- *Employed full-time*
- *Employed part-time*
- *Not currently employed*
- *Retired*

Q5. What category best describes your total household income for last year (2016)?

- *Less than 5000€*
- *5000€ to 10000€*
- *10000€ to 20000€*
- *20000€ to 30000€*
- *More than 30000€*

Q6. What is your primary mode of transportation?

- *Automobiles*
- *Public transportation*
- *Walking / Biking*
- *Other*

Q7. Do you currently own or lease a vehicle?

- *Yes*
- *No*

Q8. How often do you drive or use a car passenger vehicle?

- *Every day*
- *A few days a week*
- *A few days a month*
- *Almost never*

Q9. How safe do you feel when you are driving or using car passenger vehicles today?

- *Not at all safe*
- *Somewhat safe*
- *Moderately safe*
- *Extremely safe*

Q10. Had you ever heard of AVs?

- *Yes*
- *No*
- *Don't know*

Q11. What is your general opinion regarding AVs?

- *very negative*
- *somewhat negative*
- *neutral*
- *somewhat positive*
- *very positive*

SECOND PART: Experience with technology

Q12. Please indicate your level of agreement with the following statements:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
It is important to keep up with the latest trends in technology					
New technology makes people waste too much time					
New technology makes life more complicated					
Technology will provide solutions to many of our problems					

Q13. How often do you use the following technologies?

	Never	Few times a year	Several times a month	Several times a week	Several times a day	Several times an hour
Smartphone usage						
Social media usage						
Internet shopping						
Other Internet searching Emailing						
Text messaging						
Video gaming						

Q14. When you use internet enabled technologies or services today, how concerned are you that your data are kept private?

- *Not at all concerned*
- *Somewhat concerned*
- *Moderately concerned*
- *Extremely concerned*

Q15. When you use internet enabled technologies or services today, how concerned are you that your data are kept resilient to common cyber security threats?

- *Not at all concerned*
- *Somewhat concerned*
- *Moderately concerned*
- *Extremely concerned*

Q16. When it comes to adopting new technology, in which category do you fall?

- *Early adopter (I am among the first of my friends to adopt new technology)*
- *Late adopter (I wait before adopting new technology)*
- *Laggard (I am among the last of my friends to adopt new technology)*

THIRD PART: Intension to drive/use AVs

Q17. How well do the following statements describe you?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I would find AVs useful in meeting my transportation needs					
If I were to drive/use AVs, I would feel safer					
Using AVs driving would be more interesting					
Using AVs accidents would be decreasing					
Learning to operate an AV would be easy for me					
Interactions with AVs would be clear and understandable to me					
It would be easy for me to					

become skillful at driving/using AVs					
I generally have concerns about driving/using AVs					
AVs are somewhat frightening to me					
I have concerns about safety of AVs					
I have concerns about system security and data privacy of AVs					
I would be proud if people saw me driving/using an AV					
People whose opinions I value would like driving/using AVs					

Q18. Imagine that AVs were on the market now either for purchase or rental. What is the likelihood that you would ride in an AV for everyday use?

- *Not at all likely*
- *Somewhat unlikely*
- *Somewhat likely*
- *Extremely likely*

Q19. What is the main reason you would be unlikely to ride in an AV for everyday use?

- *Road transportation safety*
- *Security protection*
- *Data privacy*
- *Cost Insurance/liability*
- *Lack of trust in technology*
- *Something else*

Q20. How concerned are you that your data would be kept private when driving/using AVs?

- *Not at all concerned*
- *Somewhat concerned*
- *Moderately concerned*
- *Extremely concerned*

Q21. How concerned are you that your data would be kept resilient to common cyber security threats when driving/using AVs?

- *Not at all concerned*
- *Somewhat concerned*
- *Moderately concerned*
- *Extremely concerned*

Q22. How does the safety of AVs influence your desire to drive/use one?

- *very negatively*
- *somewhat negatively*
- *neutral*
- *somewhat positively*
- *very positively*

Q23. How does the system security and data privacy of AVs influence your desire to drive/use one?

- *very negatively*
- *somewhat negatively*
- *neutral*
- *somewhat positively*
- *very positively*

Q24. Overall, how interested would you be in driving/using AVs?

- *very interested*
- *moderately interested*
- *slightly interested*
- *not at all interested*

APPENDIX B

B.1 Survey#2 general information

This survey is part of a doctoral dissertation in the Department of Informatics and Telematics / School of Digital Technology / Harokopio University of Athens (HUA). The main aim of this survey is to predict and investigate the factors related to the intention to accept and drive/use autonomous vehicles.

The completion of the questionnaire is anonymous and you will need at about fifteen (15) to twenty (20) minutes to complete it. Aside from your time, there are no costs for taking part in the study.

Please be advised that for the research purposes of the above survey, all your answers will remain completely confidential.

B.2 Survey#2 topic introduction

Autonomous driving is an emerging technology which may prove to be the next big evolution in transportation. Autonomous Vehicles (AVs) are equipped with multiple sensors (radar, laser, cameras, etc.) and other instruments and are capable of performing all the elements of the dynamic driving task in some driving scenarios (traffic/road/weather conditions) with limited human intervention (SAE Level 4 – high automation) or all roadway and environmental conditions without any human intervention (SAE Level 5 – full automation), respectively.

As of now, most companies in the automotive industry are currently being advertised the introduction of AVs, planning to be available in market diffusion the next years. It is estimated that within the next ten (10) years you will be able to purchase/rent and drive/use a car passenger vehicle with autonomous driving technology.

Despite enthusiastic speculation about the potential benefits of AVs, to date little is known about the factors that will affect consumers' acceptance or rejection of this emerging technology. Gaining acceptance from end users and consumers will be critical to the widespread deployment of vehicles with autonomous driving technology.

B.3 Questionnaire survey#2

FIRST PART: Introduction

Q1. Had you ever heard of vehicles with autonomous driving technology before participating in this survey?

- *Yes*
- *No*
- *I do not know - I'm not sure*

Q2. Had you ever any experience on driving/using vehicles with autonomous driving technology before participating in this survey?

- *Yes*
- *No*
- *I do not know - I'm not sure*

Q3. Please indicate your level of interest in vehicles with autonomous driving technology before participating in this survey:

- *Not at all interested*
- *Slightly interested*
- *Moderately interested*
- *Quite interested*
- *Very interested*

Q4. Do you want to participate in this survey about vehicles with autonomous driving technology answering as honestly as possible to the following questions below?

- *Yes*
- *No*

SECOND PART: Demographic Characteristics and Transportation Profile

Q5. What is your gender?

- *Male*
- *Female*
- *I prefer not to answer*

Q6. What is your age?

- *Less than 18*
- *18-30*
- *31-40*
- *41-50*
- *51-60*
- *More than 60*
- *I prefer not to answer*

Q7. What is the highest degree or level of school you have completed?

- *Grade 12 or less*
- *High school graduate*
- *Associate's degree or some college*
- *Bachelor's degree (B.Sc.)*
- *After Bachelor's degree (M.Sc., Ph.D.)*

- *I prefer not to answer*

Q8. What is your current level of employment?

- *Employed full time*
- *Employed part time*
- *Freelance professional*
- *Student*
- *Unemployed*
- *Household*
- *Retired*
- *Rentier*
- *I prefer not to answer*

Q9. What is your average monthly personal income?

- *I do not have personal income*
- *Less than 500€*
- *500€ – 1000€*
- *1000€ – 1500€*
- *1500€ – 2000€*
- *More than 2000€*
- *I prefer not to answer*

Q10. Which of the following statements regarding your involvement with the automotive field?

- *I am working professionally in a sector related to the automotive field (e.g. automakers, sales, marketing, insurance company, etc.)*
- *I am working in a research institution and in a sector related to the automotive field*
- *I am attending a training/educational program in a subject related to the automotive field*
- *I am actively participating in social networking groups (facebook, forums, etc.) related to the automotive field*
- *I'm attending the automotive sector by personal interest*
- *None of the above*

Q11. How often do you use for your travels car passenger vehicles?

- *Rarely / Never*
- *Few times a year*
- *Few times a month*
- *Few times a week*
- *Every day*

Q12. How often do you use for your travels public transport means (metro, buses, etc.)?

- *Rarely / Never*
- *Few times a year*
- *Few times a month*
- *Few times a week*
- *Every day*

Q13. How often do you use for your travels alternative modes of transport (bicycles, walking, etc.)?

- *Rarely / Never*
- *Few times a year*
- *Few times a month*
- *Few times a week*
- *Every day*

Q14. Do you have a driving license (valid) for a car passenger vehicle?

- *Yes*
- *No*

Q15. Do you own a car passenger vehicle or do you use car passenger vehicles for your travels?

- *Yes*
- *No*

Q16. What is the usual purpose of your travels with car passenger vehicles?

- *I do not drive / use car passenger vehicles*
- *Professional (work, education, etc.)*
- *Personal (medical, family, shopping, etc.)*
- *Leisure (travels, walks, etc.)*

Q17. Which of the following driving styles represents you better when driving a car passenger vehicle?

- *I do not drive a car passenger vehicle*
- *I drive nervously*
- *I drive aggressively*
- *I drive stressfully*
- *I drive dangerously*
- *I drive carefully*

Q18. How many hours do you drive per week (on average) with your car passenger vehicle?

- *I do not drive a car passenger vehicle*
- *Less than 5 hours*
- *5 to 15 hours*

- *15 to 30 hours*
- *More than 30 hours*

Q19. How safe do you feel when you are using today car passenger vehicles?

- *Not at all safe*
- *Slightly safe*
- *Moderately safe*
- *Quite safe*
- *Extremely safe*

Q20. How safe do you feel when you are using today public transport means (metro, buses, etc.)?

- *Not at all safe*
- *Slightly safe*
- *Moderately safe*
- *Quite safe*
- *Extremely safe*

Q21. How safe do you feel when you are using today alternative modes of transport (bicycles, etc.)?

- *Not at all safe*
- *Slightly safe*
- *Moderately safe*
- *Quite safe*
- *Extremely safe*

Q22. To what extent do you believe that technology progress, until now, has contributed to improving the safety of your travels when you are using car passenger vehicles?

- *Not at all improved*
- *Slightly improved*
- *Moderately improved*
- *Quite improved*
- *Extremely improved*

Q23. To what extent do you believe that technology progress, until now, has contributed to improving the safety of your travels when you are using public transport means (metro, buses, etc.)?

- *Not at all improved*
- *Slightly improved*
- *Moderately improved*
- *Quite improved*
- *Extremely improved*

Q24. To what extent do you believe that technology progress, until now, has contributed to improving the safety of your travels when you are using alternative modes of transport (bicycles, etc.)?

- *Not at all improved*
- *Slightly improved*
- *Moderately improved*
- *Quite improved*
- *Extremely improved*

Q25. Please indicate your level of interest in issues related to road safety:

- *Not at all interested*
- *Slightly interested*
- *Moderately interested*
- *Quite interested*
- *Very interested*

Q26. Please indicate your level of interest in issues related to automotive sector:

- *Not at all interested*
- *Slightly interested*
- *Moderately interested*
- *Quite interested*
- *Very interested*

Q27. Please indicate your level of interest in issues related to "smart" mobility and "intelligent" transportation systems:

- *Not at all interested*
- *Slightly interested*
- *Moderately interested*
- *Quite interested*
- *Very interested*

Q28. What is your general opinion regarding vehicles with autonomous driving technology?

- *very positive*
- *somewhat positive*
- *neutral*
- *somewhat negative*
- *very negative*
- *I cannot express my opinion - I do not know - I'm not sure*

THIRD PART: Experience with Automation Technologies and Advanced Driving Assistance Systems (ADAS)

Q29. Please indicate your level of agreement with the following statements?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
It is difficult for me to use and apply automation technologies					
Automation technologies makes me waste too much time					
Automation technologies provide solutions to many of my problems in my daily life					
I am keeping up with the latest trends in automation technologies					

Q30. When it comes to adopting an automation technology or service, in which category do you fall?

- *Early adopter (I am among the first adopting new technology)*
- *Late adopter (I wait before adopting new technology)*
- *Laggard (I am among the last adopting new technology)*

Q31. To what extent do you trust the automation technologies or services in terms of:

	Not at all trusted	Somewhat trusted	Moderately trusted	Quite trusted	Extremely trusted
tracking – interception of sensitive information					
cyber security and data protection					
data loss – system failure (software, databases, etc.)					

Q32. How would you generally characterize your relationship with the existing technologies, which are offered on certain models of car passenger vehicles, regarding Advanced Driver Assistance Services (ADAS), e.g. cruise control system?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
It is difficult for me to use and apply them in driving					
They make me waste too much time in driving					

They make easier my driving					
I am keeping up with the latest trends in advanced driver assistance technologies					

Q33. Please indicate your level of familiarity with the following Advanced Driver Assistance Services (ADAS), which are offered today on certain models of car passenger vehicles?

	Not at all familiar	Somewhat disagree	Moderately familiar	Quite familiar	Very familiar
navigation system					
collision warning / prevention system					
lane keeping system					
blind-spot assistance system					
park assist system					
emergency braking system					
cruise control system					
intelligent speed adaptation (ISA) system					
e-call system					
seat belt warning system					

FOURTH PART: Intention to Use and Acceptance

Q34. Which of the following levels of autonomous driving technology on car passenger vehicles would make you feel "more comfortable"?

- *Level 0 - Driver only: no autonomous-vehicle technology*
- *Level 1 - Assisted automation: the automated system can conduct some parts of the driving task, while the human continues to monitor the driving environment and performs the rest of the driving task*
- *Level 2 - Partial automation: the automated system can both conduct some parts of the driving task and monitor the driving environment in some instances, but the human driver must be ready ti take back control when the automated system requests.*
- *Level 3 - High automation: the automated system can both conduct the driving task and monitor the driving environment, and the human driver need not take back control, but the automated system can operate only in certain environments and under certain conditions*
- *Level 4/5 - Full automation: the automated system can perform all driving tasks, under all conditions that a human driver could perform them*

Q35. Which of the following road categories would you feel more comfortable traveling with vehicles with autonomous driving technology?

- *motorways*
- *urban roads*
- *rural roads*
- *none of the above*

Q36. What is the main reason you would be unlikely to drive/use vehicles with autonomous driving technology for your travels;

- *Road safety*
- *Safety and protection of vehicle operations against malicious attacks by cyber criminals (hackers)*
- *Security and protection of sensitive information (vehicle position, vehicle speed, etc.)*
- *Cost (purchase / rental, operation, maintenance, insurance, etc.)*
- *Lack of confidence in technology and autonomous driving services*
- *I like to drive and have the control of the vehicle any time*
- *Lack of appropriate infrastructures and specific regulatory frameworks*
- *Another reason*

Q37. How important are the following features for you regarding car passenger vehicles with autonomous driving technology?

	Not at all important	Somewhat important	Moderately important	Quite important	Extremely important
road safety					
vehicle - environment interaction					
safe operation					
legal liability in case of accidents and damages					
vehicle security and data privacy protection					
purchase / rental costs					
operating costs					
driving enjoyment					
environmental impact					
existence of a specific regulatory framework					
road and roadside infrastructures					
ease of use					
easy to learn to operate					
human driver - vehicle					

interaction					
travel time					
employment with other activities while driving					
community trends towards vehicle automation					
social influence					

Q38. Please indicate your level of agreement with the following statements?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
AVs will be useful for my travels					
Driving/using AVs, my travels will take place in less time					
AVs will allow me to perform other tasks (working, reading, etc.) while driving					
Driving/using AVs, my driving behavior and performance will be improved					
Driving/using AVs, my safety on the road will be improved					
AVs will be easy to drive/use					
I would find AVs easy to drive/use					
My interaction with AVs would be clear and understandable					
It would be easy for me to learn how to drive/use AVs					
Having people who are important to me driving/using AVs will make me more likely to drive/use such vehicles as well					
People who are important to me would think that I should drive/use AVs					

People in my environment would support me in driving/using AVs					
The trends of the global automotive community towards vehicle automation influence my behavior and will make me more likely to drive/use AVs as well					
I would drive/use AVs if specific and appropriate regulatory frameworks are existing and supporting their driving/usage					
I would drive/use AVs if appropriate road and roadside infrastructures are existing and supporting their driving/usage					
I would drive/use AVs if there are compatible with the advanced driver assistance systems which are currently used in human-operated vehicles					
I would drive/use AVs if I could have the necessary resources and knowledge to drive/use them					
Driving/using AVs will be exciting					
Driving/using AVs will be comfortable and relaxing					
Driving/using AVs will be enjoyable					
I would like to invest money for the purchase / rental of AVs					
The benefits of driving/using AVs outweigh the cost of their purchasing / renting					
The cost of purchasing / renting AVs will be at reasonable prices similar					

to currently used human-operated vehicles					
The operating cost of driving/using AVs will be at reasonable prices similar to currently used human-operated vehicles					
I trust that AVs can get me safely to my destinations, even in the most challenging and demanding driving scenarios					
I trust that AVs can drive better than me and they can interact better with the external driving environment					
I trust that AVs can maintain the full control of the vehicle, at any moment, against cyber attacks (hacking)					
I trust that AVs can ensure data privacy protection against cyber attacks (hacking)					
I intend to drive/use AVs when they become available					
I predict I will drive/use AVs when they become available					
I plan to drive/use AVs when they become available					

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SHORT BIO

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