This project has received funding from the European Community's
Horizon 2020 Framework Programme under grant agreement 860410

Deliverable 1.3

Long-term behavioural adaptation and learning curve of humans interacting with AVs

Deliverable Status	**FINAL**
Type	**REPORT**
Dissemination level according to the Grant Agreement	**PUBLIC**

This project has received funding from the European Community's
Horizon 2020 Framework Programme under grant agreement 860410

Project Information

Project Name:	SHAPE-IT – Supporting the interaction of Humans and Automated vehicles: Preparing for the Environment of Tomorrow
Grant Agreement:	860410
Project Duration:	1 October 2019 – 31 March 2024
Coordinator	Chalmers University of Technology

Document Information

Due Date	30Nov2023	**Due date in months**	M50
Date of submission	30Nov2023	**Month of submission**	M50

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Please cite as:

Mbelekani, N., Yue, Y. (2023). *Long-Term Behavioural Adaptation and Learning Curve of Humans Interacting with AVs*. (Deliverable D1.3 in the EC ITN project SHAPE-IT). SHAPE-IT Consortium. http://doi.org/10.17196/shape-it/2023/D1.3

Acknowledgements

This is a deliverable from the SHAPE-IT project – a project that is multi-disciplinary and with substantial interaction across the early-stage researchers (ESRs), supervisors across the six host universities, and the associated partners of SHAPE-IT (see list below). We consequently want to sincerely thank all individuals and organizations that have contributed to the SHAPE-IT project. We especially want to thank the associated partners, for making the secondments support the ESRs research, but also as a way for the ESRs to get insights into how other organizations work. Finally, this project would not have been possible without the Marie Skłodowska-Curie program. That is, this project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement 860410.

List of Associated Partners

Asymptotic AI	https://www.asymptotic.ai
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Note 1: The term Early-Stage Researcher (ESR) is used extensively in this document. The ESRs are PhD candidates funded by the SHAPE-IT project.

Note 2: This document has been submitted to the EC for acceptance as a deliverable in the SHAPE-IT project. If changes are requested by the EC, the document will be updated.

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List of Abbreviations

Adaptive Cruise Control	ACC
Advanced Driver Assistance Systems	ADAS
Automated Driving Systems	ADS
Artificial Intelligence	AI
Augmented Reality	AR
Automated Vehicle	AV
Behaviour Adaptability/Changeability	BAC

Behavioural adaptation	BA
Behavioural change	BC
Behaviour Intention	BI
Cave Automatic Virtual Environment	CAVE
Crossing Initiation Time	CIT
Data Acquisition System	DAS
Deceleration to Safety Time	DST
External Human-Machine Interface	eHMI
Hand-Over Notice	HON
Highly Automated Vehicle	HAV
Human-Automation Interaction	HAI
Human-Machine Interface	HMI
Knowledge Discovery in Long-Term Assessment Research	KLEAR
Learnability in Automated Driving	LiAD
Long-Term Research Conditions	LTRC
Long-Term UX Conditions	LTuxC
Mid-Term UX Conditions	MTuxC
Multi-Agent Social Interactions	MASI
Novelty Effect	NE
Non-Driving Related Task	NDRT
Operational Design Domain	ODD
Situation Awareness	SA
Short-Term UX Conditions	STuxC
Take-Over Request	TOR
Take-Over Time	TOT
Time to Arrival	TTA
Time to Collision	TTC
User Experience	UX
Virtual Reality	VR
Vulnerable Road User	VRU
Wizard of Oz	WoOZ

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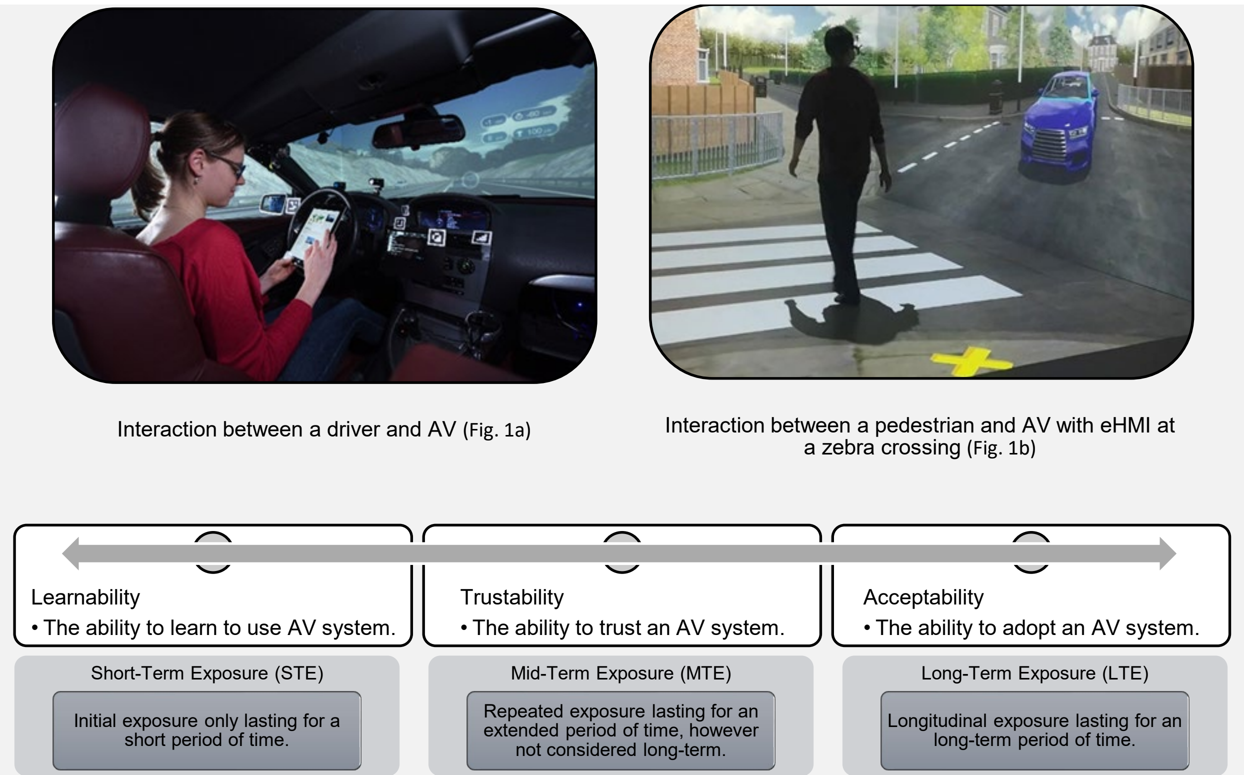
1 Introduction

Research on the long-term behavioural effects of automated vehicle (AV) use is very important for a correct assessment of AV's benefits and risks. Thus to ensure the safe and efficient implementation of automated driving technology, researchers need to understand the concept of long-term behavioural adaptation. A combination of research methods is called for to meet this goal, such as human factors research related to AVs—especially their long-term effects. Human factors research brings many challenges in terms of effort and methodological requirements. The SHAPE-IT project considered an approach (see **Fig. 1**) that brings this goal closer to reality. This deliverable has two aims. One is to assess the development of drivers' situational awareness (SA) during automated driving over time. In particular, when drivers receive a Hand-Over Notice (HON), their Take-Over Time (TOT) is influenced by factors known to play a role in their decision-making process, which is a part of their SA. Thus, changes in TOT may indicate a change in SA. Long-term behaviour changes can include safe behaviours as well as risky behaviours—such as performing Non-Driving Related Tasks (NDRT) and misusing the system (whether intended or unintended). The second aim is to assess the development of pedestrians' SA of AVs over time. Each aim is addressed by a project. In one example, pedestrians' decisions whether to yield to an AV or cross the street first, and the factors influencing their decision-making process, are examined. The drivers' and pedestrians' behavioural adaptation is the focus of our research, with behavioural adaptation described as a learning process (Forster et al., 2019) over time.

This deliverable aims to provide the reader with a meticulous discussion assessing and explaining the behavioural adaptations and changes due to long-term human-automated vehicle interactions (HAVI) or repeated AV exposure. The insights from the project have an impact on human factors and ergonomic engineering, research, and development in the context of automated driving. Both projects (driver-AV interactions and pedestrian-AV interactions, over repeated exposure) are discussed in the following sections.

2 AV repeated exposure and human behaviour

The experiences of drivers who use AVs and pedestrians who interact with them must be thoroughly considered in order to accurately evaluate AV safety. These experiences include *learnability* (the 'learning to use' process), *trustability* (trust in the automation process) and *acceptability* (the adoption of automation process). Based on these experiences, **Figure 1** illustrates factors that contribute to an understanding of behavioural adaptation research, with a consideration of interactions between (a) a driver and an AV and (b) a pedestrian and an AV with eHMI. **Figure 1** aims to help us structure the framework with a coherent level of understanding.



Interaction between a driver and AV (Fig. 1a)

Interaction between a pedestrian and AV with eHMI at a zebra crossing (Fig. 1b)

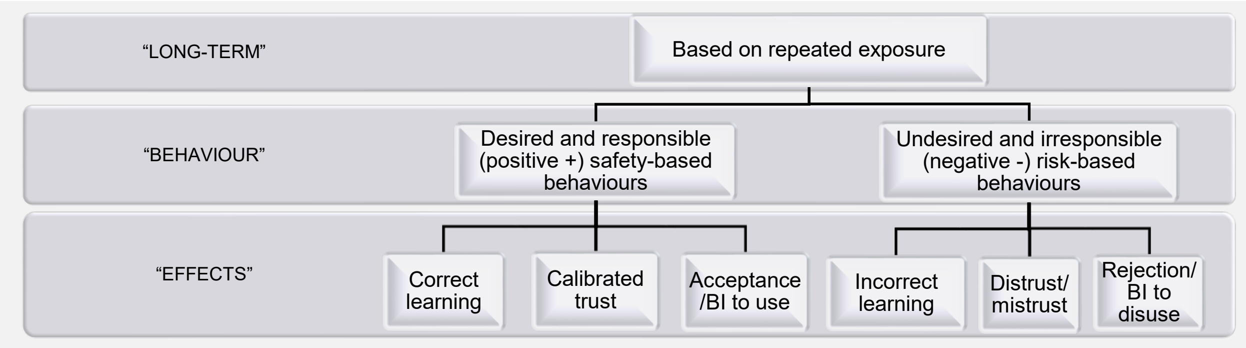


Figure 1. Contributing factors to behavioural adaptation research, considering interactions between (a) *a driver and an AV* and (b) *a pedestrian and an AV with eHMI*

Michelsen et al. (1980) defined learnability as a system's easiness for user to learn. The term "easy to learn" is also defined by Nielsen (1994) as "allowing users to reach a reasonable level of usage proficiency within a short time". Grossman et al. (2009) and Mbelekani and Bengler (2023) both described the concept using initial (the initial learning experiences or initial performance of a user interacting with a system) and extended learning (the changes of performances over the sequence of time, and after several interactions with the system) experiences. Therefore, in this deliverable, we focus on Grossman et al. (2009) and Mbelekani and Bengler's (2023) account of the concept. Due to the fact that the concept is heavily used in HCI, however, neglected in automated driving, Mbelekani and Bengler (2023) introduced the concept learnability in automated driving (LiAD), encompassing the following spectrums:

- Short-term or initial learnability in automated driving (initial LiAD: [i]LiAD)
- Long-term or extended learnability in automated driving (extended LiAD: [e]LiAD).

Furthermore, Mbelekani and Bengler (2023) expanded on the description of "easy to learn" to include "easiness to misuse". Mbelekani and Bengler (2023) argued that, "what is usually neglected is the 'easy-to-learn-to-misuse' (intentionally or unintentionally)—resulting in risk-taking behaviours." The authors emphasised that "the neglected link between ease-of-learning and misuse, as well as its association with risk-taking behaviour, is vital" (Mbelekani & Bengler, 2023). As a result, it is imperative to investigate 'efficient learning' (i.e., the system is easy to learn to use) and 'inefficient learning' (i.e., the system is easy to learn to misuse) in order to fully understand learning effects encountered over time, particularly when the concept '*easy*' is the context or standard (Mbelekani & Bengler, 2023).

As the learning experience is not static, extended learning is what really matters when assessing a system that people will be exposed to over long periods of time (see Bevan & Macleod, 1994; Dix et al., 2004; Grossman et al., 2009; Mbelekani & Bengler, 2023, etc.). Similar considerations were highlighted by other scholars (see Schneiderman, 1997; Holzinger, 2005; Grossman et al., 2009; Mbelekani & Bengler, 2023, etc.). Different scholars have suggested several metrics and research approaches to quantify the learning process over time; see **Table 1** for examples.

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Table 1. Learnability research approaches and metrics (adapted from Mbelekani & Bengler, 2023).

Methods/Parameters	Code	Factors	References
Research Methods			
Empirical approach: Strategies based on data collection	E1	In a lab experiment, survey method: Perform tasks (with a system), and after answering the questionnaire, formative/summative evaluation, and record completion time.	[9,13,46]
	E2	In a lab experiment, think-aloud method: Novice users interact with the system and vocalise their thoughts. The tutor sits next to them for questions during system use.	[47,48,49]
	E3	Naturalistic study, diary method: Interact with the system in their natural habitat and fill diary entries to keep all records of all the learning activities.	
	E4	Interviews: Cover subjective data and also fill in for missing or incomplete study entries.	
	E5	In a lab experiment and observations: Performance is observed during training and testing. Summative evaluation on performing a task.	[50]
	E7	Online survey: Online questionnaire evaluation with questions related to learnability characteristics, task match, and interface understandability.	[51]
Assessment Metrics (adapted from [21])			
Task Metrics: Metrics based on task performance	T1	Percentage of users who complete a task optimally.	[52]
	T2	Percentage of users who complete a task without any help.	[52]
	T3	Ability to complete tasks optimally after a certain timeframe.	[9]
	T4	Decrease in task errors made over certain time intervals.	[22]
	T5	Time until the user completes a certain task successfully.	[18]
	T6	Time until the user completes a set of tasks within a timeframe.	[18]
	T7	Quality of work performed during a task, as scored by judges.	[50]
	C1	Success rate of commands after being trained.	[20]

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Methods/Parameters	Code	Factors	References
Command Metrics: Metrics based on command usage	C2	Increase in commands used over certain time intervals.	[18]
	C3	Increase in complexity of commands over a time interval.	[18]
	C4	Percent of commands known.	[53]
	C5	Percent of commands used.	[53]
Mental Metrics: Metrics based on cognitive processes	M1	Decrease in average thinking times over certain time intervals.	[18]
	M2	Alpha vs. beta waves in EEG patterns during usage.	[14]
	M3	Change in chunk size over time.	[27]
	M4	Mental Model questionnaire pre-test and post-test results.	[54]
Subjective Metrics: Metrics based on user feedback	S1	Number of learnability-related user comments.	[18]
	S2	Learnability questionnaire responses.	[42,46]
	S3	Twenty-six Likert statements.	[6]
Documentation Metrics: Metrics based on documentation usage	D1	Decrease in help commands used over certain time intervals.	[18]
	D2	Time taken to review documentation before starting a task.	[18]
	D3	Time to complete a task after reviewing documentation.	[18]
Usability Metrics: Metrics based on change in usability	U1	Comparing “quality of use” over time.	[21]
	U2	Comparing “usability” for novice and expert users.	[21]
Rule Metrics: Metrics based on specific rules	R1	Number of rules required to describe the system.	[16,55]

In this project, we determined that learnability, trustability, and acceptability are useful concepts for assessing a user's experience (UX) from initial to extended exposure. Furthermore, this experience can be thought of as a learning curve, from initial/short-term experience to long-term experience.

2.1 The learning curve

Early studies in the field of advanced driver assistance systems (ADAS) often focused on the adaptive cruise control system (ACC), which helps the driver by automatically adjusting the speed and distance to the car ahead. In a month-long study, Weinberger et al. (2001) investigated how drivers learned about and got used to the ACC system in a naturalistic driving study. They asked drivers about their experiences and used Time to Collision (TTC) as a metric to measure safety. The study found that most drivers reported becoming comfortable using ACC after about two weeks or 2800km of driving. The TTC data supported this, suggesting drivers could use ACC safely after this learning phase. Another study by Beggiato et al. (2015) observed how drivers understood, trusted, and accepted the ACC system after using it ten times over two months. The findings highlighted that by the fifth usage, drivers had a consistent understanding of and trust in the system. This trend aligns with the "power law of practice" (Newell & Rosenbloom, 1981), a principle that describes how our proficiency at a task improves with repeated practice until it plateaus after a certain point.

Moving to a higher level of automated driving systems (ADSs), Forster et al. (2019) studied how repeated use of ADSs affected driver behaviour, looking at factors like experimenter rating, reaction times, error rate, and the preference-performance relationship for automated driving with human-machine interfaces (HMI) in five blocks. Their results showed the pattern portrayed by the power law of practice: behaviour stabilized after the second round of use. In a follow-up study, Forster et al. (2020) used surveys to dive deeper into how drivers' understanding of ADSs evolved over time. They found that a driver's understanding grew predictably. By the fifth time using the system, most drivers had a stable grasp of how things worked. Using LiAD as an example, Mbelekani & Bengler (2023) constructed a framework of methodological benchmarks that focused on long-term effects based on the "power law of learning" (similar description to the "power law of practice", however, substitute repeated practice with learning) over the sequence of time (exemplified on **Fig. 2**).

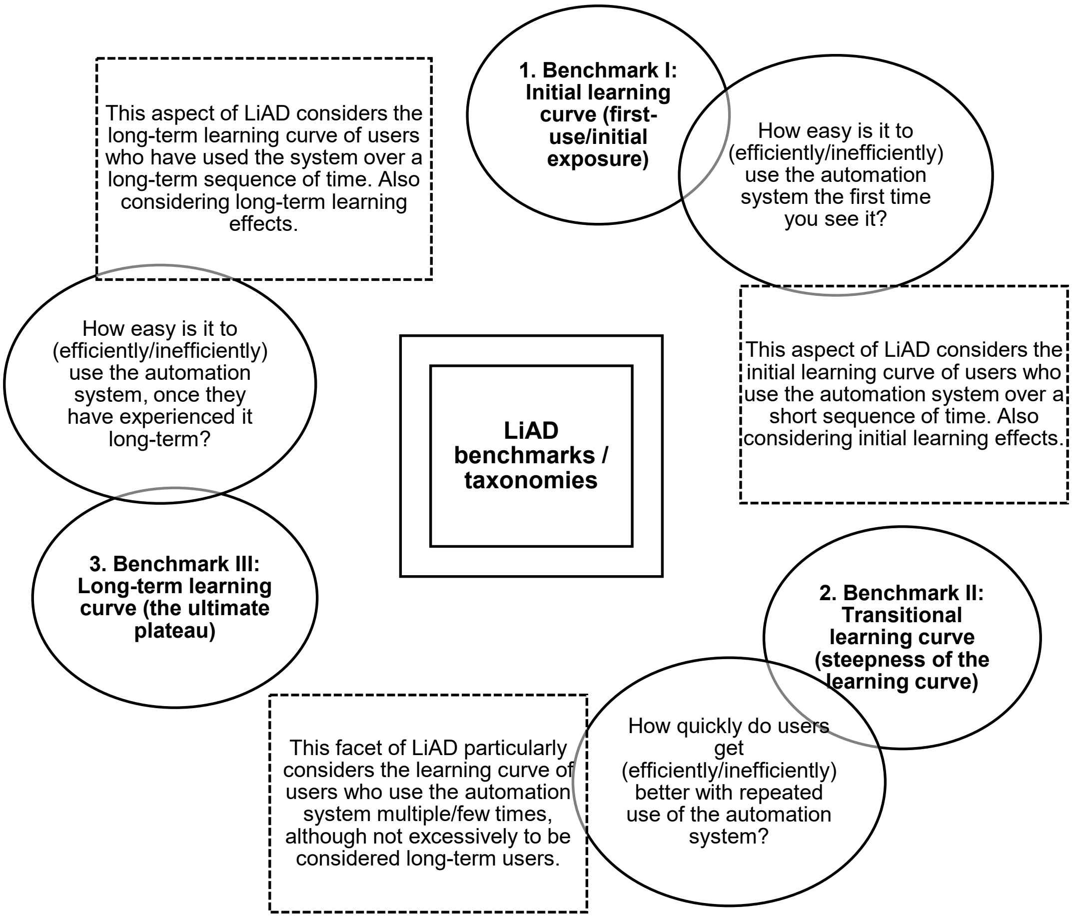

Figure 2. Methodology benchmarks: Quantifying LiAD research (adapted from Mbelekani & Bengler, 2023)

These investigations provide a comprehensive understanding of how users adapt to and engage with new automotive technologies. They collectively suggest the same pattern: As users' exposure to and experience with these systems increases, their understanding, trust, and proficiency increase, often levelling off after multiple uses. The consistent pattern of learning and trust highlighted in the studies also provides a preliminary way to measure human adaptation to automation technological advances in interactions for external users. However, when the research focus shifts to the dynamics between AVs and pedestrians, it is expected that the specific timelines and learning processes may vary. Therefore, it is imperative that we theorise the power law of learning and power law of practice from a systematic (automated driving) point of view. The emphasis should be on understanding how long-term research strategies can guide automated systems design towards optimal behaviour adaptation and/or change by drivers and pedestrians as they interact with the systems over the long term.

When “to learn” is defined as to *use, trust and accept*, the learning process can be described by a learning curve, which indicates a steep initial increase followed by stabilization of performance due to increase of experience, trials, learning, and practice (Newell & Rosenbloom, 1981; Mbelekani & Bengler, 2023). Moreover, “it can be assumed that for systems having good learnability, the gradient is bigger from the beginning, which means that ability develops quickly over time” (Mbelekani & Bengler, 2023). Newell and Rosenbloom (1981) reported the same pattern in the skill acquisition of mathematical problem solving; they also referred to the power law of practice and power law of learning. The authors noted a function with the following form. The predicted *performance* (P) is a function of the *number of trials* (N), given the *three parameters* a, b, and c which represent the asymptote of P with N increasing indefinitely, the amplitude of learning between the initial performance and asymptotical performance, the learning rate, respectively.

$$\mathrm{P}(\mathrm{N}|\mathrm{a},\mathrm{b},\mathrm{c}) = \mathrm{a} + \mathrm{b} * N^{-c}$$

In addition, the power law of practice can also describe the learning process of skill acquisition in operating in-vehicle information systems (IVIS) (Jahn et al., 2009) and the use of regenerative braking in electric vehicles (Cocron et al., 2013), to name two examples. The application in automated driving has been mainly focused on the driver’s learning process—that is, the development of a mental model along with trust in and acceptance of ACC (see Weinberger, Winner, & Bubb, 2001; Beggiato et al., 2015) and behavioural changes in AV (Forster et al., 2019). Concerning vulnerable road users (VRUs). The introduction of automation on roads and in traffic might preserve the interactions between pedestrians and conventional vehicles if an AV behaves like a traditional vehicle (Rothenbucher et al., 2016). However, the interactions can be improved (or worsened) since AV functions may influence pedestrians’ learning process (Ditta et al., 2020; Lundgren et al., 2017). The following section will introduce behaviour modification (e.g., behaviour adaptability/changeability [BAC]) and long-term studies in the AV context concerning learning effects.

2.2 Defining how long is long enough

In a forthcoming paper, Mbelekani and Bengler (n.d) outline an in-depth, long-term research taxonomy that focuses on describing how long is long enough. Their operational definition of "*How long is long enough?*" is intended to be comprehensible and applicable regardless of research domain, field of study, setting, user types, level of automation (LOA), context of use, and context of exposure (to name a few parameters). The aim is to deliver a research approach that helps assess long-term effects using Long-Term Research Conditions (LTRCs) (Mbelekani & Bengler, n.d).

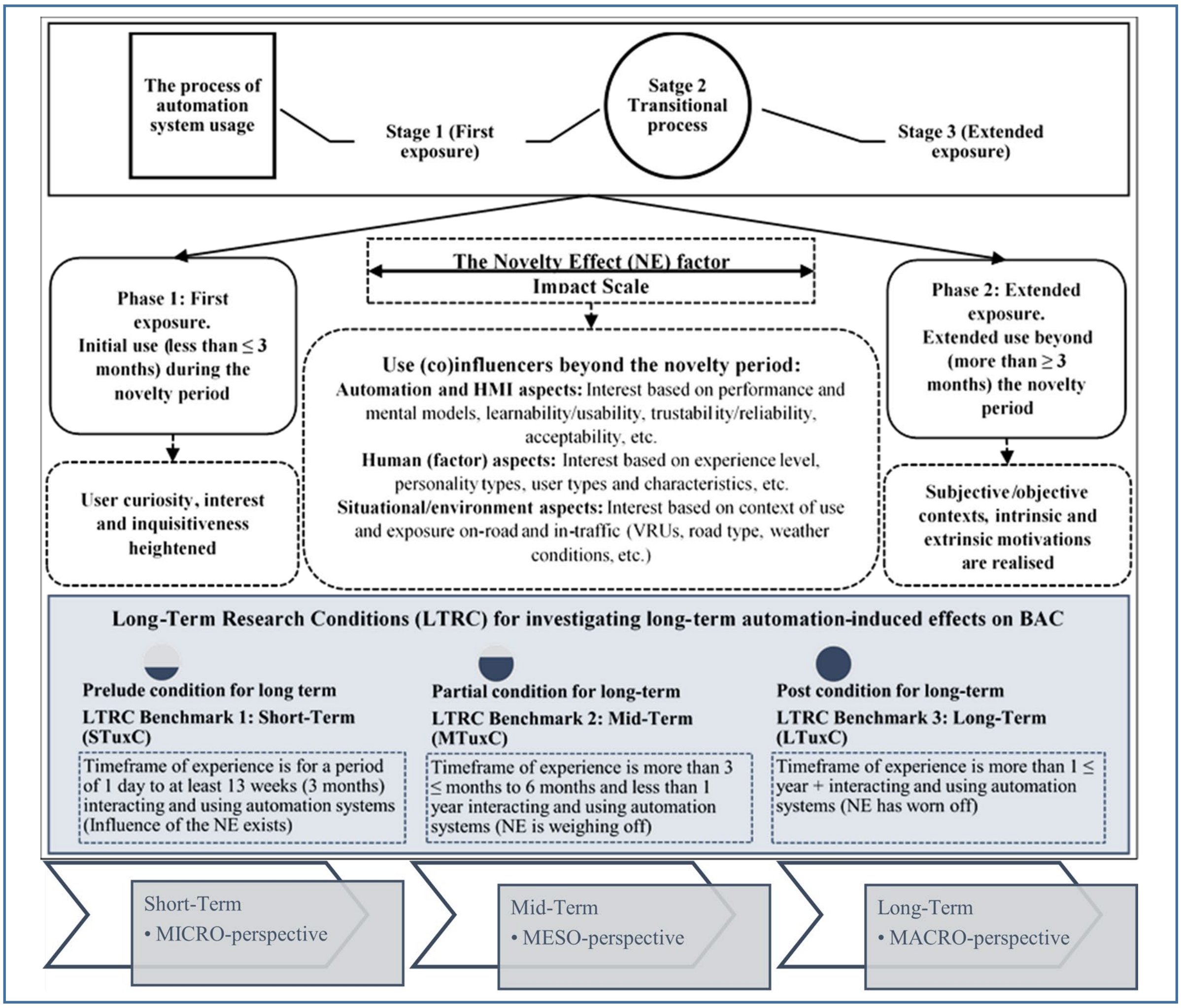

Figure 4. Knowledge discovery on **L**ong-term **E**xposure of **A**utomation **R**esearch (KLEAR) (Mbelekani & Bengler, 2023a).

The hope is to create a foundation for which a Long-Term Research Conditions Questionnaire (LTRCQ) can be formulated, to best exploit the experiences of a diverse sample of automation users in automated driving and using ADSs (Mbelekani & Bengler, n.d). Mbelekani and Bengler (2023a) systematically discussed long-term research as a way of assessing long-term effects and behaviour modification; see **Fig. 4**.

Although much as this work is directed towards drivers, we believe this can be a useful tool for understanding the behaviour modification of other road users, such as vulnerable road users (VRUs: pedestrians, motorcyclists, cyclists) and others. The discovery of refined knowledge is based on an expert-based culture of evidence about the modification of behaviour towards automation over the course of time. By answering the question: *How long is long enough?* We are able to deduce changes in behaviour based on long-term automation exposure in different situational contexts.

We drew on various concepts, approaches, and models across multiple literature sources to operationalise long-term assessment by involving different user types. Our KLEAR taxonomy has been constructed after considering definitions given by different scholars, as well as additional human factor concerns (e.g., long-term effects, automation use/interaction, mental models, BAC, etc.), automation system design, and environmental factors. These elements were combined into a coherent description appropriate for our research objective. Moreover, our definition frames knowledge from short-term (initial) to long-term (extended) perspectives, since the objective of the assessment is to implement a behaviour-based model over time. It is important to identify the effect of varying the properties of induced effects on BAC. In a sense, to define how long is long enough is to understand the different factors of influence, such as the user types, UX, the system design type, the environment of operation, and the situational context of use. Thus, the question: *How long is long enough?* remains an open enquiry that needs further validation and verification with user-centred studies.

2.3 Behaviour modification: adaptability/changeability

To translate theories about long-term effects into practice, Mbelekani and Bengler (2023) considered the correlation between learning effects and behaviour modification (e.g., BAC) through the power law of learning. Behaviour modification is influenced by many factors, including bounded knowledge acquisition, an architecture of choices, rationality/irrationality, and cognitive biases and mentality (Mbelekani & Bengler, n.d[a]). User behaviour (both individuals and groups), in the context of automated driving, is the expressed capacity of the user (mentally, physically, and socially) to respond to internal and external environmental stimuli in road traffic (Mbelekani & Bengler, n.d[a]; n.d[b]). In a sense, user behaviour is driven by internal (psychological, cognitive, etc.) and external (social, environmental) factors, as well as automation system design (usability, transparency, etc.).

Group (1990) defined BA as "the collection of behaviours which may occur following the introduction of changes to the road-vehicle-user system and which were not intended by the initiators of the change". Moreover, Martens and Jenssen (2012) described five phases of BA applicable to ADAS: first encounter/ day (1-6 hours), learning (3-4 weeks), trust (1-6 months), adjustment (6-12 months), and readjustment (1-2 years). Furthermore, risk homeostasis is one of the theories used to explain the occurrence of BA, assuming that drivers have a preferred range of perceived risks and will adapt their behaviour to eliminate any discrepancies between the preferred level of risk and perceived risk (Wilde, 1982). The continuous or intermittent adjustments lead to BA. Mbelekani and Bengler (n.d[a]; n.d[b]) described *behaviour adaptability* in the automated driving context as follows:

- BA: *Adaptability* is a person's ability to adjust to changes due to automation. It is to be understood as the ability of users to adjust their behaviour (efficient/inefficient and fast/slow) as driving circumstances change.

Studies of BA mainly emphasise the drivers' behavioural changes (BC) in various driving tasks (Draskóczy, 1994). For example, as drivers gain more experience interacting with ACC, they spend more time in the left lane (Nilsson, 1996), shorten time headways, and increase speed, acceleration, and brake force (Hoedemaeker & Brookhuis, 1998). De Winter et al. (2014) reported that, regarding BC generally, increased experience with ACC and AV could positively affect SA and decrease the mental workload. Nonetheless, according to Endsley (1995), BC could also negatively impact SA, due to over-reliance on the system and reduced vigilance. Behaviour changeability can be viewed as a sub-characteristic of adaptability, as "to adapt is to change and to change is to adapt" (Mbelekani & Bengler, n.d[a]). Mbelekani and Bengler (n.d[a]; n.d[b]) described behaviour *changeability* as follows:

- BC: *Changeability* is the quality of being changeable, thus a user's potential to change when confronted by a situation, as a user ability beyond the intended interaction corridors, with an emphasis on structural and mental processes.

In explaining behaviour modification, Mbelekani and Bengler (n.d[a]; n.d[b]) emphasised that adaptability and changeability can be regarded as two side of the same coin. They are closely related but different; in many instances they can be mutually exclusive. For a clear description of adapt and change, the following example is given. Adaptation is "adjusting" one's behaviour to something different from what was the norm (for example, manual driving to automated driving, etc.), and change is a "transition" from one state of behaviour outcome to another (for example, one decides to trust an ADS, and then after some time exposure to the ADS, one decides to distrust the ADS, etc.). For example, a user needs to adapt in order to change, and to change in order to adapt (Mbelekani & Bengler, n.d[a]; n.d[b]).

The effects of BA and BC can be positive or negative (Mbelekani & Bengler, n.d[a]; n.d[b]), depending on the different automation systems and functions (Dragutinovic et al., 2005). As a result, behaviour modification (BAC) encompasses two spectra (Mbelekani & Bengler, n.d[a]; n.d[b]):

- *Desired, responsible adaptation and/or change*: safety-based behaviour, good quality performance, responsible adaptation and/or change, intended system use, high SA, calibrated trust, etc.; and
- *Undesired, irresponsible adaptation and/or change*: risk-based behaviour, poor quality performance, irresponsible adaptation and/or change, unintended system use, misuse, negligence, reduced SA, distrust, overtrust, etc.

User behaviour can be unpredictable; the various factors that influence it are uncontainable and sometimes not accounted for by developers. These challenges mean it is all the more important that BAC, particularly over time and in interactions with AVs, be well understood. Further, this understanding must be practically incorporated into behaviour (and misbehaviour) models in order to reflect changes over time—which can include mental models, trust, and intention to use (Mbelekani & Bengler, n.d[a]). Pedestrians' BAC, in the context of the introduction of AV over time, is still a largely unexplored and neglected topic. Some researchers, however, have reported over-reliance behaviour with increased exposure to eHMIs (Holländer et al., 2019; Kaleefathullah et al., 2020b). Roughly 35% of pedestrians exhibited overtrust behaviour by walking onto the road when the eHMI was displayed, even when the AV was not decelerating (Kaleefathullah et al., 2020a). Rudin-Brown and Noy (2002) suggested that an individual's psychological factors could influence their BA. Specifically, individuals' trust in automation as well as their locus of control, sensation-seeking tendency, and mental model can all potentially affect their BAC. An increased trust level could induce risky behaviours (Rudin-Brown & Parker, 2004). It is thus important to assess individuals' decision-making processes, and the actions that they choose, by quantifying a range of influencing factors: cognitive, psychological, emotional, cultural, social, environmental, and system design.

2.3.1 Behaviour adaptation and mental models

The concept of a mental model is important to consider when aiming to understand behaviour adaptation and/or change towards automation over time. A mental model is the representation of users' understandings of external objects, the system, and the world—as well as interconnections involving actions and environmental factors (Carroll & Olson, 1987; Durso & Gronlund, 1999). Mental models guide people's expectations (Wickens, n.d.). In cognitive psychology, a mental model is a dynamic part of working memory (Wilson & Rutherford, 1989). It is also formulated in the long-term memory storage structure (Endsley, 1995; Endsley, 2000). Gentner and Stevens (1983) noted the influence of a mental model on individuals' visualisation of an automated system's physical behaviours (Gentner & Stevens, 1983). Furthermore, a mental model also allows individuals to infer and predict and decide on actions (Johnson-Laird, 1983). Craik (1943) proposed a small-scale model of the external process and its actions, translated from external events (interactions) into internal models. Clark (2013) proposed a predictive processing framework as a hierarchical generative model, illustrating how mental models generate predictions such that repeated exposure and learning facilitate better predictions (Engström et al., 2018). Mental models and acquired knowledge are important aspects of repeated practice (Endsley, 2000; Nersessian, 2009).

Cognitivism assumes two types of knowledge: declarative, acquired through education and procedural, acquired through practice (Shiffrin & Schneider, 1977). In essence, the general mental model corresponds to declarative knowledge prior to the interaction, and the applied mental model corresponds to procedural knowledge, which is dynamic and constantly evolving. Situation models combine them, connecting the bottom-up situational inputs per the applied model with top-down knowledge structures per the general model (Durso et al., 2008; Seppelt & Victor, 2020). Concerning the evolution of applied mental models, it's important to consider "a correspondence between the parameters and states of the model and the operation of the target system" (Norman, 1983). The designer's expectation is dominated by the conceptual model representing how the ADS should behave (Norman, 1983).

When people learn new technology, they reconstruct existing mental models (Kahneman, 2011; Zhang & Xu, 2011). If the model is insufficient or incompatible, the result could be rejection of the automated system as well as user confusion (how-to-use or other errors). However, if the automated system satisfies the users' expectations by being compatible with an existing mental model, the corresponding trust and user experience may be calibrated (Gefen et al., 2003). Lee and See (2004) indicate that a mismatch between an existing mental model and user experience leads to declining trust and acceptance. Clearly, inadequate mental models may interfere with the positive development of trust and acceptance (Gefen et al., 2003). Essentially, attitudes such as trust, acceptance, and adoption can be influenced by the evolution of the mental model over repeated AV exposure. Thus, it is imperative to keep in mind the long-term impact of the evolving model on functionality, transparency, safety, comfortability, learnability, usability, trustability, and acceptability. Human factors experts may also need to keep in mind the needs of different internal users while balancing them with the needs of external VRUs. Currently, there is a lack of research on how a pedestrian's mental model and decision-making process changes in AV interactions. As a pedestrian's applied mental model evolves with repeated AV exposure, it is not always accurate or complete (Norman, 1983). In fact, its accuracy, efficiency, and predictive performance regarding AV interactions—and how these tendencies develop—are unknown (Staggers & Norcio, 1993). Mental models emulate the pedestrian's beliefs and attitudes about AV; there should be a direct alliance between this model, as conceived by the AV designer and realized by the engineer, and the evolution of mental models as they gain an understanding of the AV system.

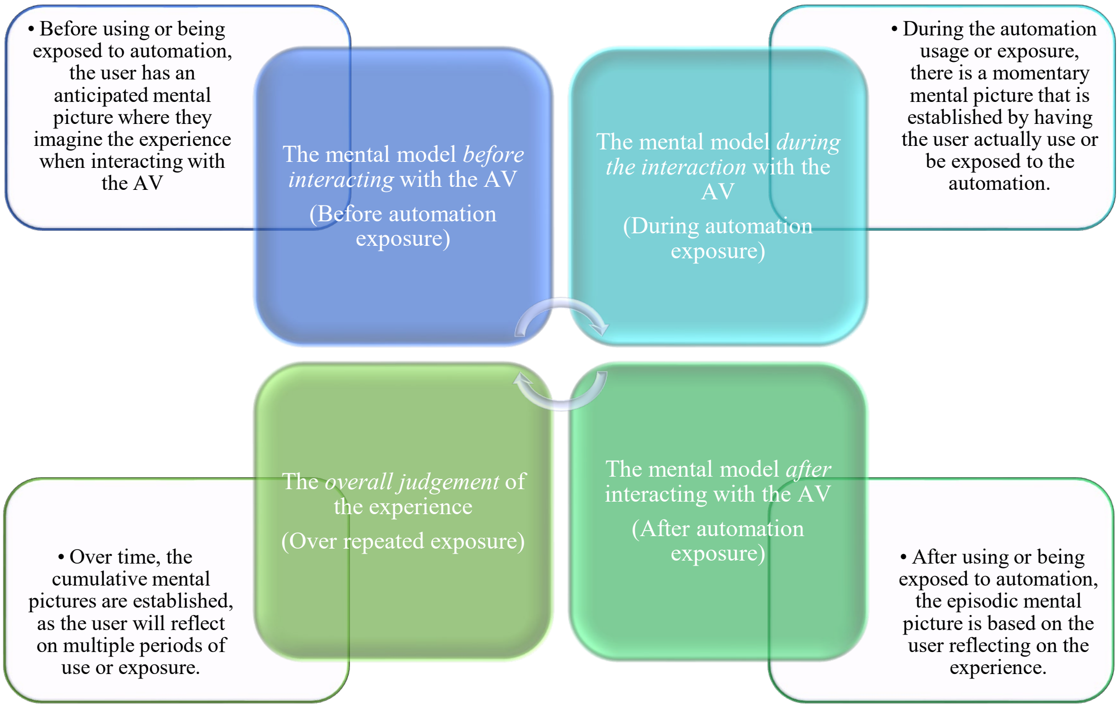

Figure 3. From mental model to mental models on *use* and *exposure* (adapted from Mbelekani & Bengler, 2022)

Investigating the accuracy of the applied mental model is important as a way of proposing efficient, intuitive automated driving and eHMIs. Attitudes and decisions are influenced by learnt information as well as by desires, goals and expectations. Studies have also highlighted the connection between mental models and emotional factors (e.g. Kahneman, 2011; Stanovich, 1999). The human affect system reflects a general judgement system and the independent cognitive system interprets knowledge (Norman, 2004). The two systems work together to convert external information into accurate representations of the world and make judgements determining how to behave (Norman, 2004). Affect is linked to emotions, which can be either discrete or independent or interrelated (Russell, 1980). In one theory, emotions and self-report affects are arranged in a circumplex model with arousal and valence dimensions (Russell, 1980). Positive emotions can increase efficiency in decision-making (Norman, 2004) and decrease the perceived risk; however, negative emotions lead to increased perceived risk and pessimistic predictions (Resnick, 2012). This model contributes to the comprehension and visualization of individuals' emotional data collected through standard questionnaires such as Self-Assessment Manikin (SAM) (Bradley & Lang, 1994). Emotions and a mental model can both determine attention allocation, in the SA model (Dolcos et al., 2020; Endsley, 2000). Research that has focused on individuals' affects during AV interactions has considered the following contributing factors: likability (Bazilinskyy et al., 2021), comfort (Bellem et al., 2018; Hartwich et al., 2018), enjoyment (Hartwich et al., 2018), naturalness (Dettmann et al., 2021), perceived risks/safety (Lagström & Lundgren, 2015; Rodríguez, 2017; Rossner & Bullinger, 2019), and stress (Lagström & Lundgren, 2015). Research on affect has mainly focused on perceived safety. However, there is a need for more exploration into the decision-making process and how it changes over time.

2.4 Theorising about long-term effects

Notably, just as the duration of exposure to automation has an effect on BAC, the level of experience in different situational contexts also has an effect. In order to fully understand long-term effects as a result of repeated exposure to vehicle automation systems or automated driving, we must, as a general rule of thumb, categorically consider destructive and constructive learning effects (Mbelekani & Bengler, 2023). Accordingly, Mbelekani and Bengler (2023) categorised effects as either first-order or second-order. In essence, first-order effects have a residual component; they induce other layers/forms of effects, which are second-order or side effects, or even secondary effects (e.g., high insurance due to crash accidents, physical disabilities, etc.). In a situation where automation is learned by a user (correctly or incorrectly), this situation may result in different interconnected effects (**Fig. 5**). Moreover, first-order effects have the potential to either transform, conform, or deform the user's (mis)behaviour in specific ways which might not have been anticipated (Mbelekani & Bengler, 2023).

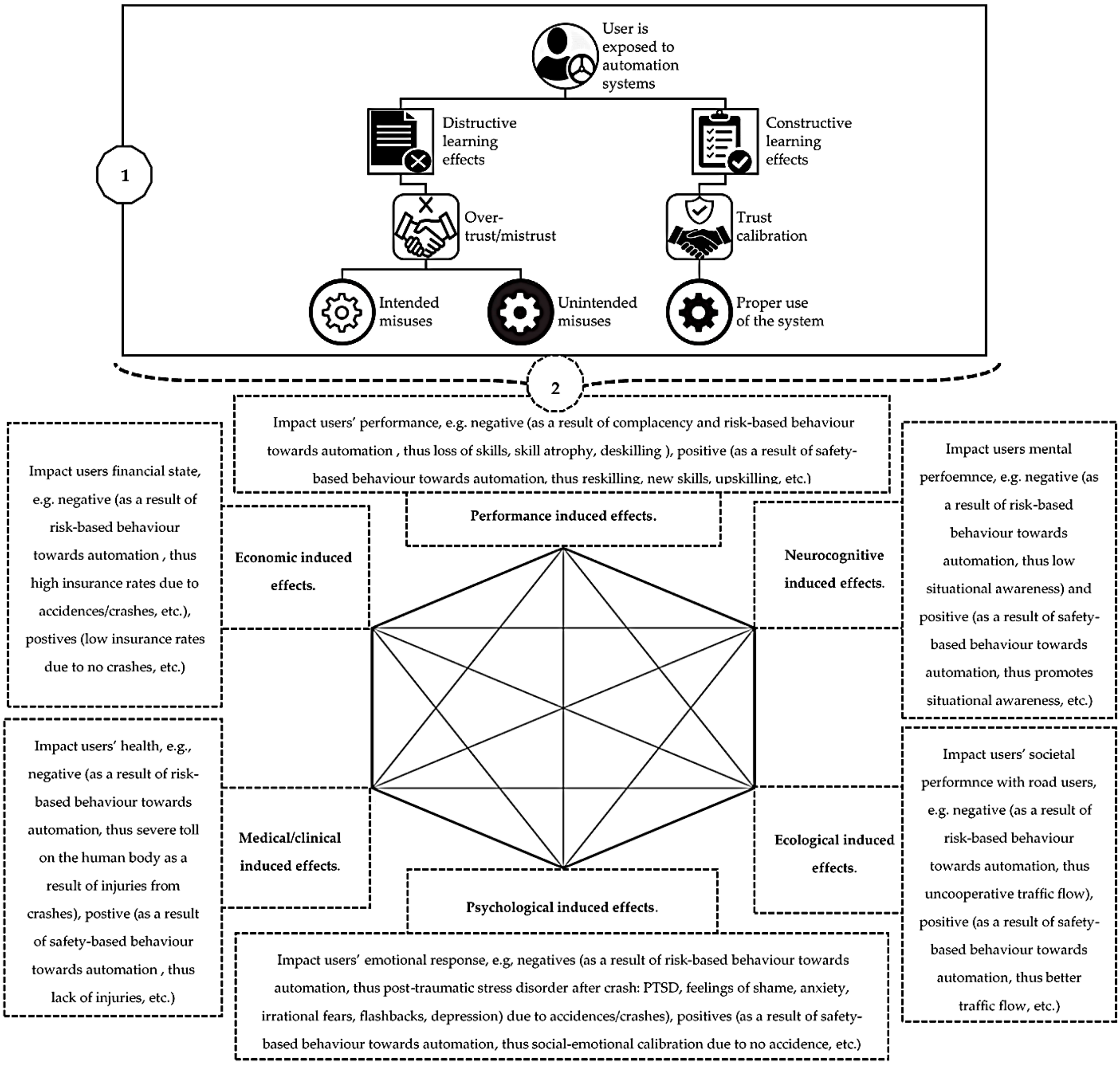

Figure 5. Locus of effects: first-order effects (circled 1) and second-order effects (dotted line, circled 2). (Mbelekani & Bengler, 2023)

3 Long-term behavioural adaptation research approaches

The following discussion points pertain to an understanding of long-term behavioural adaptation studies, from the perspective of drivers' and pedestrians' experiences in AV interactions.

3.1 Long-term effects investigations in user-AV interactions

Most researchers find a "diary approach" to be an effective and efficient research strategy for knowledge discovery about users' behaviour and experiences. To explore BAC towards automation over time, the researchers may use a precise, sequenced approach of methods (qualitative and quantitative) in order to collect data. The diary approach allows participants to experience the automation systems on their own initiative and report their experiences, often in real-world scenarios or usage situations. This advantage has been studied in uncontrolled and controlled settings using anthropological dogmas, with special attention to real-world scenarios of learned automated systems. However, there has been little investigation into its occurrence in automated driving for natural on-road and in-traffic situations—or in support of human factors engineering research into long-term effects and BAC. To address this lack, a real-world field study on user behaviour towards automation in everyday automated driving situations was performed by Mbelekani and Bengler in 2023, using diaries and structured interviews (pre- and post-diary entries) that focused on long-term effects and BAC. The study was conducted on a timeframe of three months. This long-term study was one of the first to investigate automated driving with a method that mixed quantitative and qualitative metrics. The study aim was to construct and employ a long-term research approach to assess an array of effects, and to add to knowledge discovery on BAC. The participants provided frequent digital diary logs, encompassing qualitative and quantitative assessments, which are well suited for gaining high-quality, rich data sets.

We found cross-sectional validation diary strategies to be an important tool for understanding behaviour modification while requiring little time. Thus, the participant sample, recruited through different platforms, included different automated driving user types with different UXs (low, mid, or high). The study assessed short-term effects (STUxCs), mid-term effects (MTUxCs) to long-term effects (LTUxCs) over a period of time. The validity of the Long-Term Research Conditions (LTRC) construct was tested with reference to learnability, trustability, and acceptability. Special emphasis was placed on safety- and risk-based behaviours, based on LTRC's three-dimensional knowledge components: micro-perspective, meso-perspective, and macro-perspective. This project also provides evidence for the reliability and validity of the scientific research approach, which has potential for both in-lab and real-world settings. The approach meets a need for long-term research measurements that go beyond time and physical function, complementing existing measures (surveys, experience sampling, etc.) to capture long-term effects, BAC, and what automated driving means for different user types.

The study aims to illustrate the usefulness of a long-term research approach towards user behaviour (BAC) as a generally acknowledged method for knowledge discovery. The result obtained from this cohort study will influence interaction design strategies that shape safety and risk-mitigating behaviour towards automation. As the researchers are in the process of analysing the data, the results from this study will be published in the coming months.

3.2 Long-term effects investigations into pedestrian-AV interactions

Research on drivers' automated driving behaviour effects (e.g., on habituation, trust building, and proficiency development) requires time to ensure drivers are fully familiar with the system (and even its subtlest features). In contrast, long-term studies of pedestrian interactions with AV tend to take less time. Unlike drivers, pedestrians don't have to understand the complexities of AV operation. Instead, their main concern is the predictability and safety of the AV's behaviour. That is, pedestrians focus on the AV's ability to communicate intentions and avoid hazards rather than the nuances of system operation. As a result, pedestrian adaptation and trust-building processes are arguably faster, occurring within a few encounters.

As novel communication mechanisms in the AV domain, external Human-Machine Interfaces (eHMIs) are expected to resolve ambiguities in the AV-pedestrian interaction which stem from the absence of drivers' explicit communication. Therefore, a special focus on the learning curve of pedestrians through continuous interaction is proposed in the current research area to evaluate the efficiency and usefulness of eHMIs. In previous related research, Faas et al. (2020) conducted a longitudinal video study (consisting of three sessions with seven to nine days between them) to evaluate the effectiveness of eHMIs at communicating the AVs' automated status and intent to pedestrians. The study tested three interfaces, providing increasing information to pedestrians: (i) no eHMI (baseline), (ii) status eHMI, and (iii) status+intent eHMI. The aim was to observe changes in pedestrian responses and understand their changing perceptions of AVs. They collected pedestrian crossing onset time and perceived safety, trust, acceptance, and user experience (including learnability). The two eHMIs examined (status and status+intent) were found to improve pedestrians' understanding of what was going on around them. As exposure increased, pedestrians showed higher trust and reliance on the combined interface. The eHMIs improved learnability, and pedestrians came to rely more on them. These results suggest that preliminary training may be beneficial for pedestrians to understand eHMI signals better (de Clercq et al., 2019). These findings also highlight the need to design interfaces that are capable of skilfully communicating the goals and operations of AVs to pedestrians.

In a study conducted by Lee et al. (2022), the importance of intuitively designed eHMIs was also noted. The authors' aim was to compare how quickly pedestrians obtained the information conveyed by the novel eHMI design versus a more traditional method (flashing headlights) in a CAVE-based pedestrian simulator. A mixed design approach was used, with four within-participant variables: three approaching speeds, four time-gaps, deceleration/no deceleration by the AV, and three repeated blocks. Additionally, they compared two different eHMI designs as the between-participant variable: the Slow-Pulsing Light Band (SPLB) and the Flashing Headlight (FH). The findings indicated that while the Flashing Headlight's message was quickly understood in the initial block of trials, the Slow-Pulsing Light Band required a block of 12 trials to achieve the same level of comprehension. This underscores the idea that introducing new eHMI designs may necessitate a learning phase for road users, challenging manufacturers to ensure their designs are both innovative and easily comprehensible. Thus, making sure that the learning phase is as short as possible.

As noted, investigations into pedestrians' learning process towards eHMI have significant implications for design approaches. For instance, Hochman et al. (2020) used desktop-based video simulations to measure pedestrian awareness of AV yielding intentions by looking at variables influencing their crossing decisions. The variables included the eHMI background color (red/green), message type (status/advice), and presentation modality (text/symbol). Results indicated a learning effect over time in all conditions, reflected by a shortening of response times and the reduction in the number of gaze fixations over time—regardless of the eHMI features. It is worth noting that while this study did not consider different learning patterns between different eHMI designs, another study, by de Clercq et al. (2019), did. Using a head-mounted display, participants' simulated crossing a road using hand-held buttons that signalled what they thought was safe. The percentage of "feeling safe" signals was then evaluated across several eHMI types (1. baseline without eHMI, 2. front brake lights, 3.

Knightrider animation, 4. smiley, and 5. text [WALK]). Their findings demonstrated a learning curve consistent with a power law of practice. Of the five types, text-based interfaces were found to be the least ambiguous; they showed a high feel-safe percentage initially, and little learning after exposures.

The recent research on the learning effects of interactions between AVs and pedestrians reveals a clear gap: past studies often used simplified interaction scenarios and did not thoroughly investigate the effects of more complex vehicle behaviours. To address this issue, ESR 4 of the SHAPE-IT project specifically explored pedestrians' learning processes at urban intersections, taking into account the presence of varied road infrastructure and ambiguous autonomous driving behaviours (Yang et al., 2023).

Figure 6. Interaction between the pedestrian and the AV with the eHMI on, at a zebra crossing, in the pedestrian simulator lab. The yellow cross indicates the pedestrian's starting position at the curb (adapted from Yang et al., 2023).

In this CAVE-based pedestrian simulator study (as shown in **Fig. 6**), pedestrians crossed the road in response to an AV from the right, simulating British road conditions. Half of the scenarios involved zebra crossings, and half of the time, the AVs' yielded to pedestrians. Additionally, half of the AVs that yielded used eHMIs to signal their intent. The study tracked pedestrians' head movements as an indicator of their crossing intent and SA (Kooij et al., 2019; Rasouli et al., 2018). The results show that the frequency of head-turning increased in the presence of yielding AVs. Interestingly, the number of head turns was lowest when the AV was equipped with an eHMI and zebra crossings were present. As participants became more exposed to the scenario, their head turns were less frequent without the eHMI (as illustrated in **Fig. 7**). Contrary to previous studies, no consistent learning patterns were detected with eHMI regarding pedestrians' head movements. This difference may stem from the unique yielding behaviour design; the AV edged slightly forward at the intersection, providing a challenging scenario for participants to understand and adapt to.

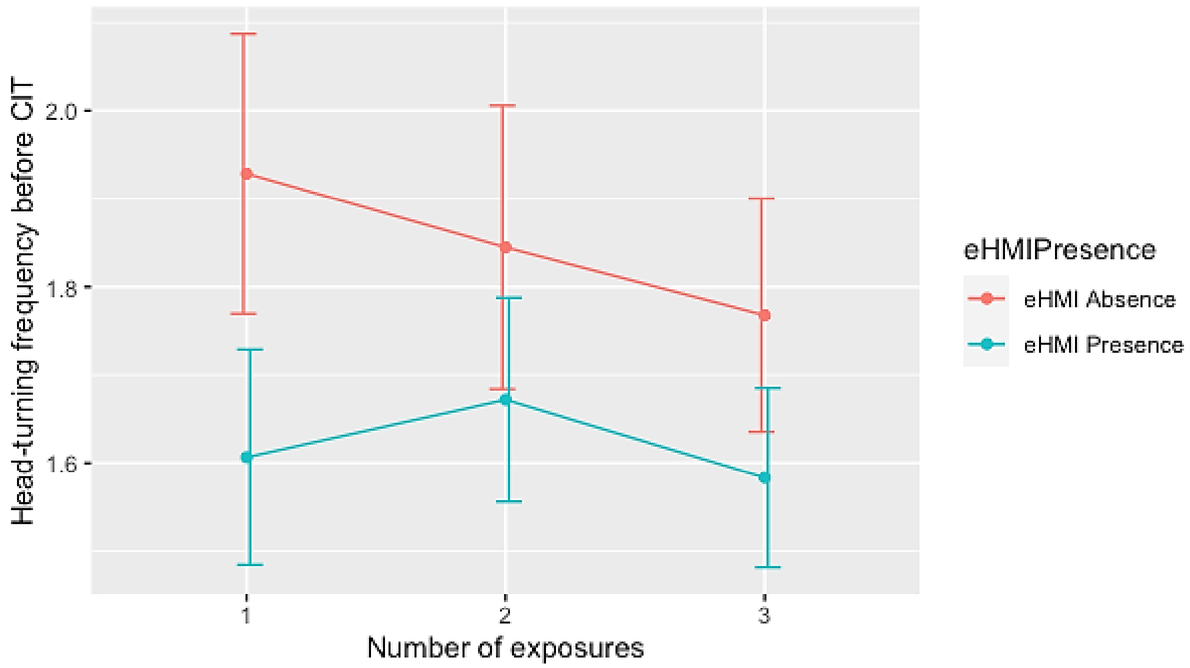

Figure 7. Pedestrians' head-turning frequency before crossing initiation time (CIT) in response to repeated exposures with or without an eHMI (adapted from Yang et al., 2023).

These results highlight the critical role of AV's motion patterns in influencing pedestrian decision-making and information collection (Lee et al., 2020). Therefore, it is imperative to design future AVs with intuitive, human-like driving behaviour and to understand how pedestrians adapt to the driving behaviour of AVs, not just how they learn with exposure to eHMIs.

4 Future outlook

Without a doubt, long-term research in the field of automated driving has been neglected. The reasons have been highly emphasised by many researchers. However, just because this type of research is challenging, tedious, expensive, and time consuming does not mean it's not a valuable asset for quality interaction design strategies. Unfortunately, due to the competing demands in the economic world of industry, many are not keen to invest time and effort in such research. They would rather take the short-term route to knowledge discovery. It should be noted that this is not to say that short-term studies are not important; however, the value that long-term research offers to understanding the design, the user or VRU (e.g., pedestrians), and understanding the interaction itself is of importance for long-term safety, satisfaction, and efficiency, among other priorities.

As already argued, it is essential to understand long-term effects from the perspectives of both drivers and VRUs (e.g., pedestrians) if the aim is to optimise AV design in terms of behaviour-based safety, mitigating risky behaviour, and constructing desired BAC. There is no existing long-term research (based on the correct definition of 'long-term', which consist of years of exposure), but there are a few repeated usage/exposure studies that have focussed on HAI, from the perspectives of driver-automation scenarios and pedestrian-AV scenarios. In these studies, the main focus has been on assessing the learning effects and behaviour adaptation from using the ACC. And as with any technological system, there are various factors that influence the interpretation of the assessment. Further, the likely occurrence of conditions when an automation system reaches the limits of its Operational Design Domain (ODD) must be considered. Furthermore, it's important to consider possible causative factors, the environment factors (road type, infrastructure, traffic signs, etc.), user type factors (user states, personality, knowledge and experience, etc.), ecological factors (weather conditions, such as fog, rain, snow, etc.), the automation system design factors (e.g. its capabilities and limitations, brand type, HMI design factors such as its transparency, comfort elements, etc.), and the interaction design factors (e.g. usability, learnability, adaptability, complexity, etc.). Most if not all of these factors have not undergone long-term investigation to understand their long-term effects. Moreover, in existing research on repeated exposure investigations between AV and pedestrian interactions, the main focus has been on pedestrians' adaptation and interpretation of eHMIs. However, there are numerous contextual factors that influence pedestrian behaviour that have not yet been fully explored for their long-term effects.

A large body of research illustrates the profound impact of sociodemographic factors such as cultural background and age on pedestrians' crossing behaviours (Yagil, 2000). These factors may also determine pedestrians' learning and interpretation of eHMIs, as well as their long-term adaptation to AVs in general.

To conclude, it must be acknowledged that while the development and evaluation of eHMIs remain important, they represent only one communication mechanism in AV and pedestrian interactions. An equally important aspect that deserves academic attention is the long-term effect of the kinematic behaviour of AVs and related pedestrian interactions. Ensuring that AVs are both intuitive and reminiscent of the driving behaviour of a human-driven vehicle can enhance predictability and mutual understanding in shared spaces.

While current research focusses on the initial learning and behavioural changes, we have demonstrated that it is also important to investigate changes over extended periods (Grossman, Fitzmaurice & Attar, 2009; Mbelekani & Bengler, 2023). In fact, it is worth noting that a considerable number of existing studies have a short duration and employ simplified environmental settings. Real-world urban environments are characterised by multifaceted interactions involving multiple VRUs, such as pedestrians and cyclists, and a range of vehicular traffic; yet these scenarios are underrepresented in academic research. Complex scenarios, especially when manual and autonomous vehicles coexist, pose unique challenges to both drivers and pedestrians.

Therefore, there is an urgent need to extend investigations into these more complex real-world settings. Mbelekani and Bengler (2022) emphasise the importance of research in long-term Multi-Agent Social Interactions (MASI). The diagram (**Fig. 8**) illustrates the interactive faculties of shared experiences and multi-agent co-experience with AV: the positioned driver/user/passenger experiences as well as VRU experiences. It is also important to consider deliberation on what people do in shared spaces compared to what they do when they use things alone (Mbelekani & Bengler, 2022). Neglecting the social aspect of group behaviours and experiences with HAV would be overlooking an important facet of being

This project has received funding from the European Community's
Horizon 2020 Framework Programme under grant agreement 860410

human, and what humans do when sharing space, as well as when no one is looking (Mbelekani & Bengler, 2022).

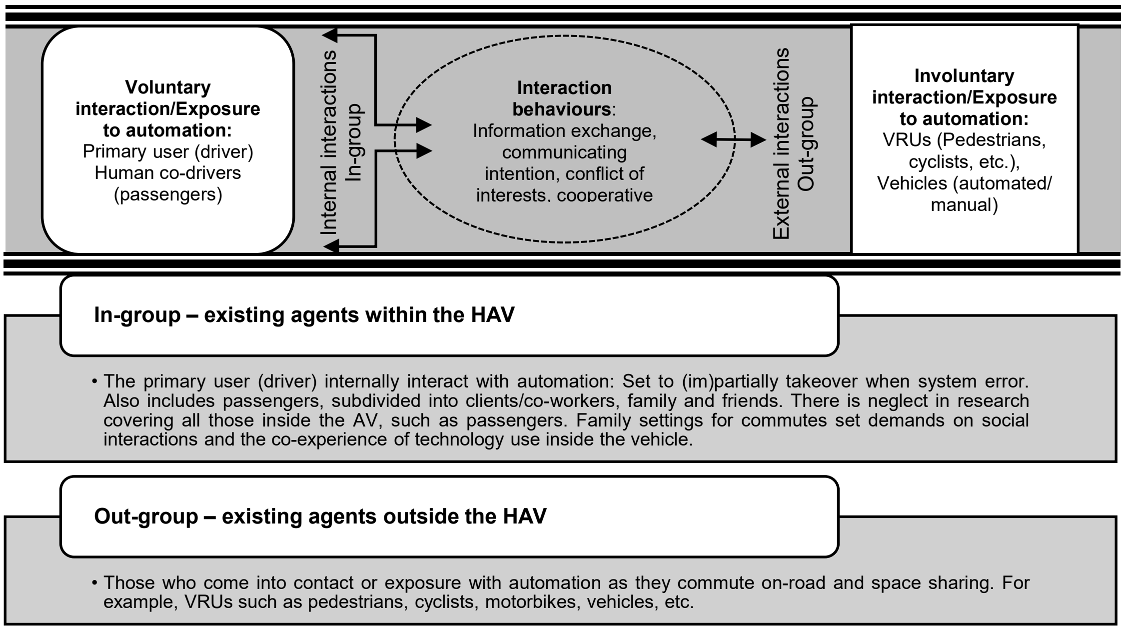

Figure 8. In-group and out-group road users – on the road and in traffic (adapted from Mbelekani & Bengler, 2022).

This space sharing may encompass different interactive factors, as humans and AVs negotiate their on-road and in-traffic interactions. Applying this thought process to MASI space sharing, each human road user within the interaction space builds up a mental model. The model is continuously changing based on various factors, e.g. emotions on a particular moment, personality, and their psychology at a particular moment, as well as environment factors (Mbelekani & Bengler, 2022).

4.1 Mixed reality simulation for MASI design and study

Mixed reality is becoming a trendy strategy for studying HAI, especially in cases where it is challenging to study systems that are not yet available for people to use. This approach allows the merging of different kinds of elements to simulate highly realistic, real-world, on-road and in-traffic scenarios and conditions, from the point of view of *in-groups* and *out-groups*. For instance, researchers could assess repeated exposure to automation, in order to understand different experience perspectives, including: the in-groups (e.g., driver/users), out-groups (e.g., VRUs), the simulated environment (e.g., on-road traffic), the HAV (e.g., driven by the driver while also connected to the virtual environment of the out-groups), the eHMI, the iHMI, and the HAV movement route (e.g., a zebra crossing scenario in which virtual vehicles and VRUs are continuously generated at regular intervals). Repeated exposure including the same participants could be conducted for a period of four weeks, in order to track changes in behaviour for both groups. This experimental design could also reveal at what point the participants' learning curves reach the ultimate plateau and whether this occurs at the same time for both groups.

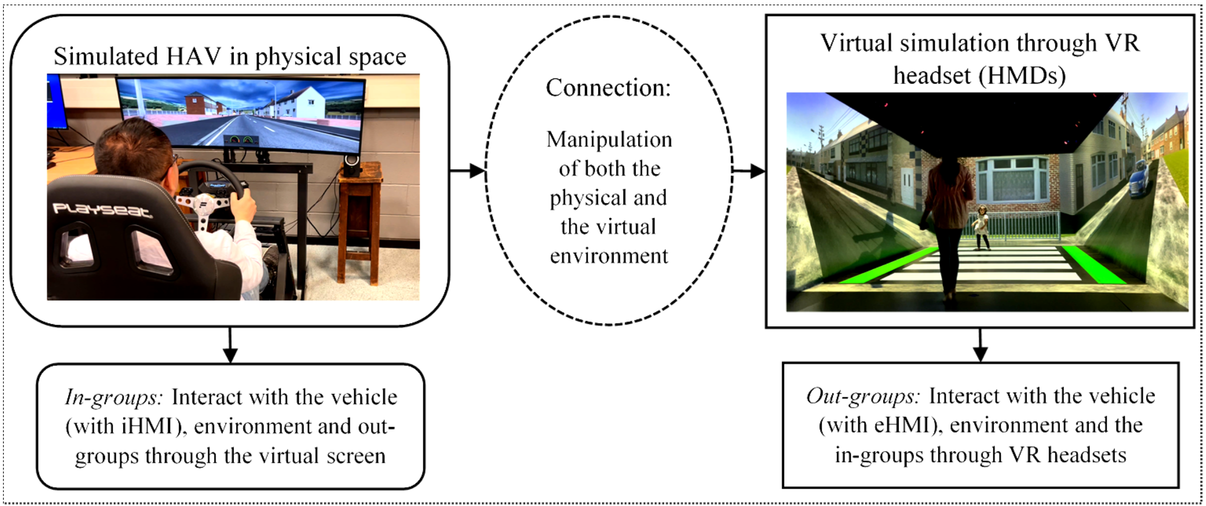

Figure 9. The virtual mixed reality environment

The aim of a study with these components can be used to understand the social cues exhibited by in-groups towards the HAVs' kinematics/behaviour on the road and in traffic situations. The reactions of out-groups towards the HAVs' different kinds of behaviours in a road crossing situation are also relevant. Social cues in this context comprise the information helping MASI realise current and future HAV behaviour.

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