BERTHA

D1.5. Definition of the model framework and its individual modules

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EXECUTIVE SUMMARY

BERTHA's details

Project name	BEhavioural ReplicaTion of Human drivers for CCAM
Project acronym	BERTHA
Grant Agreement number	101076360
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Granting authority	European Climate, Infrastructure and Environment Executive Agency (CINEA), under the powers delegated by the European Commission
Official project website	https://berthaproject.eu/

The BERTHA consortium

Nº	NAME	ROLE	COUNTRY
1	INSTITUTO DE BIOMECANICA DE VALENCIA (IBV)	Coordinator	Spain
2	INSTITUT VEDECOM (VED)	Beneficiary	France
3	UNIVERSITE GUSTAVE EIFFEL (UGE)	Beneficiary	France
4	DEUTSCHES FORSCHUNGSZENTRUM FUR KUNSTLICHE INTELLIGENZ GMBH (DFKI)	Beneficiary	Germany
5	CENTRE DE VISIO PER COMPUTADOR (CVC-CERCA)	Beneficiary	Spain
6	ALTRAN DEUTSCHLAND SAS & CO KG (CAP)	Beneficiary	Germany
6.1	VORTEX - ASSOCIACAO PARA O LABORATORIO COLABORATIVO EM SISTEMAS CIBER-FISICOS E CIBERSEGURANCA (VOR)	Affiliated entity	Portugal
7	CONTINENTAL AUTOMOTIVE FRANCE SAS (CON)	Beneficiary	France
8	FUNDACION CIDAUT (CIDAUT)	Beneficiary	Spain
9	AIT AUSTRIAN INSTITUTE OF TECHNOLOGY GMBH (AIT)	Beneficiary	Austria
10	UNIVERSITAT DE VALENCIA (UVEG)	Beneficiary	Spain
11	EUROPCAR INTERNATIONAL	Beneficiary	France
12	F. INICIATIVAS, CONSULTADORIA E GESTAO, UNIPESSOAL, LDA (FI)	Beneficiary	Portugal
12.1	F. INICIATIVAS ESPANA I MAS D MAS I SLU (FI_ES)	Affiliated entity	Spain
13	SMART EYE AKTIEBOLAG - SMART EYE AB (SEYE)	Beneficiary	Sweden

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Project's summary

The main objective of BERTHA is to develop a scalable and probabilistic Driver Behavioural Model based mostly on Bayesian Belief Networks (BBN). The DBM will be implemented on an open-source HUB (repository) to validate the technological and practical feasibility of the solution with industry, and provide a distinctive approach for the model worldwide scalability. The resulting DBM will be translated into a simulating platform, CARLA, using various demonstrations which will allow the construction of new driving models in the platform.

BERTHA will also include a methodology which, using the HUB, will allow to share the model with the scientific community, in order to facilitate its growth.

The project includes a set of interrelated demonstrators to show that the DBM can be used as a reference to design human-like, easily predictable and acceptable behaviours of automated driving functions in mixed traffic scenarios.

BERTHA is expected to go from TRL 2 to TRL 4. The requested EU contribution is €7,981,801. The consortium, formed by 13 entities from 5 countries, deems this Project as vitally relevant to the CCAM industry due to its impact for safer and more human-like CAVs and its market and societal adoption.

Document details

Deliverable type	Report
Deliverable n°	1.5
Deliverable title	Definition of the model framework and its individual modules
Lead beneficiary	IBV
Work package and task	WP1, T1.5
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Dissemination Level	PU
Purpose	Framework defining the driver model and integration of the Perception, Risk Awareness, Decision Making, Affective and Motor modules, and definition of the outputs in relation with the vehicle response concerning drivers' perception and reaction.

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Document's abstract

This report presents the framework of BERTHA's driver behaviour model (DBM), which will be the basis for its development. It is primarily aimed to developers of software and systems of BERTHA, as well as other members of the Consortium who work in tasks that involve the DBM, although it also serves as a publicly available summary of the main features envisaged for BERTHA's DBM.

The document is structured in six sections, with the first three (*Introduction*, *Background and Overview* of the *BERTHA DBM*) providing general information about the DBM, and the following ones (*Description of the individual modules*, *Interfaces*, and *Framework of the general probabilistic model*) focusing on technical details.

The information provided in the report sets the basis for the parallel developments of the modules that comprise the DBM (Perception, Risk Awareness & Decision Making, Affective, and Motor Control), as well as for their integration in a probabilistic model, with a special focus on the interactions between them and with the CARLA simulator — the architecture that will give support to the majority of tests in BERTHA. That information is crucial in order to ensure the congruency and synergy of the different software developments, in the modular and scalable architecture of BERTHA.

Document's revision history

The following table describes the main changes done in the document since it was created.

REVISION	DATE	DESCRIPTION	AUTHOR (PARTNER)
V.0.1	25/07/2024	First draft with descriptions of modules and probabilistic framework.	(See list of authors)
V.0.2	11/09/2024	Complete draft with inclusion of interfaces and CARLA integration	Helios De Rosario (IBV)
V.1.0	11/10/2024	Document ready for revision	Thierry Bellet (UGE) Shreedar Govil (DFKI) Antonio López (CVC) Helios De Rosario (IBV)
V.1.1	28/10/2024	Final version after revision.	(See list of authors)

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Terminology and acronyms

TERM/ACRONYM	EXPLANATION
ACT-R	Adaptive Control of the Thought—Rational
ADAS	Advanced Driver Assistance Systems
API	Application Programming Interface
BN	Bayesian Network
CAV	Connected Autonomous Vehicles
CCAM	Connected, Cooperative and Automated Mobility
CINEA	Climate, Infrastructure and Environment Executive Agency
DAG	Directed Acyclic Graph
DBM	Driver Behavioural Model
DBN	Dynamic Bayesian Network
EC	European Commission
HF	High Frequency
HR	Heart Rate
IVIS	In-Vehicle Information Systems
LF	Low Frequency
OOBN	Object-Oriented Bayesian Network
RMS	Root Mean Square
ROS	Robot Operating System
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SD	Standard Deviation
SR	Sleep-related
TR	Task-related
UC	Use Case(s)
WP	Work Package

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1. INTRODUCTION AND OBJECTIVES

This document presents the framework in which BERTHA's Driver Behavioural Model (DBM) is defined. The purpose of the document is to serve as a common ground for the detailed development of the modules that compose the DBM, namely the Perception, Risk Awareness and Decision Making, Affective, and Motor Control modules, in order to ensure that they are compatible with each other, and that it is feasible to develop a probabilistic DBM based on them, which can be used in the different tasks of the BERTHA project.

In order to achieve this, the three organisations in charge of the development of the modules (IBV, UGE and DFKI) have worked together with UVEG, who are responsible of building the probabilistic model in the task T1.6, and AIT as main partner dealing with the profiling of drivers (T1.2), in order to outline the shared principles and basic interactions between the DBM individual components. The proposal has also been conferred with work package leaders in order to assure its alignment with other activities of the project. This work was launched in a dedicated workshop in the Kick off meeting of the project (Valencia, November 23rd 2023), and coordinated among the participants through posterior teleconference meetings, with a monthly schedule between April and October 2024.

The results are presented in this document, which is structured as follows:

- Section 2 (BACKGROUND) presents a brief summary of the nature, scope and types of DBM in past and present research, in order to contextualize the decisions made by the BERTHA Consortium, regarding the characteristics of the DBM that will be developed in the Project, which attempts to address some of the challenges and limitations of state-of-the-art technology.
- Section 3 (OVERVIEW OF THE BERTHA DBM) presents a general view of the structure of BERTHA's DBM, based on scalable modules and a probabilistic framework, and describes how different tasks of Work Package 1 (WP1) contribute to its development.
- Section 4 (DESCRIPTION OF THE INDIVIDUAL MODULES) describes the building blocks of the DBM, which are the Perception, Risk Awareness & Decision Making, Affective, and Motor Control Modules. The structure, variables, and Key Performance Indicators (KPIs) of each module are presented, together with example cases that illustrate how they are meant to work.
- Section 5 (INTERFACES) gives further details about how the different modules will be related to each other and with CARLA's simulation, which is the informatic architecture that will give support to the majority of tests for BERTHA's developments.
- Section 6 (FRAMEWORK OF THE GENERAL PROBABILISTIC MODEL) presents the main concepts of the Bayesian Networks (BN) that have been chosen in BERTHA as a general overarching approach for the integration of the DBM. An example based on a preliminary definition of the Affective Module is given, in order to illustrate how such integration can be done.
- Finally, section 7 (GENERAL CONCLUSIONS) provides a final wrap-up to summarize the main points of the document and advances the next steps of development.

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2. BACKGROUND

The concept of Driver Behavioural Models (DBM) comprises all kinds of computational representations of the way humans behave during driving, which are the subject of a large body of research during the last half century. Through decades, this research has been motivated by the pursuit of accident prevention and improvement of safety, although the advancement of the technology involved in transportation systems has led to increased ambitions, more complex approaches and new challenges.

Early research on DBM was closely tied to the "cognitive revolution" in sciences of the second half of the 20th century, from which emerged numerous initiatives to model human cognitive processes and behaviours in both general and applied contexts. Those investigations defined perceptual, cognitive and motor skills of the drivers as the basic dimensions to be taken into account (Michon, 1985), in order to understand the factors that influence driving performance and risks, and improve training programs road safety policies. The initial decades of DBM research can be roughly divided in three phases: the emerging research of the 1970s dedicated to the description, classification and analysis of driving tasks, performance and errors; a second phase during the 1980s with a greater focus on the driver during the 1980s, which models of human information processing; and the introduction of computational models in the 1990s, which allowed the simulation of such processes (Bellet et al., 2007).

In the 21st century DBM research has been mostly motivated by its application to Intelligent Transport Systems. The growing presence of In-Vehicle Information Systems (IVIS) and Advanced Driver Assistance Systems (ADAS) raised questions about how they affect the driver's performance, mental workload and the emotional experience of driving, and what trade-offs they implied regarding risk awareness, decision making and motor control for accident prevention. In this context, the European Commission (EC) promoted the research on "eSafety" of transport as part of its thematic priorities since the 6th Framework Programme, which led to projects on this area such as AIDE (Tattegrain Veste et al., 2005), HUMANIST (Janssen, 2007) or PReVENT (Amditis et al., 2010). Those investigations led to the concept of the "cognitive car" (Heide & Henning, 2006), in line with the then growing research endeavours towards the development of connected autonomous vehicles (CAV).

The present reality about CAV brings to light safety-related challenges that involve not only the performance and potential errors of CAV, but also the behaviours of human drivers in the presence of CAV and their interaction. For this reason, it is important to develop reliable and comprehensive models of human driving, which integrate information from multiple sources, are able to detect and manage unsafe behaviours, and prevent misunderstandings and incompatibilities between human drivers and CAV in situations of mixed traffic (Hang et al., 2023).

There are many approaches to DBM, derived from the multiple contexts in which they have been researched and developed. Those approaches can be classified as theory-based, physics-based, and data-driven (Negash & Yang, 2023), such that each approach addresses different needs and priorities of the problems related to the modelling of driver behaviours.

Theory-based approaches define abstract models of the driver's cognitive aspects and the requirements of driving tasks. In those models, drivers are represented as embodied cognitive architectures — mainly in the forms of Adaptive Control of the Thought-Rational

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(ACT-R), Queuing Network–Model Human Processor (QN-MHP), or Goals, Operators, Methods, and Selection (GOMS) models (Park & Zahabi, 2024).

Physics-based approaches are usually focused on particular manoeuvres such as car following (Zhang et al., 2024) or lane change (Yunus et al., 2021), which are described in great detail, with mathematical descriptions of the kinematics and dynamics of the vehicle and the driver actions in the manipulation of its controls (chiefly steering wheel and pedals). Such models can also take into account physically measurable aspects of human behaviour such as perception and reaction times.

Data-driven approaches attempt to predict drivers' behaviours using state-of-the-art machine learning algorithms, with big datasets collected from real-life and laboratory settings. The focus of such models is, rather than the explanation of the cognitive or physical processes, the successful prediction of actions performed by drivers and their associated risks, for safer and more efficient Connected, Cooperative and Automated Mobility (CCAM) (Z. Li et al., 2023), as well as driver profiling and classification (Abdelrahman et al., 2022).

Many DBM participate to different degrees in the three approaches, putting more emphasis on one or the other. Historically, that emphasis has moved progressively from theory and physics-based to data-driven models, as the types of driving tasks grew in variety and complexity, and the improvements in computer science, sensor technologies and infrastructures have made possible dealing with Big Data and the current advances in Computer Science and Artificial Intelligence. But models based on predefined processes and rules, with adjustable parameters, are still widely used and gaining traction for CCAM applications, since black-box models based on neural networks lack interpretability and often exhibit unrealistic, even dangerous behaviour in regions of the state-space that are under-represented in the training dataset (Bhattacharyya et al., 2020).

While also participating partially in the three approaches, the focus of BERTHA's DBM is on the description of the cognitive aspects of the driver's behaviour. In such a model, as depicted in Figure 1, the driver is defined as an embodied cognitive architecture that processes the information of the surrounding environment, including the movement and signals of their own vehicle, surrounding traffic, etc., and adapts its actions and responses to the incoming stimuli in order to achieve some goal related to the driving task. Those tasks are itemized and listed in hierarchical stages, depending on the complexity of the cognition processes that they involve — from automated sensory-motor skills to knowledge-based behaviours (Rasmussen, 1983), or their scope in terms of time and space — from operational to strategic levels (Michon, 1985).

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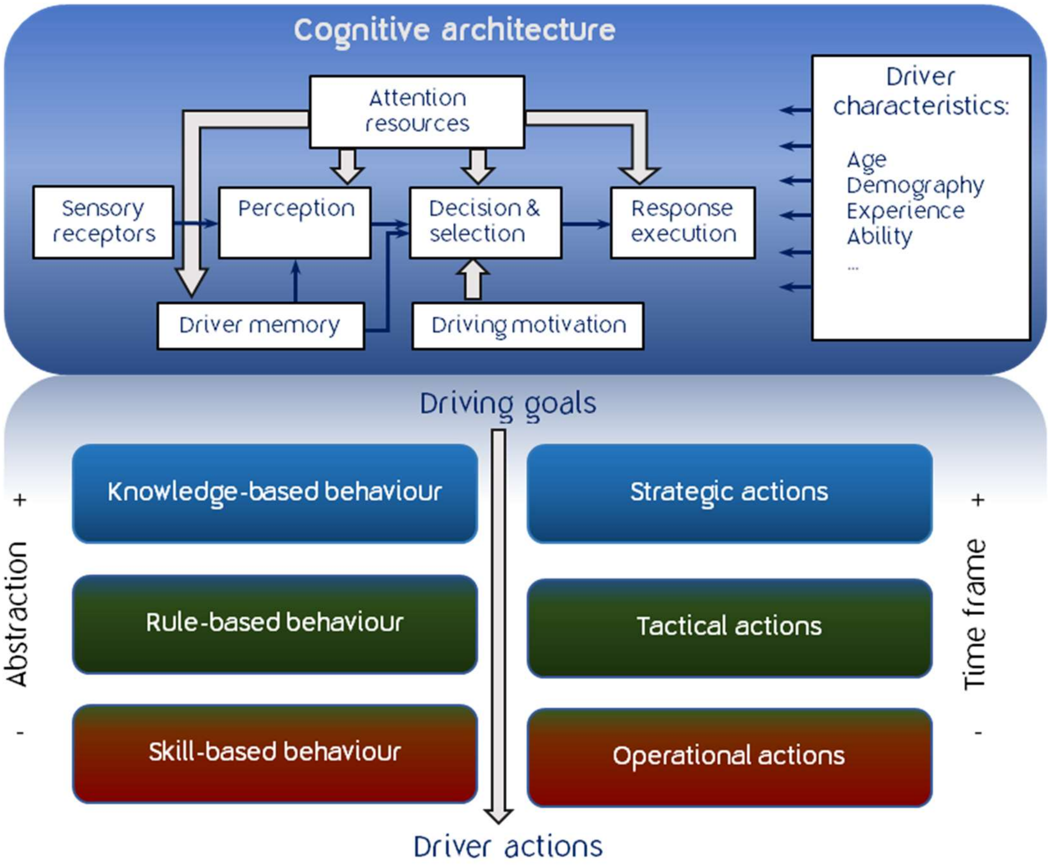

Figure 1. Driving modelling conceptual framework, adapted from Negash & Yang (2023)

An important challenge for current DMB is the difficulty of capturing the variety of complex environmental conditions and agent behaviours that can be presented in driving scenarios (Codevilla et al., 2019). This affects the scalability of the models, and their capacity of obtaining reliable solutions when the set of players and situations depart from the particular use cases considered for their definition and training.

In order to address that challenge, BERTHA's DBM has been conceived as a modular architecture (cf. section 3), which will be integrated in the framework of probabilistic modelling (cf. section 6). This will allow to build a parsimonious model capable of growing up as new evidence is gathered, and at the same time to quantify the uncertainty associated with the specific individual characteristics of drivers, environmental conditions, characteristics of the target routes, possible interactions between different drivers on the same route, etc.

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3. OVERVIEW OF THE BERTHA DBM

3.1. Modular Framework

BERTHA defines a DBM based on modules, which helps to explain the partial effects of different factors in a structured manner, and allows to scale adding other aspects of human cognition and performance. Moreover, modularity facilitates the validation of the models, since it decomposes the complexity into components that are easier to validate with fewer data.

Such a modular approach has been successfully used by the COSMODRIVE model (Bellet et al., 2007), based on the perception-cognition-action loop that characterizes information processing workflows, and is the basis of cognitive architectures in many areas of engineering (Wickens et al., 2021).

The modules of BERTHA's DBM (Figure 2) is built upon that structure, with an enlarged consideration of the aspects involved in the "cognition" block, which includes risk awareness, decision making and affective factors.

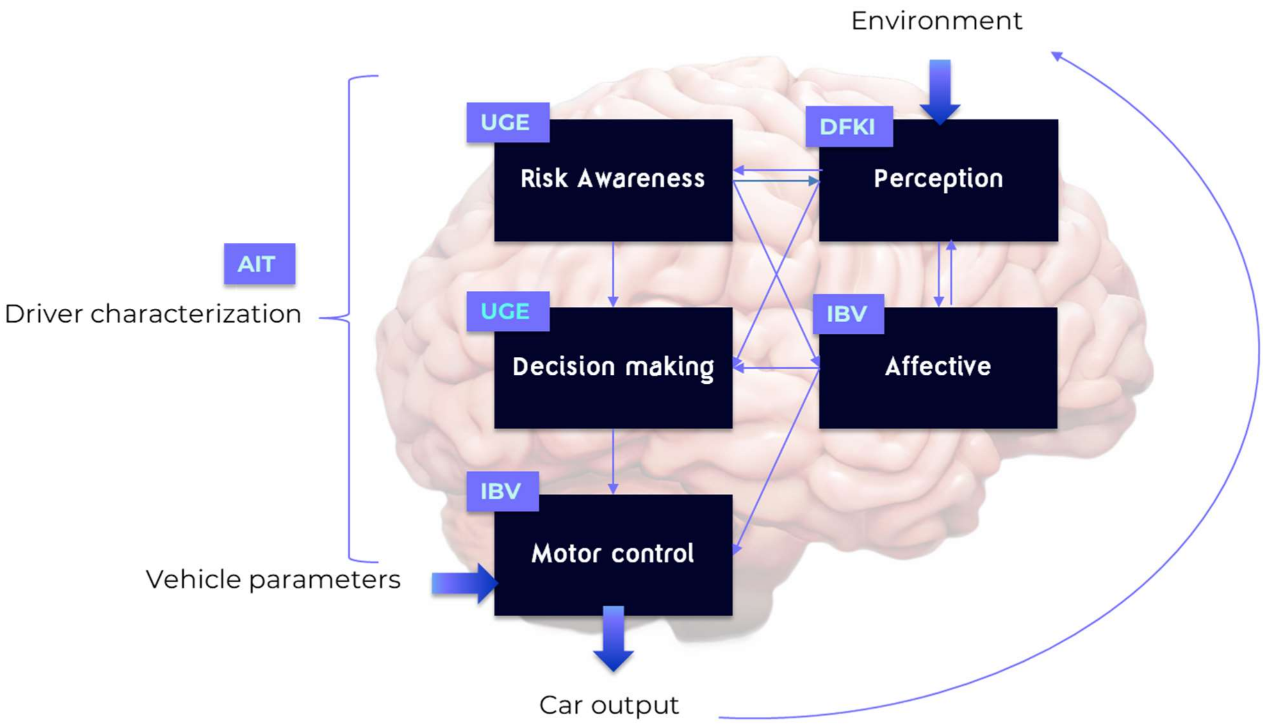

Figure 2. Modular framework of the BERTHA DBM

These modules, whose main features are described in the next section, are being developed in parallel with the lead of three different organizations within the BERTHA Consortium (DFKI, IBV and UGE, as presented in the figure).

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The ***Perception module***, developed by DFKI, will be the main entry point of information for the DBM. It will model the ability of drivers to perceive and interact with the driving environment, focusing on the inputs obtained through the visual channel, using state-of-the-art methods to obtain semantic maps from images.

A naturalistic computational model will be developed by UGE for the ***Risk Awareness and Decision Making modules***, which are meant to simulate those cognitive processes for the Use Cases of the project. As a model of real humans, these modules will simulate both (1) safe decision making and (2) naturalistic human errors (e.g., deliberatively risky behaviours or critical decision making due to an underestimation of the risk) liable to be performed by real drivers.

The ***Affective Module***, developed by IBV, is one of the specific innovations of BERTHA for the DBM. This module represents various aspects of the cognitive and emotional state of the drivers, like their level of stress, mental workload, attention and fatigue. Those are aspects that have a strong influence on driver's behaviours, and are often implied in the cognitive architectures, associated to features of the attentional and information processing mechanisms. In BERTHA we are encapsulating them explicitly as a separate, extensible module, which is meant to interact with the other modules introducing biases in the perception (e.g. by variations in attention, drowsiness, etc.), in the Decision Making module (influencing on the motivations and attitudes) and in the motor control (e.g. a softer or more aggressive driving style).

The ***Motor Control module***, also developed by IBV, is in charge of translating the sensory inputs, mediated by the cognitive processes, into the physical actions that control the vehicle, through a feedback loop that relates the path and speed planned (desired) by the driver, and the actual motion of the vehicle. Its output will be a set of vehicle control parameters, including, among others, the position of the steering wheel angle and the percentage of activation of the throttle and the brake. This will consider internal representations of the physical models that are involved, as well as time delays and other parameters of the feedback loop that depend not only on the person, but also on the situation and aspects that are being considered in other modules — particularly the affective module.

For all this this, BERTHA's DBM will consider the existing variety of drivers, in terms of experience, driving habits, physiological and psychological profiles, as well as the physics and dynamics of vehicles, taking into account how they can be influenced not only by the type of the vehicle, but also by the conditions of the environment.

3.2. Bayesian approach

The BERTHA Project is aimed at developing a DBM in a probabilistic framework, since driver behaviours are inherently stochastic and influenced by multiple factors, such as traffic conditions, weather, or individual preferences. Probabilistic models are capable of accounting for that complexity, by modelling uncertainty explicitly. This makes such kind of models them better suited for real-world scenarios where deterministic assumptions may fall short.

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Within the general approach of probabilistic modelling, Bayesian models have been chosen for the purposes of BERTHA. In a Bayesian framework, the probability distributions of the variables considered in the model are defined on top of prior knowledge or beliefs, which can be distributions obtained from theoretical models, preliminary estimations, sample data, or probabilistic parametrizations of previous results. Observed data are used to update that prior knowledge and build *a posteriori* probability distribution. Two remarkable advantages of Bayesian models are that (a) they can represent a large variety of distributions with few parameters, which facilitates their fitting with relatively scarce data, granted that there is a reasonable generation of the prior distribution, and (b) they allow incremental updates as new data arrive, which favours their scalability (Ma, 2019).

More specifically, a framework based on Bayesian Networks (BN) will be prepared, with the aim of giving support to the different modules of BERTHA's DBM, independently from the development strategy of each individual module. Section 6 of this document provides further details of that framework.

3.3. Contribution of WP1 tasks

The development of BERTHA's DBM is the overarching objective of WP1, and all the tasks of this work package converge to it. This document is framed as an activity of the **Task T1.5** ("Definition and calibration of the modules of the model") and focuses on the basic specifications of the individual modules of the DBM, but there are interactions with all the other tasks.

Prior to the current work, in **Task 1.1** (Use cases definition) a set of five use cases has been defined: (i) a collision risk avoidance on highway, (ii) an insertion on highway, (iii) a pedestrian crossing in urban area, (iv) Left turn at urban intersection (with traffic lights), and (v) a pull-back in on urban highway, which will serve as the basis for the definition, calibration and validation of the DBM. Those use cases can be applied both in simulation and in field operational tests, and are sufficiently challenging and address a variety of driving situations, adequate to encompass different perceptual, cognitive, affective and motor inputs, processes and outputs dealt with by the DBM.

In parallel to the current task, **Tasks 1.2, 1.3 and 1.4** are aimed at characterizing the main components of the context in which the DBM must operate: the spectrum of drivers, influencing parameters beyond the driver, and the vehicle's response, respectively. More precisely, T1.2 is developing a typology of driver profiles and driver reaction patterns. T1.3 focuses on situational factors of the road and traffic, other agents and the environment, as well as and the interactions with personal factors that influence driving, such as emotion, fatigue and stress. And T1.4 deals with the physics and dynamics of the vehicle, and how they are implemented in software simulations to ensure that the outputs of the DBM are realistic and match the results that are to be observed in real life.

Subsequently, **Task 1.6** (Building of the probabilistic model) will work in the integration of the different modules, with a special focus on their adaptation to the probabilistic framework that is intended to be a key feature of BERTHA's DBM. And **Task 1.7** (Validation) will put the results to test with data obtained in activities of WP2, to verify that the variability of driver behaviours provided by the DBM behaves as the recordings in real life.

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4. DESCRIPTION OF THE INDIVIDUAL MODULES

4.1. Perception module

4.1.1. Background

Driving is fundamentally a visual-motor task, meaning there is a strong connection between what a driver sees and the actions they take. Therefore, to create a human-like driver behaviour model, it is crucial to identify where a vehicle should focus—on pedestrians, cyclists, other vehicles—while filtering out unnecessary information (Alletto et al., 2016). This approach not only enhances system performance but also makes self-driving systems more explainable and trustworthy.

The perception module of Project BERTHA aims to deliver this focus by utilising onboard sensor data from the car, including camera images, GPS information, speed, and acceleration. Previous studies have shown that incorporating gaze information into autonomous vehicles can improve their driving performance (C. Liu et al., 2019; Xia et al., 2020). However, relying solely on images for gaze prediction is not enough. Drivers need contextual information, such as speed, intent, and pedestrian or vehicle movement, which greatly influences their gaze patterns.

For instance, Pal et al. (Pal et al., 2020) found that adding semantic information and pedestrian intent prediction can improve gaze prediction and attention maps. Similarly, Kotseruba & Tsotsos (2024) reported that incorporating contextual data like turning intent through GPS maps yields similar improvements. Therefore, by integrating additional contextual data, we can provide more meaningful information to the perception module, ultimately enhancing its performance.

Designing a human-like perception system is a complex task. Every driver has a unique driving style, which they adapt based on internal factors such as age, experience and external factors such as weather, time of day, and traffic conditions. This variability is addressed in Deliverables 1.2 and 1.3, which discuss the influence of these internal and external factors on driving behaviour. To develop accurate models, it is necessary to study how these conditions impact a driver's attention and decision-making processes. This requires extensive data collection and analysis.

By accounting for these variables, the perception module can help develop a more human-like and explainable perception system for autonomous vehicles. Training the system to adapt to changes in weather, lighting, and other conditions will enable a safer and more trustworthy approach to autonomous driving.

4.1.2. Structure of the module

The perception module of BERTHA will utilise a neural network architecture developed in PyTorch (Paszke et al., 2019). This architecture will include various submodules that process images, state information, map data, etc. to generate saliency maps for downstream modules. The perception module requires a CUDA-enabled GPU for faster inference, and will communicate with the other modules via ROS based real-time communication protocol.

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4.1.3. Variables of the module

Inputs

- Camera Sensor inputs such as:
    a. RGB images from the driver's perspective.
    b. Instance segmentation
    c. Depth information.
- Car state information such as:
    a. Speed.
    b. Acceleration.
    c. GPS coordinates.
    d. IMU readings.
- Task dependent information like driving intent.
- Surrounding Map information.

Outputs

- Saliency map indicating the driver's visual attention at a given time horizon.
- Attention at objects (cars, pedestrians, etc.) that need to be focused on.

4.1.4. Example case

Consider a scenario where an autonomous vehicle needs to turn left at a busy intersection. In this situation, the vehicle must be able to perceive and react to various dynamic elements in its environment. Imagine a human driver in the same scenario: they would glance at the moving cars and pedestrians, monitoring their positions and movements, while largely ignoring stationary objects like buildings or trees. The driver's attention shifts based on the context and the need to make a safe and timely decision, such as accelerating or braking.

To make autonomous vehicles more adept in such scenarios, this module aims to develop a perception model that emulates human-like attention. For example, when the autonomous vehicle approaches the intersection, the perception module will prioritise detecting and analysing moving cars and pedestrians over static objects. This model will use human gaze data to learn which features are most critical in various driving situations.

As a result, the perception module will provide downstream decision-making systems with prioritised and contextually relevant information. By focusing on the most important elements and filtering out less critical data, the vehicle can make more informed and safer decisions when navigating complex environments like busy intersections.

4.1.5. KPIs

Kullback-Leibler divergence (KL divergence, DKL), Pearson's Correlation Coefficient (CC), Normalised Scanpath Saliency (NSS) and histogram similarity (SIM) are four commonly used metrics for attention map prediction (Bylinskii et al., 2019; Kotseruba & Tsotsos, 2024; Palazzi et al., 2017; Tawari & Kang, 2017). We will use these scores to compare the performance of our model with current state-of-art models in eye gaze prediction as a baseline.

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4.2. Cognition module: Risk Awareness & Decision Making

4.2.1. Background

The Cognition module to be developed for BERTHA by UGE, combining Risk Awareness and Decision Making processes, will be based on the theoretical model COSMODRIVE (COgnitive Simulation MOdel of the DRIVEr) developed at UGE during the 2 last decades (Bellet et al., 2007, 2012; Bornard et al., 2016). Synthetically, the aim of this model is to virtually simulate the human drivers' cognitive processes implemented when driving a car, through a dynamic (and iterative) "Perception-Cognition-Action" regulation loop (Figure 3).

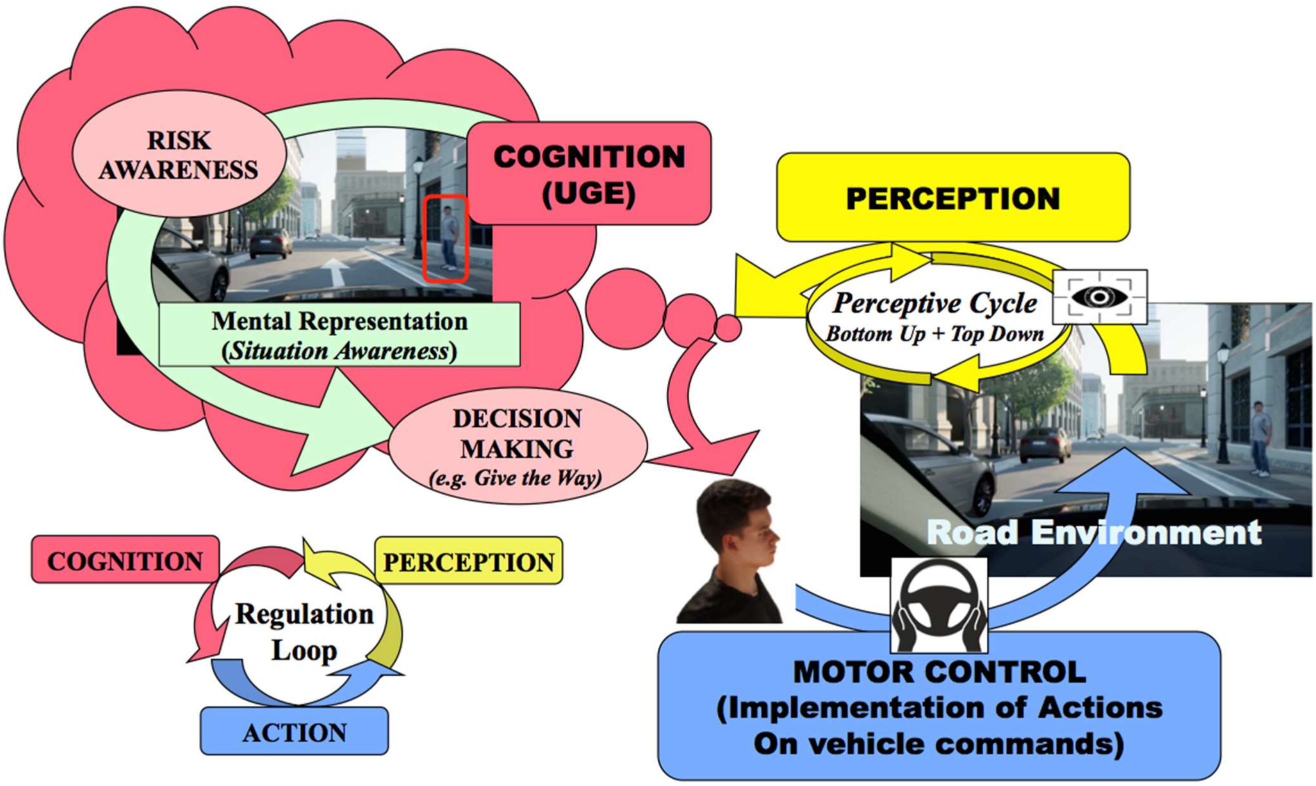

Figure 3. Driving Activity modelling as a "Perception-Cognition-Action" regulation loop in the COSMODRIVE theoretical model

The central component of COSMODRIVE theoretical model are mental representations (Bellet et al., 2009) of the driving environment, corresponding to the driver's *Situation Awareness*, according to Endsley (1995) definition of this concept (*the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future)*. Mental representations, as mental models of the traffic situation, are dynamically formulated in working memory through a matching process between (i) information extracted/perceived in the external road environment and (ii) pre-existing *operative* knowledge that are modelling in COSMODRIVE as *Driving Schemas* (Bellet et al., 2012; Bellet & Tattegrain-Veste, 1999). Based on both the Piaget's concept of *Operative Scheme* (1937) and the Minsky's *Frames Theory* (1975), a driving schema is a computational formalism defined at UGE for modelling

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prototypical situations (including related actions and events) learnt by the driver from their empirical driving experience.

From a formal point of view (Figure 4) a *Driving Schema* is a functional description of road infrastructure combining (i) a *Tactical Goal* (e.g., to turn to the left), (ii) a sequence of *States* and (iii) a set of *Zones*. Two types of zones must be distinguished: *Driving Zones* (*Zi*), corresponding to the driving path of the car for progressing in the crossroads, and *Perceptive Exploration Zones* (*exi*) corresponding to area of interest in which the driver seeks information (e.g. potential events liable to occur). Each driving zone is linked with *Actions* to be implemented (e.g. braking or accelerating, in view to reach a given state at the end of the zone), with required *Conditions* for performing these actions, and with perceptive exploration zones permitting to check these conditions (e.g. colour of traffic lights, presence of other road users). A *State* corresponds to a given position and velocity of the ego-car. The different sequences of driving zones allow the driver to go from the initial state to the final state of the driving schema (i.e. achievement of the tactical goal), by potentially using different behavioural alternatives.

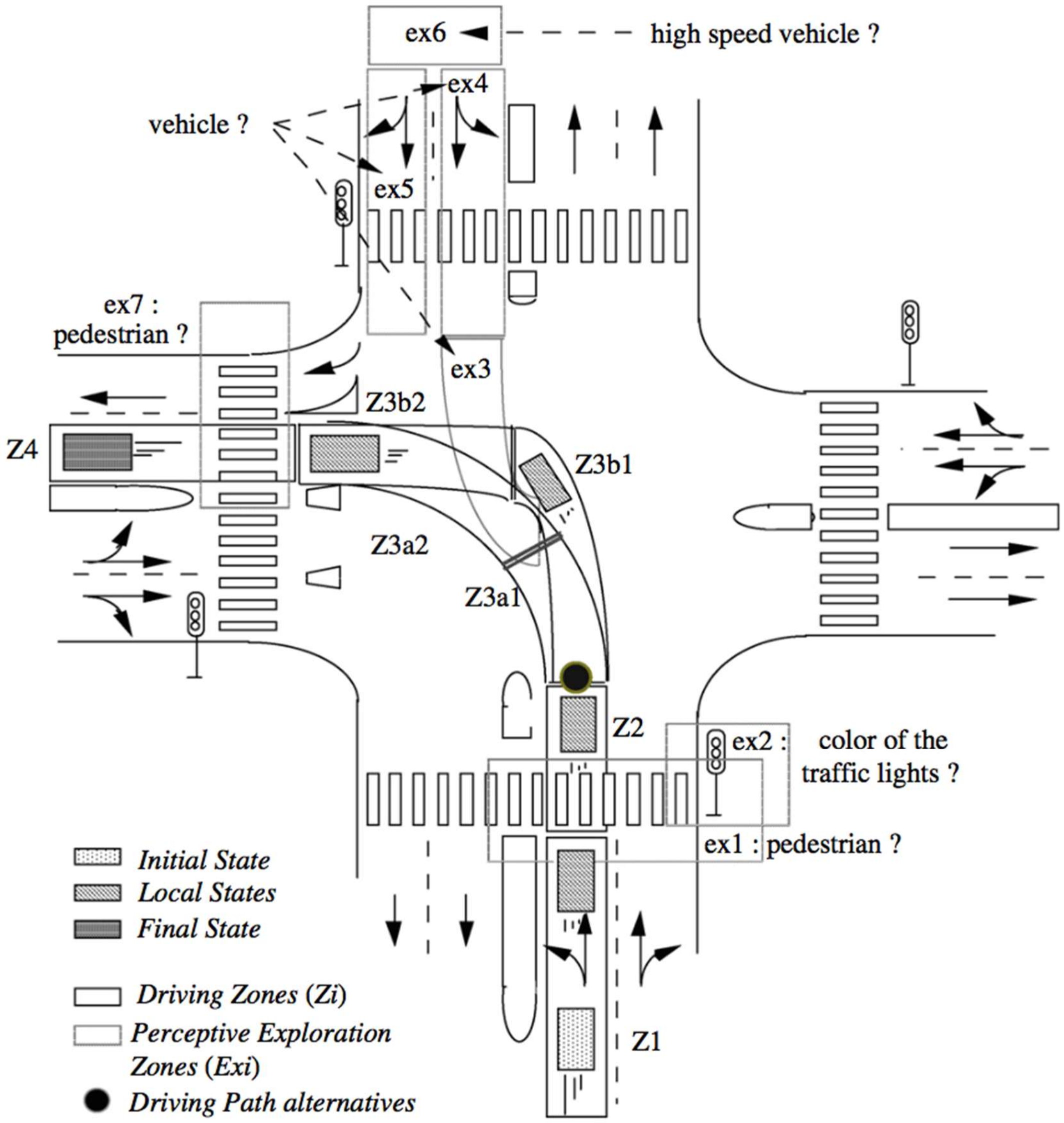

Figure 4. Example of COSMODRIVE's Driving Schema (Turning Left at a Crossroads; Bellet et al, 2012)

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Once activated in working memory and instantiated with the current traffic situation, the driving schema becomes the tactical mental representation of the driver (corresponding to their Situation Awareness), which will be continually updated as and when s/he progresses into the current road environment.

To progress along the driving schema, COSMODRIVE model regulation strategy is also based on the "*Envelope Zones*" (Figure 5). From a theoretical point of view (Bellet et al., 2007), the concept of *envelope zones* recalls two theories in psychology: the notion of *body schema* proposed by Schilder (2013), and the *theory of proxemics* defined by Hall (1990) relating to the distance to be maintained in social interactions with other humans. Regarding the car-driving activity, envelope zones also refer to the *safety margins* concept of Gibson and Crooks (1938), largely reused by several authors. At this last level, COSMODRIVE model approach is more particularly based on Kontaratos' work (1974), distinguishing a *safety* zone, a *threat* zone, and a *danger* zone (in which no other road user should enter; if this occurs, the driver automatically activates an emergency reaction). Envelope zones are "relative", because their sizes are dependent of the speed of the ego-car. They correspond to the portion of the path of the driving schema to be occupied by the ego-car in the near future (until 1.8 seconds). In accordance with Schilder's body schema theory, this 3-Dimensional "virtual skin" surrounding the car is permanently active while driving, as an *implicit awareness* (Bellet et al., 2009) of the expected allocated space for moving. It is used by drivers for assessing others' positions, motions and potential dangerousness. This highly integrated ability is therefore a key process supporting the regulation loop, but also playing a core role in hazard or the critical path conflict detection and driver's decision making. Moreover, as a *hidden dimension* of the social cognition as described by Hall (1990), these proxemics zones are also mentally projected to other road users, and are then used to dynamically interact with other vehicles as well as to anticipate and manage collision risks. Therefore, envelope zones play a key role in the regulation of social (i.e., courteous *versus* rude and aggressive behaviour) as well as physical interactions with other road users under normal driving conditions (e.g. inter-vehicle distance keeping) or for assessing critical path conflicts and dangerous situations requiring an emergency reaction.

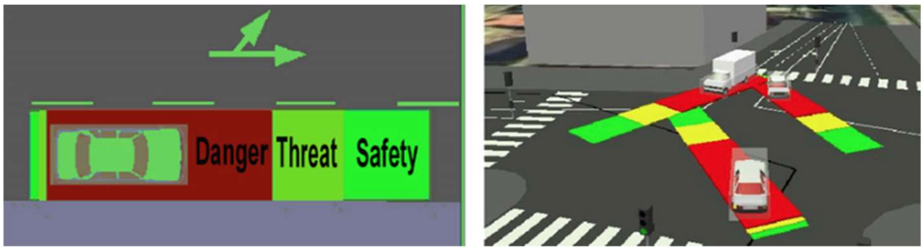

Figure 5. The "Envelope-Zones" of COSMODRIVE model, used to assess path conflict and to manage interactions with other road users (from Bellet et al; 2012)

At the tactical level (Michon, 1985), a mental representation (combining a Driving Schema and Envelope-Zones) provides an ego-centred and a goal-oriented mental model of the driving situation liable to be cognitively handled in order to compute *anticipation* (through cognitive simulations), and thus *expectations* about future situational states and/or the risk associated with alternative driving behaviours (Bornard et al., 2016). When driving, humans continually update their Situational Awareness as and when they dynamically progress on the road (Bellet, 2011). The content of their mental representations will however depends on the aims they pursue, their short-term intentions (i.e. tactical goals, such as turn left at a

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crossroads) or their long-term objectives (i.e. strategic motivations, such as reaching their final destination within a given time), their driving experience, and the attentional resources they allocated to the driving task (Bellet et al., 2009). These mental models play a key role in risk assessment and awareness (Bellet & Banet, 2012; Wilde, 1982), and support the decision making process underlying the driving behaviours to be then implemented by the driver in the current situation (Bellet et al., 2007; Bornard et al., 2012, 2016; Deniel et al., 2019).

Moreover, the aim of COMSODRIVE approach is not only to model drivers' cognitive processes in an "optimal" way, but was also developed to simulate human driving errors due to misperception of events, erroneous situational awareness, misevaluation of the situational risk and/or evaluation of the dangerousness associated to a given behaviour due, for example, to visual distraction, lack of driving experience, or advanced age (Bellet et al., 2009).

4.2.2. Structure of the module

By considering the COSMODRIVE theoretical background, in the frame of the traffic situation corresponding to the Use Case n°3 of BERTHA (cf. D.1.1), the COGNITION model to be specifically developed for the project by UGE will be made of two main cognitive modules: *Risk Awareness* and *Decision-Making* (Figure 6).

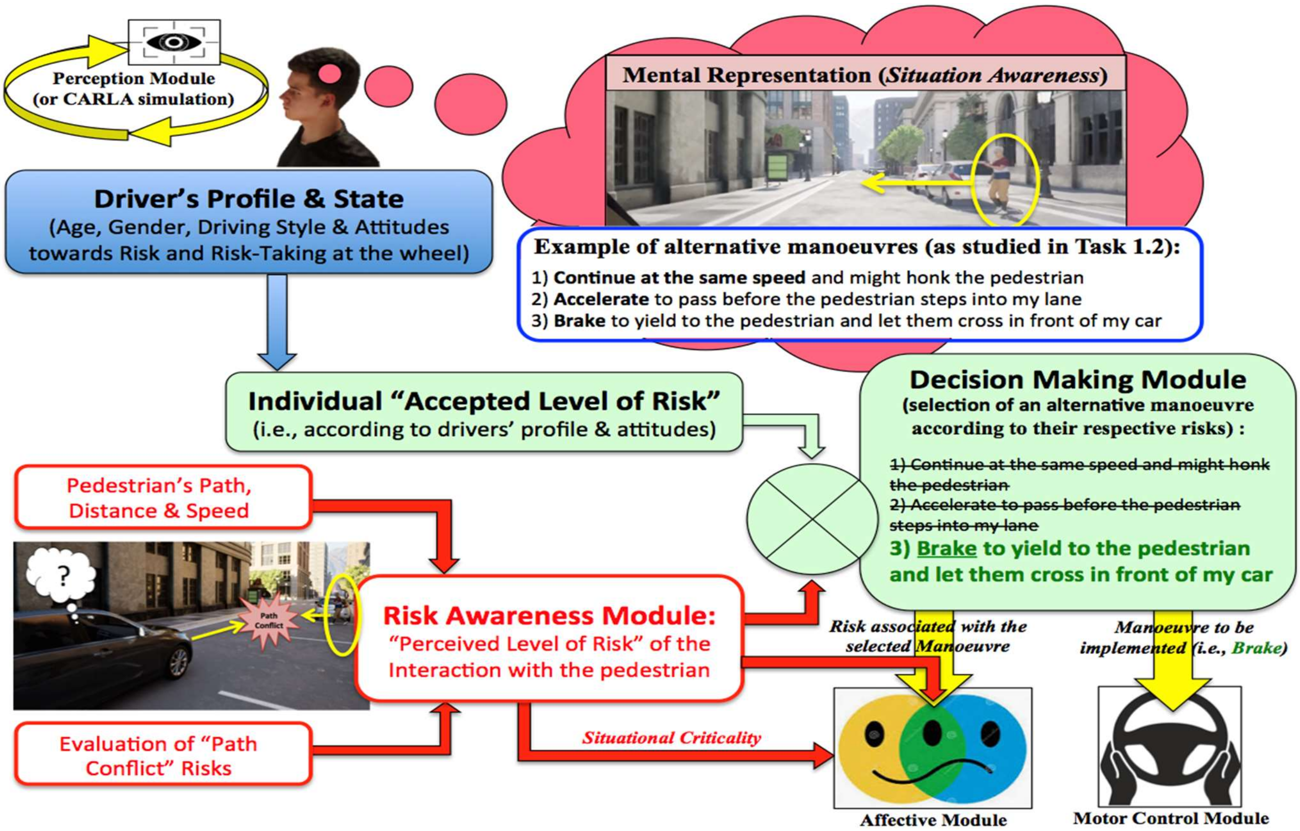

Figure 6. Functional architecture of the Cognitive model to be developed for BERTHA

The Risk Awareness module: From the information collected in the road environment (provided by the PERCEPTION module or directly extracted in CARLA simulation), the COGNITION module will be first elaborate a *mental representation* of the traffic situation (corresponding to the driver's Situational Awareness) including particular events or hazards liable to interfere with the ego car trajectory (like a pedestrian crossing the road, in the traffic

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situation considered in Figure 6). Facing to this event, the Risk Awareness module will be in charge to evaluate the *Situational Criticality* by computing a conflict risk between the ego-car (according to its position, speed and trajectory related to the driving action currently performed), and the pedestrian's path, speed and distance (collision point). This value of *Situational Criticality* may be sent to the affective module to consider its impact on drivers' emotional state (e.g., a highly critical situation may generate stress or fear, for instance).

The Decision-Making module: From the *Perceived Level of Risk* associated with the driving task as currently performed by the driver (assessed by the Risk Awareness Module), the Decision Making Module is in charge to select an appropriate way to react. By computing the respective levels of risks associated with alternative driving behaviour (like keeping the same speed, accelerating, or braking to yield the pedestrian), the *Decision-Making* Module will determine the most appropriate manoeuvres to be effectively implemented to manage the interaction with the pedestrian. However, this decision will be dependent of the driver's profile, more specifically regarding their attitudes towards risk and risk taking while driving, which will determine their individual *Accepted Level of Risk* (Wilde, 1982). Once an alternative manoeuvre is selected, it is then provided (as an input of the Decision Making Module) to the MOTOR CONTROL module in charge to pilot the CARLA ego-car accordingly. In addition, the level of risk associated with the selected manoeuvre - which is liable to impact the driver's emotional state - will be provided to the affective module.

4.2.3. Variables of the module

The COGNITION module (combining risk awareness and decision-making cognitive processes) will require, as **Inputs,** information coming from the perception module or directly extracted in CARLA, regarding the traffic situation, including:

- **Environmental conditions**: weather (e.g., raining, fog) and day/night
- **Road scene and road infrastructure characteristics**: OpenDRIVE description of the road network, road signs information (e.g. speed limit) and position (OpenDRIVE coordinates), traffic lights status (i.e., colour) and position (OpenDRIVE coordinates)
- **All road users behaviours and characteristics** (specifically regarding critical events manipulated in the scenarios): Position (OpenDRIVE coordinates), speed (3 axes), and trajectory (3 axes) of all other road users (at a minimum, the one with which interaction is required within the scenario). Moreover, status of the other vehicles' turn signals, and their use of the horn or flashing of the headlights if occurring.
- **Ego car's commands status** (i.e., CARLA vehicle piloted by the DBM): current speed and position (OpenDRIVE coordinates), state of the pedals (level of activation), steering wheel angle, state of the indicators and the headlights.

Two main types of **Outputs** will be generated by the Cognition Module (according to the underlying computations related to the risk awareness and decision-making):

- **Toward the AFFECTIVE module**: the "Situational Criticality" computed by the Risk Awareness process and the "Perceived Level of Risk" / "Dangerousness" associated with the manoeuvre selected by the Decision Module will be provided to the Affective Module, in order to simulate affective states liable to be impacted by the perceived risk and/or by a deliberate risk taking / risky decision while driving.

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- **Toward the MOTOR CONTROL module**: the cognition module will provide the tactical goal of the key "driving manoeuvre" to be performed for each BERTHA UC/driving scenario (like implementing an "Emergency Braking" versus a "Lane Change" for the UC1, Cross "Before" versus "After" the incoming car to Turn Left at crossroads [UC4] or "Go" versus "No Go" decision to Insert on the Highway for the UC2), to be then achieved by the motor control module by acting accordingly on the vehicle commands of a CARLA vehicle (i.e., pedals, steering wheel, indicators, etc).

4.2.4. Example case

If we consider the Use Case of BERTHA n° 4 (see D1.1, Figure 7), the main task of the cognition module of the driver piloting the red car (i.e., the "ego" vehicle, to be controlled by the DBM) is to determine when and how to make a Left Turn at the intersection when the traffic lights are green and an oncoming vehicle is approaching (i.e., blue vehicle in Figure 7).

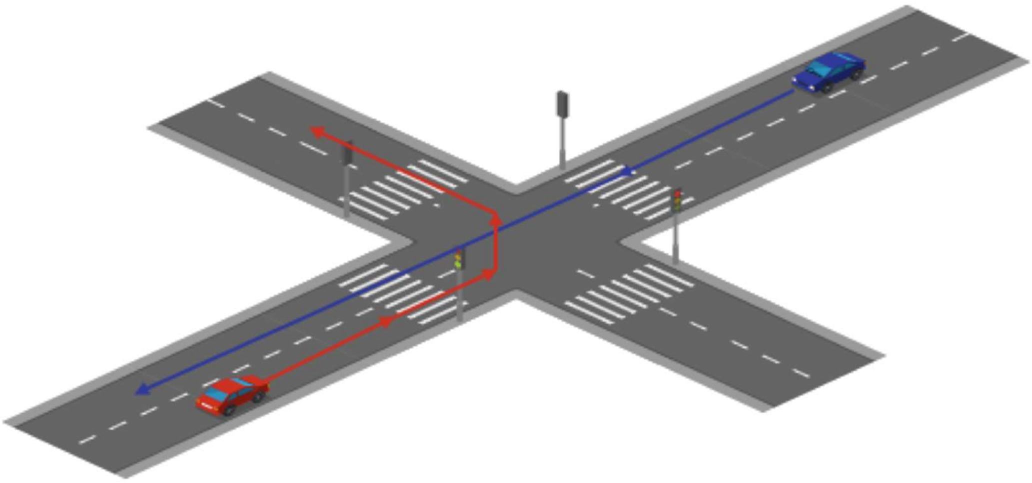

Figure 7. BERTHA Use Case n°4: "Turning Left at an urban crossroads with traffic lights"

To do so (Figure 8), the Risk Awareness module must first evaluate the potential path conflicts between the oncoming vehicle and the ego vehicle intending to make the Left Turn. Then, this module will estimate, for each vehicle, the time required to reach this "path conflict point".

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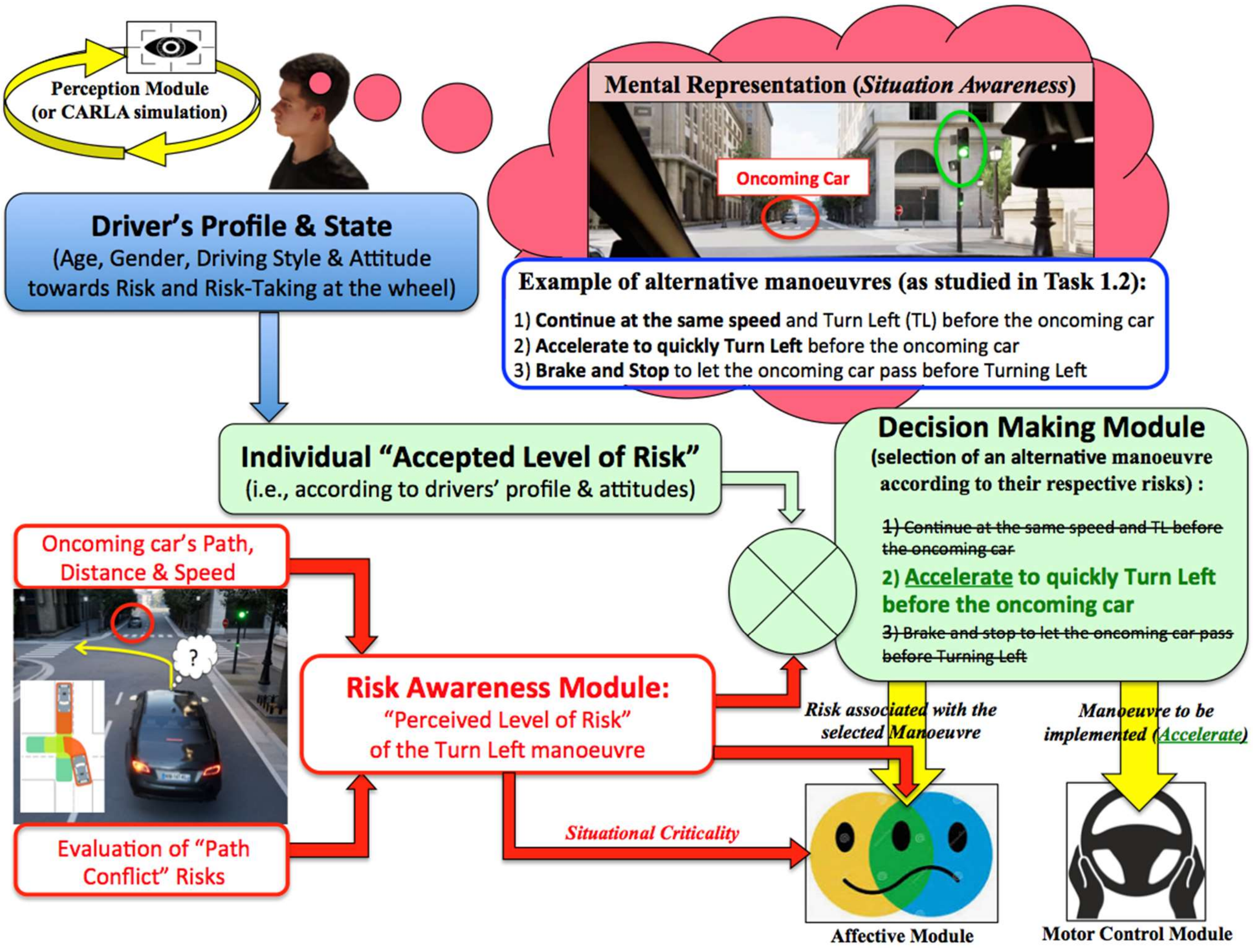

Figure 8. Risk Awareness and Decision Making modules to Turn Left at a crossroads with traffic lights

Based on this "time to conflict," the decision-making process will then select which alternative manoeuvre is the most appropriate. For instance, if we focus on the three alternative behaviours defined in T1.2 for this interaction scenario (see D1.2 [1] "***Continue at the same speed*** *and turn left before the oncoming car*," [2] "***Accelerate*** *to quickly turn left before the oncoming car*," or [3] "***Brake and stop*** *to let the oncoming car pass before turning left*"), the decision-making process must determine which behaviours are possible (i.e., without causing a collision) and their respective levels of risk. For instance, turning left at the same speed might, in some variations of this scenario, will allow the ego car driver to pass before the oncoming blue car, but very closely (e.g., 2 seconds before it reaches the conflict point). In this case, the gap used will be considered by the blue car driver as very dangerous, which could be surprised by this choice. Alternatively, the decision module could choose a more aggressive driving style by accelerating to pass the oncoming vehicle more quickly, though this manoeuvre would be harder to perform and thus riskier for the ego car driver. Finally, the driver of the ego car may decide to brake and stop to let the oncoming blue vehicle pass and only then execute the left turn. This last decision will be considered safer under such traffic conditions, but will cause the ego-car driver to lose time in reaching the tactical goal of completing the left turn and, beyond that, to reach their final destination.

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4.2.5. KPIs

As defined as SO3 in the BERTHA proposal (cf. p.3), the KPI related to the Cognition module will be its ability to simulate 70 % of the decisions made by the real humans of different profiles (i.e., to be defined in accordance with the results of the T1.2 survey) involved in UGE experiments on driving simulator.

4.3. Affective module

4.3.1. Background

Affective driving models are designed to understand and adapt to the emotional and **psychological conditions** of drivers, significantly impacting their behaviour and decision-making processes. In the context of driving, **affective states** (such as stress, anger, fatigue, distraction, etc.) can compromise safety. Research in psychology and neuroscience has demonstrated that these emotional states alter cognitive processes and motor functions, leading to impaired driving performance.

These states can lead to cognitive impairment and compromised motor functions, significantly increasing the risk of accidents. **Cognitive states**, closely related to affective states, refer to the driver's condition of being, such as alertness, situational awareness, certainty, and knowledge. Together, these states influence how a driver perceives and interprets information, ultimately affecting driving performance.

Affective driving models integrate concepts from psychology and neuroscience to monitor, interpret, and respond to the affective and cognitive states of drivers. These models are grounded in the understanding that emotional and cognitive states are dynamic and can change rapidly in response to internal and external stimuli.

Research in psychology and neuroscience has shown that emotional states like stress and anger can activate the autonomic nervous system, leading to physiological changes that impair cognitive function and motor skills. For example, stress can lead to tunnel vision, slower reaction times, and impaired decision making. Anger can result in aggressive driving behaviours, while fatigue can cause lapses in attention and slower reflexes.

Identifying the most critical mental states that affect driving is essential for developing effective driver monitoring systems and enhancing road safety. Extensive research in traffic psychology and human factors has identified several key mental states that significantly influence driving performance.

To justify the selection of the mental states—active fatigue, passive fatigue, drowsiness, mental stress, mental workload, attention and distraction, and emotional states—as critical factors influencing driving, we can draw upon recent studies and advancements in the field of traffic psychology and human factors.

Active and **passive fatigue** are well-documented in their impact on driving performance. Recent studies have shown that fatigue significantly affects cognitive functions such as reaction time, attention, and decision making, thereby increasing accident risk. For instance, a study by Saxby et al. (2013) demonstrates that even mild sleep deprivation can impair

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critical driving skills, leading to higher accident rates. Additionally, the distinction between active and passive fatigue is crucial, as different types of fatigue affect drivers' performance in unique ways (O'Connell & Stokes, 2007).

Drowsiness, a severe manifestation of fatigue, poses a significant risk. Recent research indicates that drowsy driving is responsible for a substantial number of accidents, with microsleeps being a common factor. A study by Gwak et al. (2020) highlights that microsleeps can occur without the driver's awareness, making drowsiness particularly dangerous.

Mental stress and **mental workload** are critical factors that impair driving performance. High levels of stress and cognitive workload can overwhelm a driver's cognitive resources, reducing their ability to process information and react to hazards. A study by Liu et al. (2023) demonstrates that increased cognitive workload significantly reduces situational awareness and reaction times, which are vital for safe driving. This is supported by findings from a study by Hancock & Desmond (2019), who show that stress and workload can degrade performance in complex driving scenarios.

Attention and **distraction** are leading causes of traffic accidents. The impact of distractions, whether from mobile devices or in-vehicle technologies, has been extensively studied. A report by the National Highway Traffic Safety Administration (Stewart, 2023) reveals that distracted driving contributes to a significant percentage of road accidents. Moreover, research by Regan et al. (2011) emphasizes the importance of maintaining attention and minimizing distractions to enhance driving safety.

Emotional states are also crucial, as they can profoundly affect driving behaviour. Emotions such as anger or happiness can alter risk perception and decision-making processes. Recent studies, such as those by Jain et al. (2023), have shown that emotions can lead to aggressive driving or impaired judgment, further increasing accident risk. Moreover, a study by Mou et al. (2023) highlights the role of emotional states in influencing driver behaviour and decision making, underscoring the need for integrating emotional state monitoring into driver assistance systems.

In summary, these mental states—active fatigue, passive fatigue, drowsiness, mental stress, mental workload, attention and distraction, and emotional states—are critical in understanding and mitigating risks associated with driving. Their selection is supported by recent research, underscoring their significance in enhancing driver safety and performance.

4.3.2. Structure of the module

4.3.2.1. Fatigue

Fatigue is a state caused by extreme tiredness resulting from mental or physical exertion or illness (O'Connell & Stokes, 2007; Saxby et al., 2013). Driver fatigue can be subcategorized into sleep-related (SR) and task-related (TR) fatigue based on the causal factors contributing to the fatigued state (May & Baldwin, 2009). TR can be active or passive depending on the task demand level.

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- **SR fatigue (drowsiness)**: sleep deprivation, sleep restriction and circadian rhythm affect SR fatigue. It is a low mental alertness which shows itself in a drop-in physiological activity and which is sensed subjectively as a feeling of doziness and reduced situation awareness (Tejero Gimeno et al., 2006).
- **Active TR fatigue**: is derived from continuous and prolonged, task-related perceptual-motor adjustment (Hancock & Desmond, 2019).
- **Passive TR fatigue**: develops over a number of hours of doing what appears to be nothing at all (Hancock & Desmond, 2019).

4.3.2.2. Stress

Stress is a natural psychophysiological response to a stimulus that is demanding or threatening. Part of the autonomic nervous system, the sympathetic nervous system, responds to stressful or dangerous situations. The sympathetic nervous system is activated to increase the heart rate (HR) and provide more blood to areas of the body that need oxygen to help us respond to the dangerous situation. The stress response is regulated by the Hypothalamic Pituitary Adrenal (HPA) axis, which controls the secretion of cortisol, adrenocorticotropic hormone (ACTH), adrenaline and noradrenaline (Amid et al., 2023).

Stressors produce a generalized stress response. In the context of driving, these stressors can be congestions, time pressure or inclement weather. It is important to notice that in the driving context, stress is affected also by anxiety, worry, anger and fatigue, by the stress-based level (Dorn, 2017).

4.3.2.3. Mental workload

Mental Workload is a complex concept whose level cannot be detected directly, however, it has been found that relates to limitation of individual internal resources to accomplish the task, and also involves a multi-dimensional variable (Butmee et al., 2019).

There are numerous proposals of the concept of mental workload in literature, one of the last ones defines it as a multidimensional construct, that it is described by 'task' (e.g. demand and performance), 'operator' (e.g. skill and attention) characteristics, and the environmental context. Thus, mental workload is the result of an interaction between task demands and individual characteristics (Young et al., 2015).

4.3.2.4. Attention

Attention is a state of concentration of the mind upon something, where one is able to integrate the higher mental processes at their maximum, while distraction involves a diversion of attention away from something, disturbing one's concentration. Inability to focus is common, but the consequences range from merely reducing the quality of life, to causing one to be more prone to accidents while driving (Lavie, 2010; Regan et al., 2011).

Driving involves complex sensorimotor tasks, such as perception and processing of stimuli from the environment, planning of responses by the brain, and their execution by the musculoskeletal system. Attention is crucial to keeping a safe drive and preventing accidents (Najafi et al., 2023). In fact, distractions reduce the driver's awareness, altering their ability to make decisions, and leading to potential accidents or crashes (Regan et al., 2011).

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4.3.2.5. Emotional states

The structure of the affective model consists of the interaction between the main mental states identified as is shown in Figure 9.

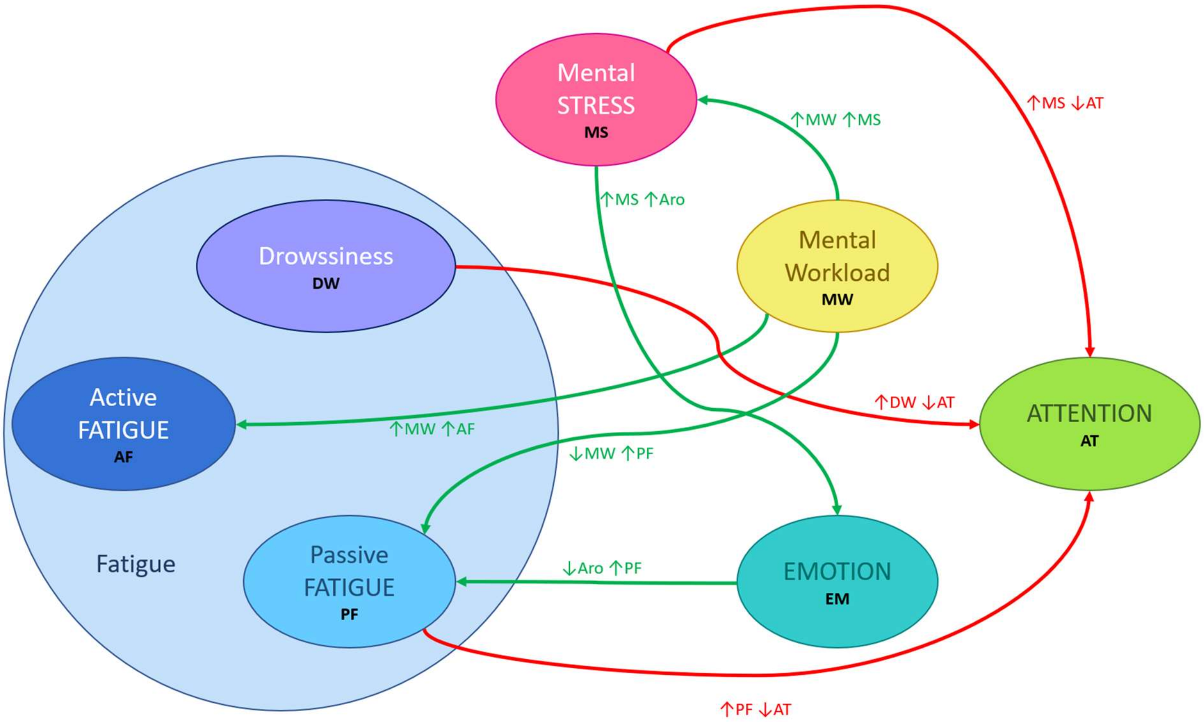

Figure 9. Structure of the Affective Module

4.3.3. Variables of the module

Inputs

Heart Rate Variability (HRV) parameters:

- **SDNN (standard deviation of NN intervals):** measures the overall variability in heart rate; indicates the health of the autonomic nervous system.
- **RMSSD (Root mean square of successive differences):** reflects the short-term variability in heart rate; higher values indicate better parasympathetic activity.
- **pNN50 (percentage of successive NN intervals that differ by more than 50 ms):** represents the proportion of intervals that show significant variability; used to assess parasympathetic activity.
- **LF (low-frequency power):** represents both sympathetic and parasympathetic activity; frequency range typically between 0.04 and 0.15 Hz.
- **HF (high-frequency power):** associated with parasympathetic (vagal) activity; frequency range typically between 0.15 and 0.40 Hz.
- **LF/HF ratio:** used to assess the balance between sympathetic and parasympathetic activity; higher ratios indicate greater sympathetic dominance.
- **SD1 and SD2 (poincaré plot indices):** SD1 measures short-term variability related to parasympathetic activity; SD2 measures long-term variability reflecting overall autonomic balance.

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Electrodermal Activity (EDA) parameters:

- **Skin conductance level (SCL):** measures the baseline level of skin conductance; indicates general arousal and emotional state.
- **Skin conductance response (SCR):** measures transient changes in skin conductance; indicates momentary arousal responses to stimuli.
- **Number of SCRs:** counts the number of distinct skin conductance responses; used to assess the frequency of arousal events.
- **Amplitude of SCRs:** measures the magnitude of skin conductance responses; indicates the intensity of arousal responses.
- **Latency of SCRs:** measures the time delay between stimulus and response; used to assess the responsiveness of the autonomic nervous system.

Respiration parameters:

- **Respiratory rate:** measures the number of breaths per minute; indicates the overall breathing pattern and can reflect stress or relaxation.

Facial Action Units (AUs):

- **AU1 (inner brow raiser):** indicates surprise or fear.
- **AU2 (outer brow raiser):** indicates surprise.
- **AU4 (brow lowerer):** indicates anger or concentration.
- **AU5 (upper lid raiser):** indicates surprise or fear.
- **AU6 (cheek raiser):** indicates genuine happiness (Duchenne smile).
- **AU7 (lid tightener):** indicates anger or fear.
- **AU9 (nose wrinkler):** indicates disgust.
- **AU10 (upper lip raiser):** indicates disgust.
- **AU12 (lip corner puller):** indicates happiness.
- **AU14 (dimpler):** indicates contempt.
- **AU15 (lip corner depressor):** indicates sadness.
- **AU17 (chin raiser):** indicates doubt or sadness.
- **AU20 (lip stretcher):** indicates fear.
- **AU23 (lip tightener):** indicates anger.
- **AU24 (lip pressor):** indicates anger or determination.
- **AU25 (lips part):** indicates readiness to speak or surprise.
- **AU26 (jaw drop):** indicates surprise.
- **AU27 (mouth stretch):** indicates fear or surprise.

Personal factors:

- **Demographic factors:** age, gender, region and socioeconomic background.
- **Driver typology:** parametrized in terms of the typology that is being defined in task T1.2 (subject to possible changes after the analysis is finished), based on a multidimensional characterization of:
  - Risk tolerance.
  - Self-confidence.
  - Efficiency.
  - Attention.
  - Interaction.

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Situational and environmental variables:

- **Time of day**.
- **Weather**: interacting with the time of the day, to create clearer or darker surroundings, and modulate stress derived from visibility and road conditions.
- **Traffic density:** number of vehicles on the road and proximity to the ego car.
- **Road type and conditions**: highway / urban / rural scenarios, road surface quality, frequency, width and visibility of road curves.
- **Driving duration**: time and distance that the driver has been driving, and remaining to reach the destination.
- **Other stressors and distractors**: e.g. presence of pedestrians or cyclists, traffic signals and signs, noise levels, and accidents.

Outputs

- Probability of Active Fatigue
- Probability of Passive Fatigue
- Probability of Drowsiness
- Probability of Mental Stress
- Probability of Mental Workload
- Probability of Attention and Distraction (Concentration Level)
- Probability of Emotional States

4.3.4. Example case

Consider the scenario turning left on a city crossroad with possible vehicles and pedestrians crossing. The Affective module can be used in two complementary contexts:

A. **Determination of states on the basis of driver typology and the situation**. The user is preliminary profiled as baseline type, based on the five dimensions of driver's typology. That baseline type can be a combination of "cautious (defensive)", "alert", "assertive", "distracted" or "aggressive" drivers. The context of driving, with its stressors and distractors, triggers context-depending emotional states that modulate those characteristics.
B. **Characterization of emotions through physiological signals**. This is used in the laboratory to obtain objective measurements of the emotional states, but can also be extrapolated to real-life situations in cars with sensors (e.g. cameras) able to capture part of the physiological signals, like heart and respiration rates, and facial expressions. For instance, if physiological indicators suggest high stress levels and facial analysis shows signs of frustration, the module infers that the driver is experiencing a high level of stress. Conversely, if physiological signals indicate calmness and positive facial expressions, the driver is assessed to be in a relaxed state.

Based on the determined mental state, the behaviours of the driver may change. For example, a driver exhibiting high stress and aggressive tendencies may respond to a high-density traffic situation by accelerating and making abrupt steering adjustments. In

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contrast, a driver with a calm demeanour or in a relaxed situation can be expected to respond with smoother manoeuvres, such as gradual braking and controlled steering.

The mental state also influences the abilities of the driver to pay attention to the risks (e.g. delayed or diminished visual processing due to fatigue or distraction), or can bias the assessment of their magnitude.

The outputs from the affective module contribute to adaptive vehicle control strategies. By integrating the driver's mental state into the vehicle's control systems, the module enables the vehicle to respond more appropriately to the driver's current psychological and emotional condition.

4.3.5. KPIs

To evaluate the effectiveness and performance of the affective module in a controlled and realistic environment, the accuracy in detecting specific mental states is proposed as chief KPI:

- **Description**: assess the accuracy of the module in detecting the driver's mental states (stress, fatigue, inattention, etc.) compared to a baseline or "ground truth" derived from the driver's subjective self-assessment of their mental state. This self-assessment will be collected through questionnaires or self-evaluation tools that allow the driver to reflect their personal perception of their mental state in real time.
- **Metric**: percentage accuracy of the module compared to the driver's self-assessments.
- **Target**: ≥80% accuracy in detecting mental states relative to the subjective self-assessment.

4.4. Motor Control module

4.4.1. Background

The purpose of the motor control module is replicating the sensorimotor skills involved in driving. This module translates sensory inputs into motor commands to control the vehicle effectively.

Wolpert (1997) proposed principles of sensorimotor learning that have significantly influenced the development of motor control modules. These principles include optimal feedback control, which suggests that the nervous system minimizes the discrepancy between desired and actual outcomes through feedback mechanisms, and the use of internal models to predict the consequences of motor commands.

Furthermore, the UMTRI driver model, as presented by MacAdam (2001), offers a comprehensive framework for modelling driver behaviour. This model considers internal vehicle dynamics, steering control dynamics, physiological and ergonomic constraints, and path planning based on the previewed scene. Integrating the UMTRI model into the motor control module enhances its realism and predictive accuracy.

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4.4.2. Variables of the module

The variables that rule the module can be classified between state variables, inputs and outputs.

State variables

The main state variables that govern the module. Most of them should be influenced from the outputs of the Affective module and the environmental factors.

- Driver delayed time: Time spent between the input perceived by the driver, the processing of the cognitive module and the start of the response of the motor control (typically between 0.01s-0.02s).
- Preview time: The time in which the driver predicts trajectory of the vehicle to feed forward the controls (typically between 0.6s-2.0s)
- Internal model of the vehicle dynamics: The inferred vehicle dynamics according to driver experience that is used to predict the trajectory and adapt the changes.
- Response of the neuromuscular system, as a gain dependent on the predicted trajectory and desired trajectory.
- Maximum lateral acceleration accepted by the user.

Input variables

The input variables should be, mostly the output of the Decision Making module.

- Desired speed of the vehicle.
- Tactical decision made by the user.

Output variables

The output variables are the ones that govern the vehicle, plus the path ahead, which is fed back to the state variables.

- Speed change: Either accelerating or braking the vehicle.
- Steering of the vehicle

4.4.3. Structure of the module

The main structure of the module consisted of (Figure 10):

1. The internal model of vehicle dynamics
2. The steering and speed control processor
3. Path ahead estimation

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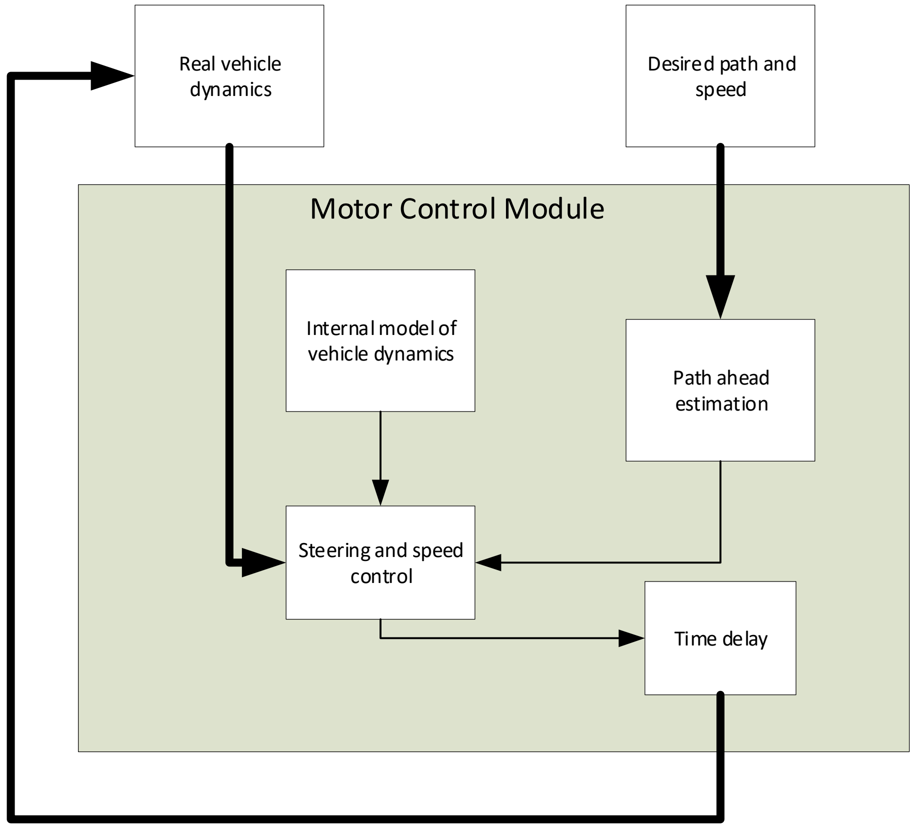

Figure 10. Structure of the module adapted from MacAdam (2001).

Driver parameters should be dependent on inputs from other modules in particular:

- Preview time is dependent on preview conflicts. When a conflict with other car or the environment is foreseen, the previewed time is decreased. Therefore, this state variable should be dependent on the risk awareness.
- Driver delayed time should be dependent on the affective state of the driver. In relaxed states, the driver delayed time can increase while in stressful states should be reduced.
- Maximum lateral acceleration accepted should be dependent on driver skill. More skilled drivers accept higher lateral accelerations.
- Response of the neuromuscular system should be dependent on the driver skill and driver age.

Other interactions could arise after user experimentation.

4.4.4. Example case

Consider the scenario turning left on a city crossroad with possible vehicles and pedestrians crossing.

- Inputs to the module are the tactical goal and the desired speed when the decision module determines the moment is adequate to perform the tactical manoeuvre.
- The module processes these inputs and predicts the necessary steering adjustments to maintain the vehicle's trajectory.

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- The steering and speed control determines the optimal steering angle and throttle input to negotiate the trajectory properly.
- Action execution involves translating these decisions into precise steering commands, modulating throttle and brake inputs to control the vehicle's speed and stability.
- The outputs of the module result in smooth and accurate vehicle control, simulating the nuanced driving behaviour exhibited by human drivers in challenging terrain.

This example demonstrates how the motor control module operates within a specific scenario, effectively replicating human-like driving behaviour through the integration of sensory processing, decision making, and action execution mechanisms.

4.4.5. KPIs

For the key performance indicators (KPIs) that could assess the effectiveness of your work on the DBM motor control model, you might consider the following metrics:

Accuracy of Predicted Steering Adjustments

- **KPI**: Percentage of successful trajectory adjustments in different driving scenarios (e.g., city crossroad turns, lane changes).

Rationale: Measures how well the model predicts steering adjustments to maintain a vehicle's intended trajectory.

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5. INTERFACES

5.1. Interfaces between modules

Although the modules described in the previous section are developed individually, they interact with each other, and work with data from the vehicle, the environment, situation and the driver profile, that can be shared and exchanged. Table 1 presents the types of information processed by the modules, that can be sourced from the outputs of other modules in the framework of BERTHA. Those interactions are also presented graphically in Figure 11, which is the detailed abstract representation of the information network contained in the pictorial representation of the DBM (Figure 2 in section 3).

Table 1. Scheme of information exchange.

TARGET / SOURCE	PERCEPTION	COGNITION (RISK & DECISION)	AFFECTIVE	MOTOR CONTROL
PERCEPTION	——	Saliency maps + Semantic Information	——	——
RISK & DECISION	——	——	Situation criticality Risk taking / dangerousness	Manoeuvres for tactical goals
AFFECTIVE	Attention + Passive fatigue	Stress + Mental workload (capacity to process) Emotions (biases)	——	Active fatigue + Drowsiness (reaction)
MOTOR CONTROL	——	——	——	——

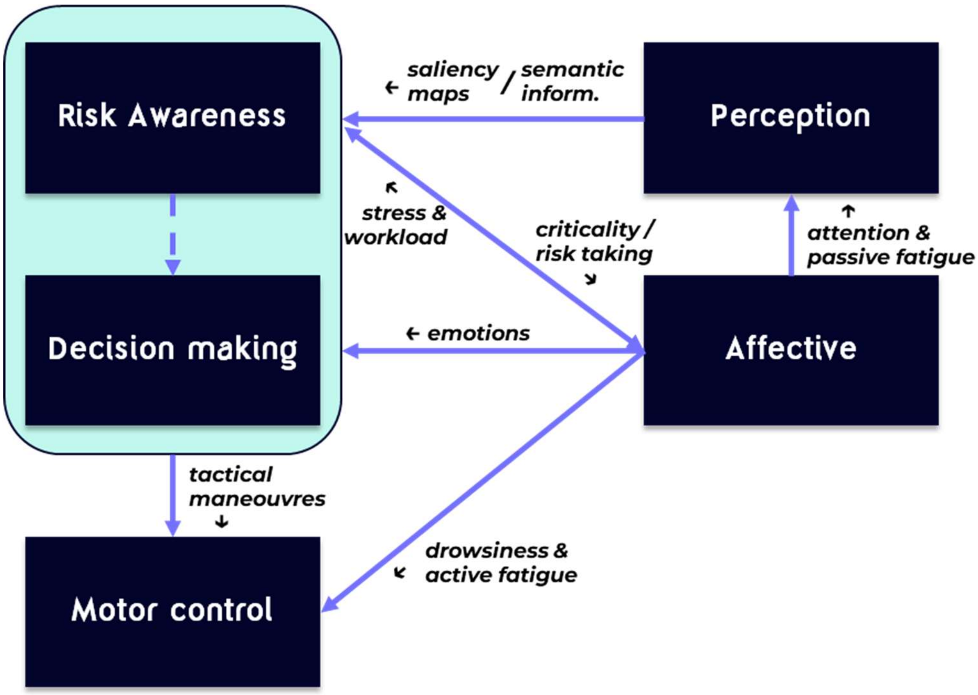

Figure 11. Flows of information exchanged between modules.

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As commented before, the flow of information arranged in the ensemble of modules of the DBM follows the general scheme of the perception-cognition-action loop commonly used in cognitive engineering (Wickens et al., 2021). In a broad scale, this implies that the Perception and Motor Control modules are respectively the input and output gates of the DBM, with the Risk Awareness, Decision Making and Affective modules being intermediate building blocks, among which there are major bidirectional interactions.

The main loop is closed indirectly by the effects of the Motor Control outputs on the vehicle and the environment (movement of the car in the scenario, as well as the indirect behaviours of other agents in response), which are fed back to the Perception module, as shown in the general depiction of the DBM (Figure 2). But there are also intrinsic inner loops defined in the information flows of the DBM, thanks to the interactions referred to in the lower triangle of Table 1, which define upstream data flows.

Thus, the Risk Awareness and Decision-Making modules receive inputs not only from the Perception module (or directly from the CARLA simulation) but also from the Affective module, which can influence the driver's cognitive ability to process information at any given moment and impact their decision-making based on their emotional state. For example, a distracted or tired driver may be less attentive to certain pieces of information, while a stressed (e.g., running late) or angry driver may deliberately take more risks and make more aggressive decisions.

Likewise, the attentional resources available to the Perception module can be constrained by aspects modelled in the Affective module such as the level of attention and passive fatigue, which will affect the performance and quality of the outputs of perception. The inclusion of such inner loops is a scalable approach to increase the complexity of the situations dealt with by the DBM.

That information will be exchanged through ROS 2 messages.[1] ROS is the abbreviation of *Robot Operating System*: an open-source framework originally designed for robotics applications, which is integrated in the ecosystem of CARLA, and has been chosen in BERTHA as the standard tool to enable real-time data communication protocols. (Cf. the next subsection about CARLA, and the deliverables D2.2 and D3.1 regarding the choice of ROS 2.)

During development, other lower-level means of integration are envisaged, which may enable access to information that is not planned to be included in the ROS messages. For that end, each module is expected to present an application programming interface (API) to the others, with the public classes and methods of the objects that are meant to be accessible by other components. Since three of the modules (Perception, Affective and Motor Control) are being developed in Python, the preferred framework for that low-level integration is in Python itself, which also serves as interface with CARLA (see next subsection). The Bayesian Network that implements the probabilistic model (see section 6) will be programmed in R, which can also be used in a Python environment through the rpy2

[1] https://ros.org/

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bridge.[2] And there is also the Python rclpy package,[3] as an API for interacting with ROS 2 from that language.

5.2. Connection of modules and the DBM with CARLA

CARLA (https://carla.org/) is the main platform that will be used in BERTHA to run simulations for research and demonstration purposes. Accordingly, the integration of the DBM with CARLA is a key aspect that must be taken into account during the development of the modules and the general overarching model.

CARLA is an open-source platform that supports flexible specifications of sensor suites, environmental conditions, and control of all static and dynamic actors, as well as of maps. Therefore, it is possible to adapt it to work in arbitrary scenarios, in principle with any kind and quantity of elements — chiefly constrained by the computational resources of the machines used for the simulations, and the complexity of the programs. Nonetheless, in order to optimize resources and ensure good performance, at least during the first stages of development it is convenient to focus on test cases using objects and variables that are efficient to deploy and fetch, taking into account standards and commonly used APIs.

5.2.1. DBM inputs from CARLA

Insofar as possible, the objects, signals and other data of the environment used as inputs of the DBM and its modules shall be elements of the maps and scenarios comprised in the following formats:

- **OpenDRIVE**,[4] an XML structure defined by the Association for Standardization of Automation and Measuring Systems (ASAM) for the generation of maps, including roads, lanes, and other static elements.
- **SCENIC**,[5] a domain-specific probabilistic programming language, started at UC Berkeley, for the description of dynamic content in driving simulations, in order to create scenarios with complex, synchronized manoeuvres that involve multiple entities, e.g. vehicles, pedestrians and other traffic participants.

Those formats define maps and scenarios that can be accessed by CARLA through its Python API. There is a set of 12 maps available to CARLA 0.9.1, with a variable set of layers, including a variety of small towns, urban, highway, residential, and rural environments.[6]

The signals used by the DBM and its modules can be of two types, with respect to the way they are accessed to in CARLA:

- **Privileged Information** provided by the simulation engine in real time, such as the location, trajectories and velocities of all the vehicles, pedestrians and other agents

[2] https://pypi.org/project/rpy2/
[3] https://docs.ros2.org/latest/api/rclpy/index.html
[4] https://www.asam.net/standards/detail/opendrive/
[5] https://docs.scenic-lang.org/en/latest/quickstart.html
[6] https://carla.readthedocs.io/en/latest/core_map/#carla-maps

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and objects that are present in the scenario, dynamics of the "ego" vehicle, or status of the traffic lights, among others.

- **Sensor Data** obtained from virtual sensors configured in the simulation, e.g. RGB or depth cameras to capture the images of the scene, inertial sensors for motion data of the ego vehicle, RADAR/LIDAR sensors, collision or lane invasion detectors, etc. CARLA's documentation contains a list of sensors and their characteristics and properties built-in in the platform.[7] Retrieving information from sensors can involve heavy data processing, e.g. in the case of image and video obtained from virtual cameras. Therefore, the possibility of real-time processing Sensor Data depends on the capacity and available resources of the infrastructure.

CARLA has an API for Python[8] that provides direct access to Privileged Information and Sensor Data through different types of objects. Besides, there is a generic *carla.Sensor* and *carla.SensorData* classes to define custom types of sensors and associated data, although there is no foreseen development of new types of sensors for BERTHA.

From the perspective of the driver (or a human-like autopilot) modelled by the DBM, in a realistic situation, only Sensor Data and part of the variables of the map and the scenario would be theoretically available. However, there are variables for which Privileged Information might be used as a convenient proxy to Sensor Data, achievable without the overhead of data processing, when an equivalence between both can be assumed (e.g. motion variables of the ego vehicle that can be obtained through an inertial sensor, but is also Privileged Information of *carla.Vehicle* objects).

Privileged Information can also be used in some paradigms of DBM training, even if its acquisition is beyond the theoretical capabilities of the driver. Such paradigms mimic the type of training done by a teacher that provides students with hidden information that exists in explanations, comments, comparisons, and so on (Vapnik & Vashist, 2009). Thus, in a first stage Privileged Information is used to train a "teacher model", which in a second stage is used as an instructor that trains the DBM developed as a purely sensor-based model (Chen et al., 2020).

Next are listed the most relevant variables that are envisaged to be needed from CARLA for the modules of the DBM, and the sources where they can be obtained in CARLA's API.

RGB images (from the driver's perspective)

This information can be obtained from virtual camera sensors, placed in the ego vehicle's cabin.[9] Those cameras are by set with a constrained, but configurable field of vision, and can be rotated to simulate the driver's changing their point of view.

Location and motion of the ego vehicle and other road users:

[7] https://carla.readthedocs.io/en/latest/ref_sensors/
[8] https://carla.readthedocs.io/en/latest/python_api
[9] https://carla.readthedocs.io/en/latest/ref_sensors/#rgb-camera

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There are various options to obtain those data. Generally, road users are modelled as objects of classes that are derived from the class *carla.Actor*[10] (e.g. *carla.Vehicle*, *carla.Walker*, etc.), which have the following methods to query their location and motion variables:

- *get_acceleration*: Returns the actor's 3D acceleration vector the client received during last tick.
- *get_angular_velocity*: Returns the actor's angular velocity vector the client received during last tick. The method does not call the simulator.
- *get_location*: Returns the actor's location the client received during last tick.
- *get_transform*: Returns the actor's transform (location and rotation) the client received during last tick.
- *get_velocity*: Returns the actor's velocity vector the client received during last tick.

All objects have also defined bounding boxes, which can be used to detect collisions and departures.

Locations must be transformed to *carla.GeLocation* data[11] to convert points in the simulation coordinates to world coordinates, through the method *carla.Map.transform_to_geolocation*. The geographical location of the map is defined inside OpenDRIVE within the tag.

Alternatively, motion can be obtained as Sensor Data from virtual IMUs, which provide acceleration, angular velocity and rotation signals.[12]

Some sensors can also determine the relative positions of actors, detecting imminent collisions and departures, as an alternative to the Privileged Information of bounding boxes.

Environmental conditions: weather (raining, fog) and day/night

CARLA allows to set weather parameters, which can be also read from the corresponding configuration files,[13] as those variables are meant to be invariable in a given scenario (they are not affected by driver's actions or other undetermined events in the course of the simulation). Those parameters manage sun position, clouds, rain, wetness, dust and fog — which affects scattering of light. Snow is not currently supported.

It must be considered that weather conditions set in such configuration have only visualization purposes, i.e. they influence the aspect of the scenario, but not other properties (e.g. slipperiness of the road, forces exerted by wind, etc.). Those aspects, to the extent that they are relevant for dynamic feedback (e.g. by the Motor Control module), should be configured separately: for instance, if road adherence is meant to be reduced due to the presence of wet ground in a rainy scenario, that scenario could change the friction of tires in the *carla.VehiclePhysicsControl* parameters.[14]

[10] https://carla.readthedocs.io/en/latest/python_api/#carla.Actor
[11] https://carla.readthedocs.io/en/latest/python_api/#carlalocation
[12] https://carla.readthedocs.io/en/latest/ref_sensors/#imu-sensor
https://carla.readthedocs.io/en/latest/python_api/#carla.IMUMeasurement
[13] https://carla.readthedocs.io/en/latest/core_world/#weather
[14] https://carla.readthedocs.io/en/latest/python_api/#carla.VehiclePhysicsControl

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Road scene and road infrastructure characteristics

Stops, yields and traffic lights are considered actors of CARLA, i.e. subclasses of *carla.Actor* just like vehicles and pedestrians. Other elements of the road network, like junctions, sets of lanes in the road, etc., are subclasses of *carla.Landmark*,[15] coded in the OpenDRIVE file of the map, which can be read, or directly accessed from the simulation through the *carla.Map* class.[16]

The position of those objects can be expressed in different coordinate systems, which refer either to the global map (*x*,*y*,*z*), the road trajectory (*s*,*t*,*h*, with *s* tangent to the road line and *h* normal to the road plane), or the local orientation of the vehicle (*u*,*v*,*z*), see Figure 12.

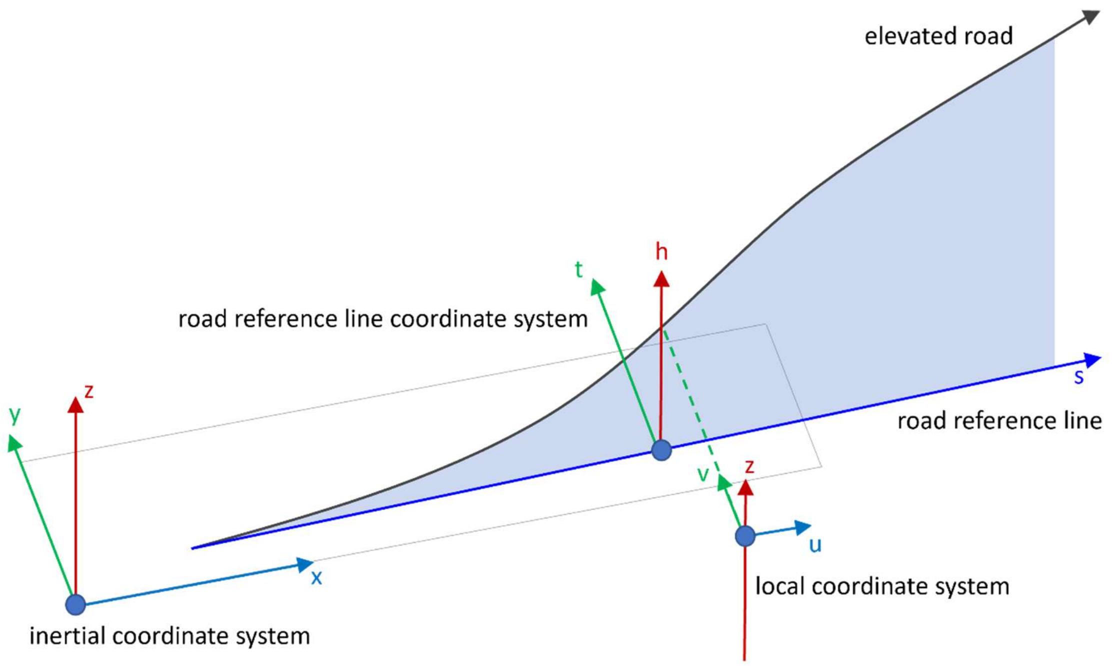

Figure 12. Coordinate systems in OpenDRIVE. Source: https://publications.pages.asam.net/standards/ASAM_OpenDRIVE/ASAM_OpenDRIVE_Specification/latest/specification/08_coordinate_systems/08_01_introduction.html

Available dynamic OpenDRIVE information for generic points of the road like junctions includes the *s* local coordinate (but not *t* or *h*), whereas for landmarks (e.g. speed limits signs, traffic lights etc) CARLA also provides the *t* coordinate of their lateral distance. The global coordinates (*x*,*y*,*z*) are available for all points.

Ego car's command status

The following elements of the car can be easily managed in CARLA:

- Lights,[17] including their status, blinking and types of lights (front/back lights, reverse, fog, or interior).
- Doors:[18] front, back, left and right, and control their opening.

[15] https://carla.readthedocs.io/en/latest/python_api/#carla.Landmark
[16] https://carla.readthedocs.io/en/latest/python_api/#carlamap
[17] https://carla.readthedocs.io/en/latest/python_api/#carla.VehicleLightState
[18] https://carla.readthedocs.io/en/latest/python_api/#carla.VehicleDoor

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- Vehicle control:[19] throttle, steering, brakes and reverse. For the purposes of CCAM in BERTHA, vehicles will be assumed to use automatic gear shift. See more about this below, with respect to CARLA's outputs for the DBM.

Other elements not available as such kind of Privileged Information, like honking the horn, could be implemented through vehicle-to-any (V2X) sensors.

5.2.2. DBM outputs for CARLA

In its interaction with CARLA, the relevant outputs of the DBM are the vehicle control parameters, which can be obtained through the method *get_control* of the *carla.Vehicle* class, and also set through different methods of the *carla.VehicleControl* class (see above). These include:

- *steer* (continuous range)
- *throttle* (continuous range)
- *brake* (continuous range)
- *hand_brake* (yes/no)
- *reverse* (yes/no)
- *gear* (set of fixed values)
- *manual_gear_shift* (yes/no)

Continuous values are defined in a normalized range between 0.0 and 1.0 for throttle and brake, and between ±1.0 for the steering. The association between those parameters and their corresponding physical actions (rotation of the steering wheel, or level of activation of the pedals) is not modelled in CARLA, and should be calibrated outside of it.

[19] https://carla.readthedocs.io/en/latest/python_api/#carla.VehicleControl

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6. FRAMEWORK OF THE GENERAL PROBABILISTIC MODEL

6.1. Background

The General Probabilistic module of the BERTHA project in WP1 will be developed by the Instituto de Biomecánica de Valencia (IBV) and the Universitat de València (UV). The primary objective of this task is to incorporate variability into the general construction of a Driver Behavioural Model (DBM), allowing for the analysis of system uncertainty that can improve safety and user experience in the DBM implementation of autonomous vehicles in the future. According to K. Wang et al. (2023) there is a necessity to develop model uncertainty in this field.

The ideal statistical tools for this task are Bayesian networks. These can be briefly defined as probabilistic models based on directed acyclic graphs (DAGs), where each node of the graph represents a random variable. In this section, we will properly define Bayesian networks and provide a summary of previous studies that have applied these types of models in the field of car driving. We will select the most relevant ones for the BERTHA project and outline how to apply these models in different modules of the project.

6.2. Bayesian Networks

Bayesian networks (BNs) are probabilistic models related with DAGs. Graphs are mathematical structures that allow pairs of objects, nodes and edges, to be linked. DAGs are graphs whose edges have directions but no cycles (Diestel, 2017).

Nodes in BNs are random variables. Edges are probabilistic relationships between the nodes that involve real causal relationships. BNs provide a general framework for assessing model uncertainty by combining the world of the probability and graph theory (Holmes & Jain, 2008). Following Pearl & Russell (1995), the most relevant feature of BN are “direct representations of the world, not of reasoning processes”. The history of the BN is very recent and dates back to the pioneering work of Pearl (1988), who introduced the probabilistic approach to intelligence and expert systems. Since then, BN have become an indispensable tool in mastering AI in uncertain environments (Wiegerinck et al., 2013).

Let us consider a general BN with nodes ***X*** = *(X1, . . . , Xn)*. Define the parents (*Pa(Xi)*) of the variable *Xi* of the network as the group of nodes whose relations are directed to *Xi* and consider the conditional distribution *p(xi | Pa(Xi))* as the probabilistic connection between this variable and its parents. This distribution will be continuous or discrete depending on the nature, discrete or continuous respectively, of the node *Xi*. In the case of the node *Xi* has no parents, its random behaviour will be described by its unconditional distribution p(xi). Since BN are probabilistic models involving the random vector ***X***, its complete specification is via its joint probability distribution

$$p(\boldsymbol{x}) = p(x_1, \dots, x_n) = \prod_{i=1}^{n} p(x_i \mid Pa(X_i)).$$

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This condition is usually referred as *global semantics* of the network. Probabilistic *local semantics* with regard to independence assumptions encoded by the graph indicate that each node is independent of its nondescendants nodes given its nodes parents.

The process of constructing a BN for a given stochastic system involves different stages. The most important are the search for a network structure that best describes the available data (structure learning) and a subsequent statistical learning phase (also called belief updating). The latter is usually data-driven and, consequently, inferential procedures are applied to estimate the associated joint probability distribution from which we can perform forward (predictive) or backward (diagnostic) types of research (Cai et al., 2020).

Statistical learning in BNs can be performed using either exact or approximate inference methods. Exact inference involves several algorithms to compute marginal distributions of the variables in the network. Variable Elimination systematically removes variables by summing them out, breaking the network into smaller components for localized computations. The Junction Tree Algorithm transforms the original BN into a junction tree, facilitating efficient message passing by leveraging the tree structure to optimize the inference process. Message Passing involves nodes exchanging messages about their probability distributions, conditioned on observed evidence, allowing for iterative computation of updated beliefs across the network.

Approximate inference relies basically on importance sampling schemes and Markov chain Monte Carlo methods (Chib, 2001). The approximated samples obtained from the BN's joint probability distribution are then used to approximate any relevant joint, marginal, or conditional distribution of the network. Techniques such as Gibbs sampling and Metropolis-Hastings are commonly employed in this framework.

Dynamic BNs (DBNs) and Object-Oriented BNs (OOBNs) are generalizations of (static) BNs. DBNs introduce time in the structure of the network. DBNs are more suitable than static ones for modelling time-varying systems, but the inclusion of temporal or spatial elements adds much complexity and difficulty to their treatment. OOBNs deal with complex domains defined in terms of hierarchical structures in different levels (Cai et al., 2020).

6.3. Bayesian Networks in driving cars

Although deep learning, in the form of neural networks or deep neural networks, is the most widely applied methodology in autonomous vehicle problems, there is a lack of quantifiable data and model uncertainty in this field (K. Wang et al., 2023). BN and DBN are ideal for dealing with this type of problem.

The application of BNs to automobilism problems is quite widespread, and the subject matter extremely varied. Without intending to conduct an exhaustive review, and although it is often difficult to differentiate them, we have found in the scientific literature two main sections on this topic: one related to autonomous car driving and the other related to human behaviour during driving.

As pioneers in the use of DBNs in autonomous car driving, we highlight Forbes et al. (1995). The aim was to build probabilistic models that allow autonomous vehicles to incorporate into regular highway traffic using simple schemes. Kafai & Bhanu (2011) and Liu & Wang (2014) developed DBNs to classify vehicles from video information, aiming to incorporate

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these systems in autonomous cars. A vehicle classification system is essential for effective transportation systems, parking optimization, law enforcement, autonomous navigation, and more. Another effective application of these models is assessing the potential risk of collision, as demonstrated by Russo et al. (2017) and D. Wang et al. (2022). In addition, Gomes & Wolf, (2021) developed a DBN for monitoring the integrity of the different software components in an autonomous car, to ensure the correct functioning of all systems. Recent works, such as Verma (2023), analyse the risk of accidents in self-driving cars depending on the levels of automation in the vehicle, the age of the driver, traffic congestion, and other factors. BNs are also used to assess the vulnerability of cybersecurity in autonomous cars (Y. Wang et al., 2022).

Over the past few decades, numerous studies have employed BNs or DBNs to assess human manoeuvre behaviour in traffic environments. The primary objective of many of these studies is to introduce alert systems in cars or implement predictive models in autonomous vehicles, thereby achieving more naturalistic driving behaviours.

For instance, Li et al. (2019) developed a DBN trained with real data that predicts human drivers' lane changes based on prior lane changes and various types of information, such as road structure characteristics, interaction features with other cars, and other physics-based features like vehicle type and velocities. A more recent example is found in Jiang et al. (2022), where a DBN was developed to predict the trajectory of drivers, intended for incorporation into the lateral driving-assistance system of the car. Other studies that have explored this type of model related to driver intention or human manoeuvre include Schulz et al. (2018), Kherroubi et al. (2019), He et al. (2019), and Song (2021). Additionally, given that a Hidden Markov Model (HMM) is a particular case of DBN, it is noteworthy to highlight the works done by K. Li et al. (2016), Ye et al. (2016), or Yao et al. (2021), among others.

Additionally, Joo et al. (2022) proposed a BN model to assess the risk of a driver crashing, taking into account various variables such as gender, type of licence, age and type of driving violations. Another study demonstrating the capability of DBNs in determining driving styles based on acceleration, cornering and braking patterns is Obuhuma et al. (2018). More examples on the topic can be found in Yan et al. (2017) and Peng et al. (2021).

Y.-Q. Liu & Wang (2020) developed a BN that analyses how emotions affect a driver's behaviour. Specifically, it induces eight emotional states: anger, surprise, fear, anxiety, helplessness, contempt, relief, and pleasure. The aim is to determine whether these prior emotions influence the behavioural tendency of a driver. Meanwhile, Q. He et al. (2015) use DBNs to analyse driver fatigue based on certain indicators such as electroencephalogram signals or head nodding angles. It is interesting how they utilise latent variables. In fact, the variables of interest, namely alert and drowsy levels, are rightly hidden and fed by the indicators and contextual variables. A similar approach can be found in Yang et al. (2010).

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6.4. Bayesian Networks in BERTHA

Due to the modular architecture of the DBM, it is important to reference significant studies regarding each module. Table 1 presents the bibliography of applied BN models relevant to each module of the project. It is noteworthy that, as far as we know, there are no studies that use BNs directly to produce outputs to control the vehicle. Typically, other methodologies are used for such tasks. On the other hand, there are numerous studies related to the cognitive module. There are also examples related to the perception module. However, there may be a need to develop more effective models for the perception of autonomous cars. The computation of this type of BNs can be very expensive since it may involve data from videos or images.

Table 2. High related references by module.

Module	Example references
1. Perception	Kafai and Bhanu (2011), Liu and Wang (2014) and Imanishimwe and Kumar (2023).
2. Cognitive	Forbes et al. (1995), Li et al. (2016), Ye et al. (2016), Russo et al. (2017), Schulz et al. (2018), Li et al. (2019), Kherroubi et al. (2019), He et al. (2019), Song (2021), Yao et al . (2021), Wang et al. (2022) and Jiang et al. (2022).
3. Affective	Yang et al. (2010), He et al. (2015) and Liu and Wang (2020).
4. Motor Control	——

It's important to highlight that although we have found few studies related to the affective module, they appear highly relevant as they are easily replicable in our project, especially the approaches of He et al. (2015) and Yang et al. (2010). Let us suppose we want to identify a driver's stress state based on certain indicators, as exemplified by a graphical Bayesian network. This model is similar to the one that will be developed in the affective module. To achieve this, we have induced stress in individuals through two means: emotionally and physically (stressor). Additionally, we measured the perceived level of stress by the user (E) across three registers: basal, stressful, and recovery (register). We considered two types of variables: basal variables and dynamic variables. The former contains information about age (age), gender (sex), height (height), weight (weight), the individual basal stress level over the last month (PSS), and their average physical activity level (level_AF). The latter were taken at each register and include systolic pressure (PS), arousal level (SAM_A), dominance level of the situation (SAM_D), and valence level (SAM_V). A possible architecture for the resulting Bayesian network can be observed in Figure 13. In this case, it is interesting to note that SAM_A, SAM_V, and SAM_D depend probabilistically, directly or indirectly, on E and PS. In turn, E depends on register.

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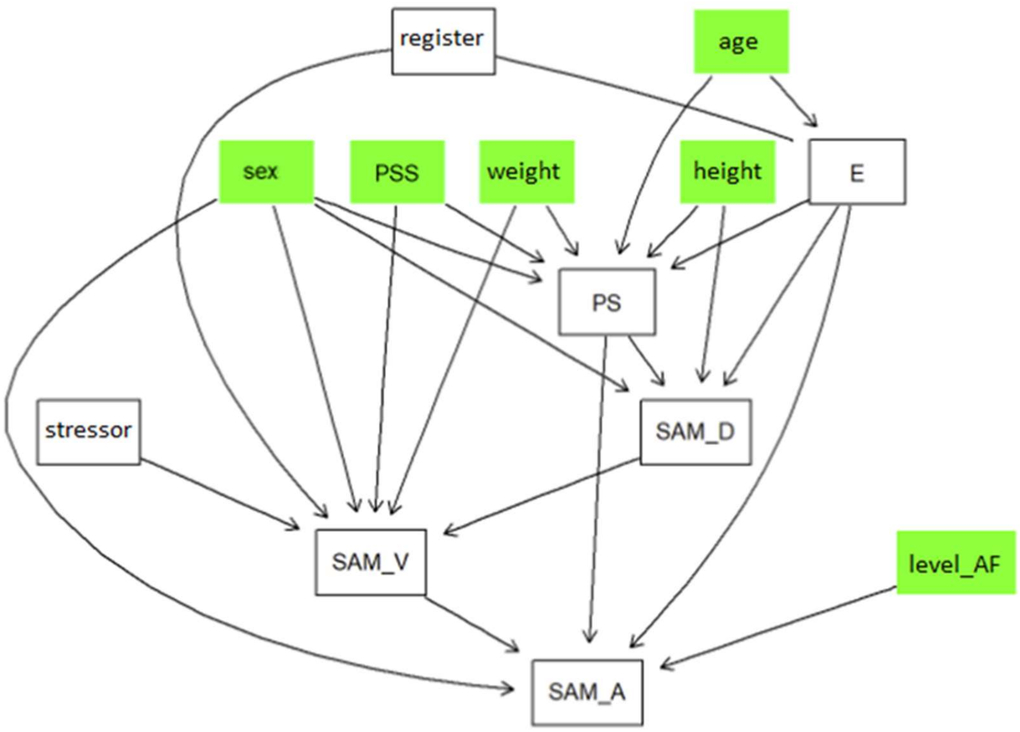

Figure 13. Bayesian network describing the probabilistic relationships between different variables associated with an affective model. Green boxes indicate basal variables, and white boxes, dynamic ones.

In conclusion, it is feasible to use Bayesian networks to model the problems present in each module, with the possible exception of the Motor Control module. Additionally, due to the various connections between the different modules and the flexibility of Bayesian networks, it is possible to construct a complex probabilistic network. This network can incorporate at least one probabilistic model (or one random variable) associated with each module, connecting them to each other through probabilistic relationships.

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7. GENERAL CONCLUSIONS

The DBM presented in this document is the basis of many of the developments and research activities envisaged in the BERTHA project. That DBM is defined as a modular architecture, prepared to be integrable in the framework of probabilistic modelling. These two features will facilitate the scalability of the model, making it possible to grow and improve as new scientific evidence is gathered to build increasingly sophisticated modules, while still providing useful outputs in its first prototypes, capable of quantifying and managing uncertainties.

The set of modules that have been defined comprise Perception, Risk Awareness, Decision Making, Affective traits and Motor Control. These are parts of a cognitive architecture that processes the information of the surrounding environment, and adapts its actions and responses to the incoming stimuli in order to achieve some goal related to the driving task.

The entry point of this architecture is the Perception module, which will make a semantic mapping of the objects and movements seen in the scene. That information will then be processed by the components that simulate the cognitive processes of the driver: the Risk Awareness and Decision Making modules, based on the COSMODRIVE, a theoretical model that defines the mental representations made by the driver of the traffic situation, and considering their knowledge, experience, profile and state, produce tactical goals (e.g. braking, turning, changing lane…), and computes the levels of risk or dangerousness associated to the different manoeuvres and situations.

The profile of the driver (as defined in the task T1.2 of the Project), together with the stressors and information provided by the cognitive modules, will be used by the Affective module to model their levels of fatigue, stress, mental workload, attention and emotion of the driver, which in turn can influence the perception of risk or the driver's willingness to take risks, and alter the performance of the perceptual, cognitive and motor control tasks. This latter part is modelled by the Motor Control, which sets the movements of the steering wheel and the actions on acceleration and braking pedals, according to the tactical actions derived from the Decision Making module.

The previous sections of this document describe in detail the principles of those modules and the interactions between them, with examples based on the Use Cases defined in task T1.1, as well as KPIs to assess their effectiveness. There is also an account of the relationships between the variables considered by the modules and the APIs of the CARLA driving simulator, which is the main platform that will be used in BERTHA to run simulations for research and demonstration purposes. Finally, the probabilistic modelling principles based on BBN are described, as the computational framework that will be used to process the outputs of the model, in order to create a DBM that handles uncertainties, and can effectively adapt to new situations.

The definition of the DBM presented in this document is one of the major contributions to the first milestone of the BERTHA project. The different components that have been described will be developed as Python and R code, which will be delivered through the next year in order to achieve the second milestone, expected for the 24th month of the project (October 2025), although partial results will be made available to partners as needed for the development of other parts of the Project.

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