UNIVERSITY OF CALIFORNIA
SANTA CRUZ

COGMOD: SIMULATING COGNITIVE & PERCEPTIVE LIMITATIONS IN HUMAN DRIVERS

A thesis submitted in partial satisfaction of the
requirements for the degree of

MASTER OF SCIENCE

in

COMPUTATIONAL MEDIA

by

Abdul Jawad

June 2023

The Thesis of Abdul Jawad
is approved:

Professor Jim Whitehead, Chair

Assistant Professor Adam Smith

Peter Biehl
Vice Provost and Dean of Graduate Studies

Table of Contents

List of Figures

List of Tables

Abstract

CogMod: Simulating Cognitive & Perceptive Limitations in Human Drivers

by

Abdul Jawad

Autonomous Vehicles (AVs) will share the roads with humans, where they will regularly interact with different participating agents such as human-driven vehicles, cyclists, pedestrians, etc. Scenario-based testing is a simulation-based AV testing process where many possible scenarios can be tested inside a simulator to verify that an AV interacts appropriately in corresponding scenarios. According to the current approaches, the participating vehicles in those scenarios are modeled using static, predetermined, time-stamped trajectory information, which fails to obtain the behavioral variability of human drivers. Moreover, such a modeling approach limits the usability of the scenario with continuous software updates of the AVs, as surrounding vehicles remain static while the AVs behavior changes due to system updates. To address this issue, we created CogMod, a cognitive theory-inspired human driver behavior model built on a cognitive framework that integrates two complimentary cognitive architectures, QN-MHP and ACT-R, to reflect human cognition while driving. Contrary to most models, where control is directly based on observed variables, the control actions of CogMod agents rely on a temporally persistent internal representation. This internal representation results from a novel gaze mechanism that enables the CogMod driver to have a selective update of the surrounding environment. The model can simulate human drivers' perceptive and cognitive limitations and thereby capture human driving variability. We put our model through two different simulations to test its ability to generate variable driving behavior. In the first simulation, we explored the influence of decision-making latency, a consequence of variable cognitive processing capacity. This variation, simulated by our model and facilitated by the hybrid cognitive architecture, was evaluated based on the distribution of stopping distances under differing cognitive processing capacities. In the second simulation, we test CogMod's ability to augment real-world naturalistic driving data. To test the model's ability to generate a variety of scenarios from a given scenario, we used car-following scenarios from the HighD dataset. The microscopic distributions obtained from the naturalistic dataset are compared with the simulation results using agents based on Intelligent Driver Model and CogMod. Our results show that with variable driving behavior, our model can augment an existing scenario and increase its complexity.

1 Introduction

While testing AVs on real-world roads is necessary, it is expensive and limited in scope, rarely covering unusual or risky situations. Simulation-based testing is a more cost-effective and safe solution that allows for a greater focus on specific challenging situations. Scenario-based testing, a subset of simulation-based testing, enables repeatable, safe, and parallel testing of critical scenarios, saving time and effort. The majority of current scenario-based testing research focuses on extracting and constructing representative scenarios. The development of accident and near-accident scenarios, which are critical for AV testing, has received little attention. Some proposed frameworks are capable of automatically generating critical scenarios [1, 2], but research has largely focused on generating static aspects of scenarios, such as the environment and infrastructure [3], rather than the variation of dynamic elements, such as surrounding vehicles. To overcome this, computational models for dynamic elements in AV simulations must be developed.

Extensive research conducted in the field of driver modeling, spanning psychology, cognitive science, computer science, and traffic modeling, has resulted in two types of models: abstract motivational models inspired by psychology and cognitive science and task-specific models discussed in computer science. While the psychology and cognitive science-inspired models lack precise definitions, making their implementation in simulations challenging, the simulation models in computer science oversimplify human perception and cognition by assuming unlimited capacity and accuracy. These simulation models, typically validated to be collision-free, struggle to create critical scenarios. Additionally, computational models usually discuss driving in parts (lateral and longitudinal subtasks) and lack completeness in modeling. In sec 2, we discuss different existing driver behavior models in detail.

Variability in driver behavior can be attributed to numerous factors, both abstract and tangible. Abstract factors encompass elements such as motivation, personality traits, and other subjective aspects. On the other hand, variability arises from disparities in drivers' cognitive and perceptual abilities. Although driving may not be as complex as piloting an aircraft or as simple as walking, it still demands the processing of relevant information, requiring moderate levels of perception and cognition. Each individual driver possesses unique physical, sensory, cognitive, and information-processing abilities, imposing different constraints and capabilities. To accommodate these limitations, certain in-vehicle design features like side mirrors with a wider field of view and the implementation of regulations such as speed limits have been introduced to enhance road safety. However, despite these measures, road accidents persist. Many incidents occur due to faulty perception, stemming from the imperfect acquisition and processing of information. These failures in driving, as discussed by Rumar, can be categorized into two main types: cognitive failures and perceptual failures [4]. Both types of failures significantly diminish driver performance and increase the likelihood of accidents.

There is a need for a theory that integrates task-specific driving behavior into the broader context of driving with the goal of creating a more realistic human driver model that takes into account psychological and cognitive aspects and closely mimics real-world behavior. Human drivers face limitations in cognitive abilities and perception, such as neuromuscular delays, sensory constraints, and limited information processing. Cognitive architectures like SOAR [5], QN-MHP [6], and ACT-R [7] provide valid frameworks to model these limitations. In sec 3, we introduced a comprehensive approach to driver modeling by proposing a computational model of human driver behavior based on a hybrid cognitive architecture. The model incorporates perceptive and cognitive aspects that account for different cognitive and perceptive limitations inherent to humans to replicate real-world behavior and provide a more precise characterization of factors contributing to accidents.

Our proposed model, CogMod, incorporates working and long-term memory [8], schema theory [9], and visual gaze modeling to simulate drivers with a restricted field of view and sensory range. Behavioral studies have shown that working memory plays a crucial role in compensating for these limitations by approximating the actions and locations of relevant objects. To emulate this process, CogMod utilizes a dead-reckoning-based approximation mechanism to update information about objects outside the FOV. This incomplete information is then stored in its working memory to inform decision-making. In order to mirror the observed variability in information processing speed among human drivers, CogMod's access to and processing of both working and long-term memory are deliberately restricted. This limitation is integrated into the hybrid cognitive architecture employed by CogMod, enabling the model to simulate the variability of human driving behavior realistically. We also provide a framework to incorporate existing task-specific models using schema and subtasks (see sec 3.3).

CogMod's ability is assessed through simulation in two distinct car-following scenarios. In sec 4, the details of the simulation setup are provided. A detailed discussion on the implication of the simulation result can be found in the evaluation section (sec 5). In the first evaluation, referred to as the **braking scenario**, CogMod demonstrated its capability to exhibit variable behavior. This was achieved by simulating a scenario where the preceding vehicle abruptly halted after braking sharply once the following vehicle reached a specific trigger distance. By simulating varying cognitive processing abilities, CogMod successfully produced different stopping distances within this scenario. The evaluation of the model focused on analyzing the distribution of stopping distances across different cognitive processing times. In the second evaluation, referred to as the **follow scenario**, a car-following scenario from the HighD dataset was utilized to examine CogMod's capacity for scenario augmentation. In comparison to the Intelligent Driver Model (IDM), CogMod effectively enhanced the existing scenario by incorporating variable driving behavior, thereby increasing its complexity.

The novelty of this research is three-fold; First, we provide a computational model for human driving behavior that takes into account the cognitive and perceptive limitations of humans. Second, we provide a framework to ingrate different task-specific driver models within a cognitive architecture. Finally, we evaluate the model's capability to generate critical scenarios by comparing it with the intelligent driver model by using scenarios from the HighD dataset.

2 Related Work

Understanding and modeling human drivers have been extensively studied in various disciplines such as psychology, computer science, behavioral science, cognitive science, ergonomics, and accident research, resulting in a wide range of theories and models. These studies aim to improve traffic infrastructure and regulations for a more efficient mobility ecosystem. Human driver modeling research can be broadly categorized into general behavioral theory and frameworks, as well as detailed computational models of specific driving tasks.

2.1 General Behavioral Theory and Frameworks

Research in the field of human driver behavior can be classified into two main categories: theories and frameworks that describe motives, decision-making processes, and driving decision categories, primarily studied in psychology and cognitive science, and qualitative descriptions of human driver behaviors. These researches encompass motivational models of driving and interdisciplinary efforts in mental workload and multiple resource theories. The major drawback of these models is that due to explaining the general trend of driving, they are often very abstract. Implementing them in a simulation will require concrete definitions and details.

2.1.1 Motivational Models

Research under this category presents theories and frameworks to describe the overall motive behind human driving behavior and what process makes drivers prefer one decision over another. These models often introduce the concept of “homeostasis” to explain the satisficing nature of driving. Homeostasis means maintaining a steady state for risk and capability despite external environmental changes [10, 11, 12].

Fuller et al. identified three types of risk: objective risk, subjective risk estimation, and the feeling of risk, where objective risk is factual and after-event, while the other two are personal perceptions and reactions [13]. Fuller also proposed a model where driver decision-making is based on the subjective evaluation of task difficulty rather than risk [12]. This model suggests that task difficulty results from the dynamic interplay between driving task demands and the driver’s capabilities. The task is deemed too hard when demand surpasses capability, leading to potential loss of control and accidents. Gibson and Crooks’ concept of the “field of safe travel” aligns with subjective risk and refers to the possible unimpeded paths a driver can take based on their risk assessment [14]. Risk-threshold models suggest that drivers strive to balance subjective and objective risk, and behavior is directly tied to perceived risk. Under their zero-risk model, drivers generally perceive no risk until it exceeds a threshold, triggering risk mitigation [15]. In our CogMod model, we adopt the performance degradation idea of the human drivers with increased task demand and driver capabilities. The model makes assumptions about the task demand and models the driver capacity to simulate driving performance degradation.

2.1.2 Information Processing Models

Information processing models describe driving as an output of a sequential information-processing system, often applying the perception-cognition-action (PCA) framework to explain information transformation [16]. These models include cognitive architecture-inspired driver modeling, although only a subset of driving tasks has been implemented in this context. Related theories include mental workload and resource theory, frequently discussed in tandem with driving [17, 18, 19]. Resource theory explores human mental resources (perceptual, cognitive, and motor), emphasizing resource demand, overlap, and allocation. Two principal perspectives exist; the undifferentiated resource pool [20] and Wicken's multiple resource theory [17], the latter proposing multiple resource supplies and better task timesharing when tasks use different levels across the three dimensions [21]. It later incorporated a fourth dimension, visual channels [17].

Mental workload mainly concerns the resource demand aspect and outlines the demands tasks impose on limited human mental resources. Different subjective and physiological measures of mental workload have been identified in driving experiments [22, 23, 24]. Both low and high-complexity situations can provoke overload, demanding high vigilance and strategic approaches [19]. Information processing models, mental workload, and resource theory have been instrumental in studying performance degradation in dual-task driving situations. Our model adopts the idea that demand overload can significantly impair driving performance. CogMod places deliberate restrictions on different cognitive resources to simulate the information processing overload situation.

2.2 Task Specific Computational Model

Detailed computational models of human driving behavior have been researched under traffic modeling research, computer science, cognitive science, and ergonomics. Traditionally the focus of traffic simulation models has been to study the impacts of road design and traffic management in congestion situations. Usually, these model explains driving partially (for only a small subpart like lane following, lane changing, etc.). However, CogMod provides a framework to integrate these models in a coherent way so more aspects of driving can be modeled together.

2.2.1 Microscopic Driver Model

Models under this category usually divide driving into specific tasks and build computational models for those tasks. Driving is divided into lateral and longitudinal movements and decision-making, which are usually modeled separately. Usually, lateral and longitudinal models describe drivers' behavior using analytical equations containing various parameters [25, 26, 27, 28]. Separately modeling specific tasks provides the flexibility to examine each task independently; however, the interaction between these specific tasks is not thoroughly understood. A framework that can realistically integrate these task-specific models can increase that understanding. CogMod does exactly that by combining specific tasks to simulate their interaction under a coherent framework.

Longitudinal vehicle movement models: The Gazis-Herman-Rothery (GHR) model proposes that acceleration is a function proportional to the ratio of relative velocity to the distance between the following vehicle and the leading vehicle [26]. This calculation includes the reaction time of the following vehicle to measure the relative speed and distance. However, to counter the GHR model's constraint with zero relative velocity, Newell proposed the notion of adiabatic dependency of velocity on the relative distance [29]. Additionally, the Gipps model introduced a dual-mode representation of driving, including free-flow mode and car-follow mode, to express a vehicle's longitudinal movement [27]. The intelligent Driver Model (IDM) represents the vehicle's velocity using relative distance, relative velocity, and desired gap. The equation is the combination of two-equation describing two modes [25]. In the free-flow mode, the vehicle accelerates according to the desired acceleration of the driver. The other part represents the deceleration tendency when the vehicle perceives a leading vehicle in close proximity. CogMod uses IDM for the longitudinal subtask with the following changes. Instead of using perfect information and directly outputting the velocity, CogMod uses imperfect information from the working memory and adds a delay in executing the control values. Any of the existing longitudinal models is usable in CogMod by making the above-mentioned changes.

Lateral vehicle movement models: Lateral movement models, essential for vehicular lane-change decisions, generally adopt rule-based methodologies. In the Gipps model, the rule-based method asks three questions to decide when to perform a lane change [27]. These questions are about the possibility, necessity, and desirability of the lane change. Ahmed's model categorizes lane changes into mandatory and discretionary, using a random utility approach to model responses [28]. Wiedemann's model, another rule-based model, distinguishes lane changes into shifts to faster or slower lanes based on the situation. These models focus on the decision-making process, including drivers' intentions, the favorability of target lanes, and the physical possibility of lane change [30]. Lastly, the Minimizing Overall Braking Induced by Lane change (MOBIL) model encapsulates the compromises drivers make during a lane change, with a 'politeness factor' that accounts for the potential discomfort imposed on other drivers [31]. These models collectively offer insights into the complex processes governing lane-change decisions in vehicular traffic. In its current form, CogMod does not include any lateral movement model. In the next iteration of this research, we plan to include a lane change model with CogMod.

These models mostly do not involve cognitive modeling and have limited to no ability to describe driver behavior under extreme situations. However, some research extended the existing equations by adding new parameters to account for human variability [32, 33].

2.2.2 Cognitive Architecture-based Driver Model

Several research studies have used cognitive architectures, namely ACT-R [34] and QN-MHP [35], to develop models that simulate human driving behavior. Salvucci et al. utilized ACT-R to model lane following and changing behaviors [36]. Despite simulating some complex behaviors, it fell short in modeling multitasking scenarios due to ACT-R's limitations. In response, Yenfei et al. modified the ACT-R framework to process rules in parallel but encountered synchronization issues [7]. Conversely, QN-MHP has shown more capability in multitasking scenarios. Various models based on QN-

MHP have been proposed for steering, speed control, lane-changing, and car-following behaviors, exhibiting a common implementation pattern from stimuli perception to action initiation [37, 6, 38].CogMod uses theories from ACT-R and QN-MHP to create a hybrid cognitive model.

3 Cognitive Driver Behavior Model: CogMod

The driver model in our study is primarily composed of two central components: the vision module and the cognitive architecture module. The vision module features the gaze component, which dictates the driver's line of sight [Fig 1]. The cognitive architecture module defines what information to process and how much time it takes to process information and take action. [Fig 4] shows the complete architecture of the cogmod driver.

3.1 Gaze Triangle

Our modeling approach divides the gaze element into eight distinct directions, as illustrated in Figure 1. Essentially, the gaze takes the form of a triangle, defined by its direction (from the driver's perspective), the field of view's (FOV) angle along that direction, and a specific distance. The gaze's orientation is denoted by a theta value, determined from the driver's vantage point, with a rightward head movement signifying a negative theta. This direction informs the creation of two vectors drawn by two lines inclined at a FOV/2 angle. We then select a point on each of these lines based on the specified distance. Connecting these two points with the driver's eye location, we form

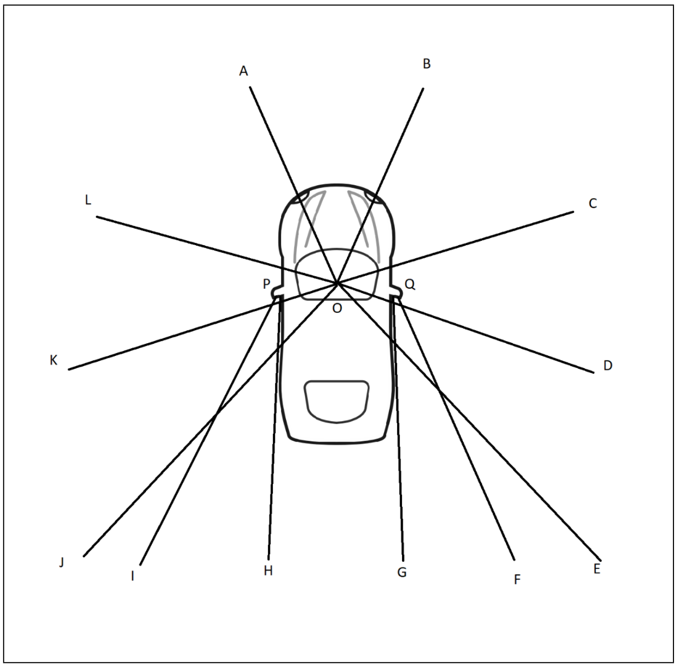

Figure 1: Gaze Triangle

the gaze triangle.

In our simulation, drivers perceive objects within this gaze triangle, with their information updated based on actual values from the simulation. For objects outside the gaze triangle, the model uses a simple dead reckoning process to assume they maintain their perceived speed and course. We sample the gaze direction at each simulation step from a Gaussian distribution, which varies according to specific tasks. The distribution's mean and variance reflect a task-based emphasis on different areas. For instance, a driver on a straight road with no leading vehicle will gaze away more from the center, whereas the presence of a lead vehicle causes the driver to focus more centrally due to the moving vehicle ahead. Another realistic way to model would be to use wrapped normal distribution. We plan to explore this in our future work.

The driver requires some time to transition from one visual direction to another. The time required for the transition is usually a variable. In CogMod, a driver requires one simulation step for transitioning. The driver gets the exact information in the next simulation step. These constraints restrict the CogMod driver from changing visual direction too frequently.

Direction Name	Gaze Direction (degree)	FOV	Distance	Gaze zone
Center	0	50	100	AOB
Left	70	70	70	AOL
Right	-70	70	70	BOC
Left Blind Spot	130	30	20	KOJ
Right Blind Spot	-130	30	20	DOE
Left Mirror	160	20	50	IPH
Right Mirror	-160	20	50	FQG
Back	180	45	100	JOE

Table 0.1: Different Gaze direction used in CogMod

3.2 Cognitive Architecture

Cognitive architectures like QN-MHP and ACT-R simulate human cognitive abilities. QN-MHP employs queuing network and symbolic approaches, dividing processes into perception, cognition, and motor subnetworks [Fig 2]. ACT-R consists of programmable modules and a production system [Fig 3]. The Queuing Network-Model Human Processor (QNMHP) is a computational architecture that integrates two cognitive modeling approaches (queuing network and symbolic). QN-MHP decomposes the mechanism from sensory stimulus to initiating actions into three parallel subnetworks of processes: perception, cognition, and the motor subnetwork. On the other hand, ACT-R is a hybrid cognitive architecture. It comprises a collection of programmable information processing modules: visual, goal, declarative, and manual, and a production system coordinating communication between modules. We use the Queuing Network Theory from QN-MHP and adopt ACT-R's buffer-centric memory access mechanism to create the new architecture. There exists a recent Python implementation of the ACT-R architecture, which is more suitable for linguistic research. We created our own simpler implementation in python to integrate ACT-R and QN-MHP. The combined architecture allows us to use existing task-specific analytical traffic simulation models for lane/car-following and lane maintenance.

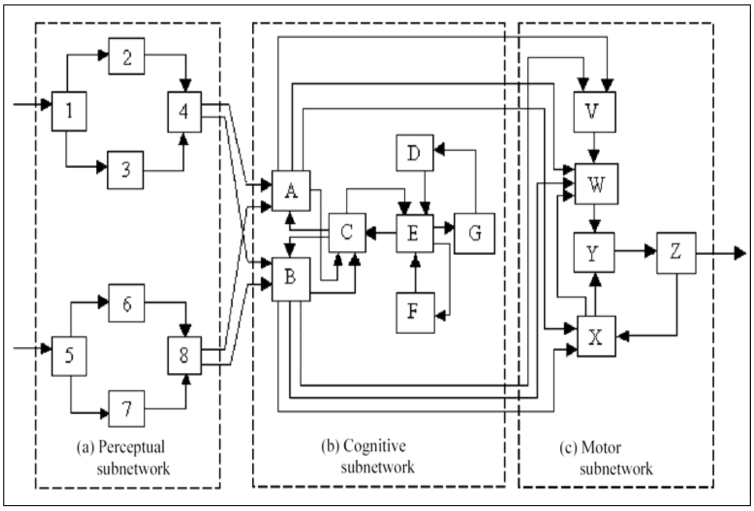

Figure 2: The Queuing Network-Model Human Processor (QN-MHP) (from [39]). (a) Perceptual: 1=common visual processing; 2=visual recognition; 3=visual location; 4=location and recognition integrator; 5=sound localization; 6=linguistic processing; 7=processing of other sounds; 8=linguistic and other sounds integrator. (b) Cognitive: A=visuospatial sketchpad; B=phonological loop; C=central executor; D=goal procedures; E=performance monitoring; F=high-level cognitive operations; G=goal selection. (c) Motor: V=sensorimotor integration; W=motor element storage; X=movement tuning; Y=motor programming; Z=actuators.

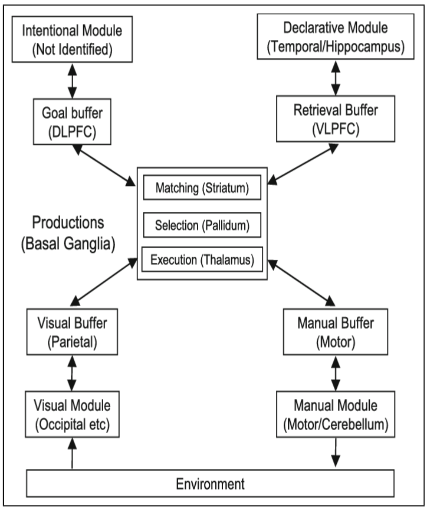

Figure 3: The Adaptive Control of Thought-Rational model (from [40]) .

Our new architecture integrates the Queuing Network theory from QN-MHP and ACT-R's buffer-centric memory access mechanism, allowing us to use analytical traffic simulation models for car-following and lane maintenance tasks. CogMod architecture includes working memory, a central executor, three server units, and two distinct PID controllers. The working memory serves as a short-term repository, enabling temporary storage and processing of information to assist cognition and action. Although theoretically capable of retaining accurate world simulations, we've implemented constraints to simulate limited human information processing capabilities. The central executor, equipped with instant access to buffers and working memory, manages the driving algorithm composed of monitoring, decision-making, and control functions. Each of the server units hosts a queue and a buffer, processing schema requests at adjustable frequencies. Lastly, two separate PID controllers are employed to translate target direction and speed into vehicle control inputs. One handles braking and throttle controls (longitudinal PID), while the other adjusts the steering input (lateral PID).

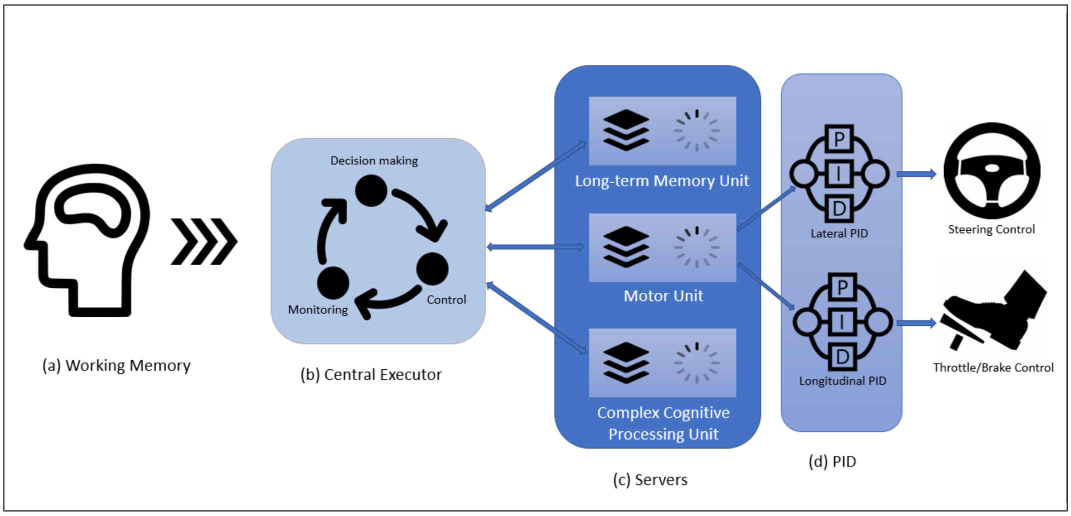

Figure 4: CogMod architecture.

3.3 Subtask and Schema

Driving is a multifaceted activity composed of numerous tasks. In CogMod implementation, we've subdivided the core driving task into two critical subtasks, longitudinal and lateral control, modeled using schema theory principles [41]. According to schema theory, knowledge is stored in memory in the form of schemas. A schema may be defined as a structured mental pattern of thoughts or actions that aids in the organization of knowledge. A schema may contain a large amount of information but can be processed in memory as a single element. High-level schemas incorporate low-level schemas in an automated manner that can be manipulated easily in memory after extensive learning episodes [42]. Skilled performance develops by building increasing numbers of ever more complex schemas by combining lower-level schemas into higher-level schemas [43].

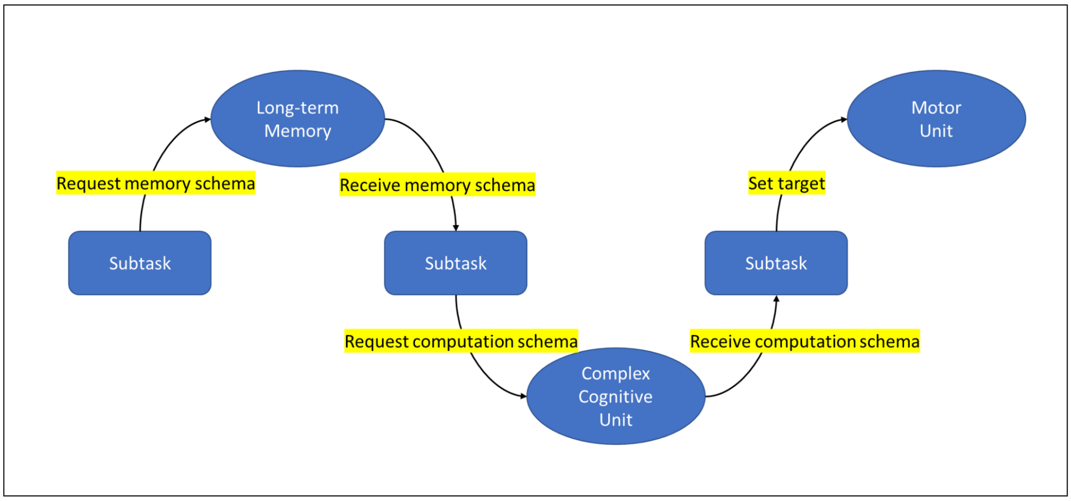

Figure 5: Subtask execution model

Subtasks are modeled using schema. The rationale is that drivers go through a learning process before getting their driving license. During this time, drivers develop different schemas to deal with necessary maneuvers on the roads, such as left/right turns, lane changes, etc. This knowledge, encoded in the architecture as memory and computation schemas, is pivotal to proficient task performance. Memory schemas, stored in the long-term memory unit, provide the parameters required to execute computation schemas stored in the complex cognitive process unit. Computation schemas, in turn, use memory schemas and information from the working memory to generate short-term targets for vehicle speed and direction.

In the longitudinal driving subtask, we employ the Intelligent Driver Model (IDM) to regulate speed control, which involves managing the vehicle's speed through brake and throttle adjustments. This subtask transitions from lane-following to car-following when another vehicle is nearby. In contrast, the lateral control, or lane-keeping subtask, requires continuous steering adjustments to keep the vehicle centered in its lane. The driver uses two points, near and far, to maintain the vehicle's position and anticipate the road's curvature. Each subtask initiates a specific memory schema request during execution, pausing until the processed schema request is received. The subtask then generates a computation schema request, yielding the next short-term speed and direction targets. These targets are sent to the motor unit as a memory schema, replacing the previous targets, and are then converted into actual vehicle control values by PID controllers, thus completing the driving process.

4 Simulation Setup

We used Carla [44] to simulate and evaluate our model. Carla is an AV simulation engine built on top of the Unreal game engine. The simulator can take road network descriptions in OpenDRIVE [45] format and has several prebuilt agents (basic and behavioral agents) and vehicle models. The vehicle control has normalized throttle, steer, and brake control values along with hand brake, reverse mode, and gear values. We used a subset of these controls (steer, brake, and throttle).

4.1 Brake Scenario

We used the straight road of a T intersection for our simulation [fig 7]. We used two agents (Carla's basic agent and the CogMod agent) to simulate the car-following scenario for our evaluation. In fig 9, the pictorial depiction of the scenario is provided.

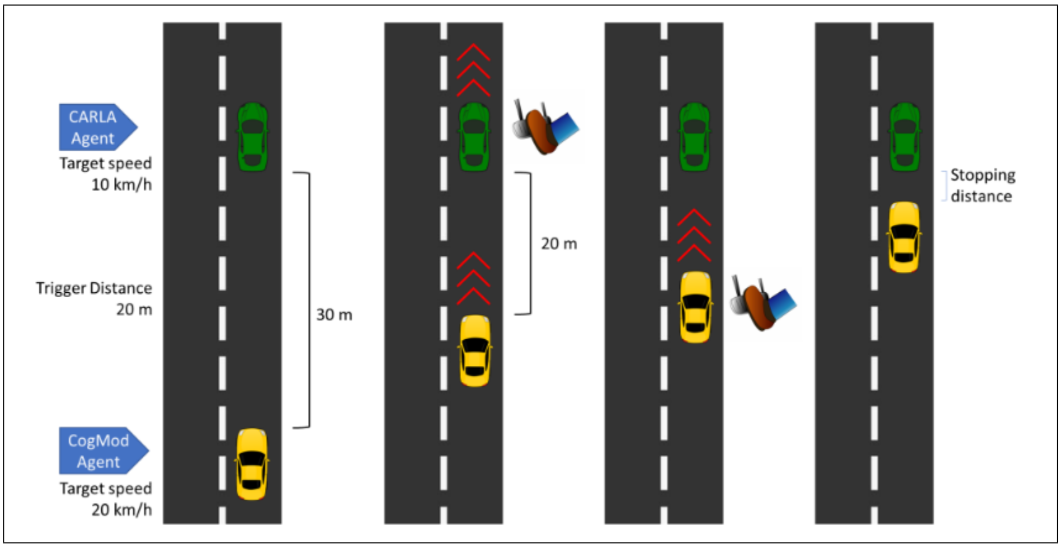

Figure 6: Simulated braking scenario

4.1.1 Scenario Description

The simulation starts with spawning the basic and CogMod agents with a 30-meter initial distance. The basic agent is set with a target speed of 10 km/h. So at the start of the simulation, the basic agent gains speed to reach the target speed. The CogMod agent following behind is set to get a max speed of 20 km/h. Eventually, the distance between the agents decreases due to positive relative speed. We start recording data for the car-following scenario after the distance between vehicles reaches the trigger distance and both vehicles are close to their target speed. We used 20 meters as the trigger distance for our scenarios. The basic agent brakes sharply after the scenario starts with a constant brake value. We used the normalized value 0.5 (50% maximum brake pressure) as the brake value for the Carla basic agent. The CogMod driver notices the basic agent is inside a 30-meter radius due to limitations imposed on the working memory. After perceiving the vehicle at the front, the CogMod agent slows down to stop to avoid the collision.

4.1.2 Simulation Run

We varied the processing time of the CogMod agents by varying the time required to process schema in different servers and simulated the car-following scenario 100 times for each configuration to find the distribution of the minimum stopping distance. We used 7 msec as the simulation delta time. So one step in the simulation takes 7 msec. It takes one simulation step to create the schema request and one step to send the request to the servers. Each server takes the defined amount of simulation steps to process schema requests. We varied the processing time of the servers from 1-3 simulation steps which means servers take 7-21 msec to process the schema request. The lowest time for executing a subtask (from creating memory schema for long-term memory to sending schema to the motor server) is 84 msec (if only one subtask is running). Server processing time increases with the simultaneous execution of multiple subtasks. Due to the variable processing time and the other uncertainty (using Carla asynchronous mode simulation), the CogMod driver stops at different distances in the simulated scenario.

4.2 Follow Scenario

The following section describes the steps we took in order to simulate the HighD scenarios. We build a highway road exactly to the definition provided in the dataset using the RoadRunner [46] software. RoadRunner outputs the FBX file that

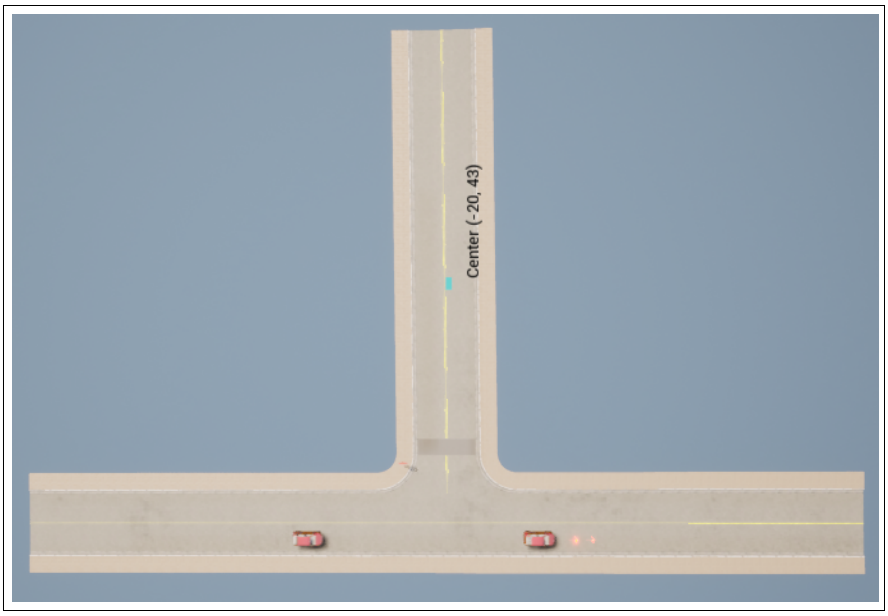

Figure 7: Birds eye view of the simulation world for braking scenario

Figure 8: Simulator view of the follow scenario simulation from HighD

can be imported into the Unreal Game Engine using the Carla plugin.

4.2.1 Scenario Filtering

Our principal data source is the HighD dataset, consisting of 60 individual recordings. Our attention was specifically drawn to the dataset from location id 2, representing a section of the German autobahn devoid of any speed limits. This dataset comprises numerous vehicular actions. Yet, for our validation, we focused exclusively on scenarios where one car was following another. It was essential to confirm that the leading car was unimpeded, i.e., no other vehicles disrupted its path during the recording session. It should be noted that the dynamics alter when more than two cars participate in the following scenario. Moreover, we only incorporated scenarios where the car-following event persisted for more than 5 seconds (equivalent to a minimum of 125 frames as HighD records data at 25 fps).

In an attempt to record the CogMod drivers' reactions precisely, we chose scenarios with an initial vehicle-to-vehicle distance surpassing 50 meters. This specification ensures that the trailing CogMod agent doesn't visually detect the leading vehicle until they're within this defined distance. We also ensured the selected scenarios had segments where the distance between vehicles was reduced from the starting measurement. The rationale behind this is that scenarios with a continuous increase in the distance suggest that the leading vehicle is outpacing the following one, generally leading to less risk for the following vehicle. Our criteria were met by five scenarios in total from the initial dataset. We used the scenario that has the lowest TTC value (TTC = 31).

4.2.2 Simulation Run

We utilized Carla to simulate the car-following scenario. The simulation process began with the spawning of the leading vehicle, followed by positioning the trailing vehicle 800 meters away. This distance was chosen to provide adequate time for the following vehicle to attain the target speed to initiate the scenario. The target speed was defined as the speed of the following vehicle in the first frame of the scenario. Upon reaching this target speed, the following vehicle maintains it until the scenario commences. The scenario is initiated when the preceding vehicle enters a predefined trigger distance, set to the initial gap between the vehicles in the first frame. After the scenario trigger, the target speed is adjusted to 50 m/s (equivalent to 180 km/h). For model evaluation, we used two different models in the simulation. One model only uses IDM to generate the target velocity at each frame based on the surrounding, while the other model uses CogMod to simulate the same scenario. Each model was simulated 10 times in Carla synchronous mode. In fig 10, we showed a comparative result of both models.

4.3 Model Parameters

The following parameters are used during the simulation [Table 0.2]. These parameters remained constant for each simulation run.

Table 0.2: Model parameters

	Braking Scenario	**Follow Scenario**
Working Memory		
Tracking Radius	30 m	61.8 m
Controller		
PID_lateral k_p	1.95	1.95
PID_lateral k_i	0.05	0.05
PID_lateral k_d	0.2	0.2
PID_longitudinal k_p	1.0	20.0
PID_longitudinal k_i	0.05	5.0
PID_longitudinal k_d	0.0	0.0
Throttle_max	0.75 (normalized)	0.95 (normalized)
Brake_max	0.3 (normalized)	0.5 (normalized)
Steer_max	0.8 (normalized)	0.8 (normalized)
Subtask - Lane Following		
Desired Velocity	5.56 m/s (20 km/h)	50 m/s (180 km/h)
Safe Time Headway	1.5 s	0.5 s
Max Acceleration	2.73 m/s^2	2.9 m/s^2
Comfortable Deceleration	1.67 m/s^2	1.67 m/s^2
Preferred Stop Distance	6 m	6 m
Minimum Distance	1 m	1 m
Vehicle Length	4 m	4 m
Acceleration Exponent	4	4
Subtask - Lane Keeping		
Far Distance	100 m	100 m

5 Evaluation

In this research, we used Time-to-collision (TTC) and stopping distance as a surrogate to measure the criticality of a scenario. A TTC value at an instant t is defined as the time that remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained [47]. The safety stop distance is the distance between the vehicle after it stops and the obstacle ahead. The time-to-collision distribution has been applied in several studies to identify traffic safety. Usually, lower

TTC values represent increased criticality. We showed that our model could generate a variety of scenarios with variable stop distance in a hand-authored scenario and with lower TTC by augmenting the HighD [48] data.

5.1 Braking Scenario

The increased processing time increases the reaction time for the agents. According to [49], response time for drivers can be decomposed into a sequence of components: mental processing time (time required to perceive cue and decide on a response), movement time (time required for motor movement), and machine response time (time a mechanical device takes to perform its response). In our model, we varied only the mental processing time by applying constraints on the servers. The motor movement time is zero. Machine response time is also zero, so no time is required for the applied control to take effect. We set the preferred stopping distance to 6 meters, which increased the likelihood of scenarios with that stop distance.

How far behind the agent will stop is determined by how much time CogMod agents require to process driving-related information. Due to increased processing time, drivers stop early or late, resulting in an increased deviation from the preferred stopping distance. We showed our results in figure 9. Figure 9 shows nine distance distributions with varying server processing times split into four groups. The legends are displayed in numeric pairs. The pair specifies the processing time of the long-term memory (lm) unit and complex cognitive (cc) processing unit accordingly. The green line in figure 9(a) shows the stopping distance with the highest processing time among the simulation

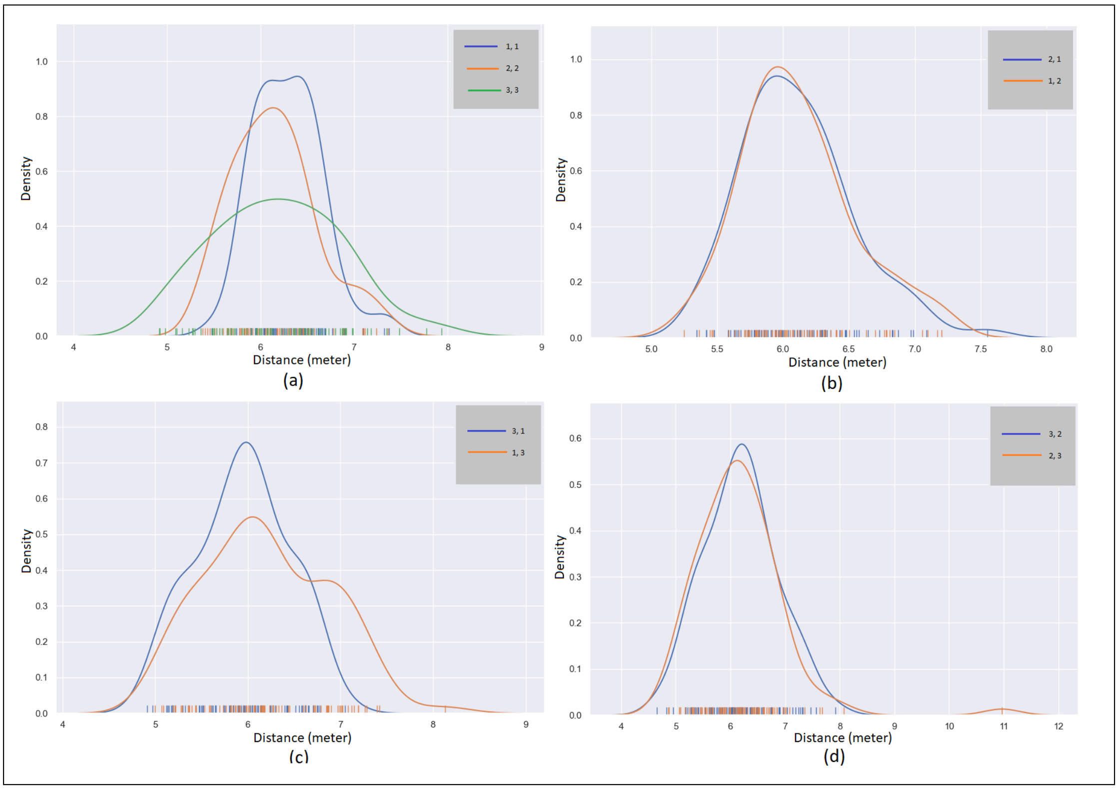

Figure 9: Stopping distance distribution with varying processing time. The numeric value denotes the required amount of simulation steps in long-term memory (lm) and complex cognitive (cc) process server accordingly. **a.** (blue) lm: 1, cc: 1; (orange) lm: 2, cc: 2; (green) lm: 3, cc: 3. **b.** (blue) lm: 2, cc: 1; (orange) lm: 1, cc: 2. **c.** (blue) lm: 3, cc: 1; (orange) lm: 1, cc: 3. **d.** (blue) lm: 3, cc: 2; (orange) lm: 2, cc: 3.

results.

5.2 Follow Scenario

Simulation results from the following scenario indicate that employing the CogMod driver model enables us to amplify the criticality of a scenario by increasing the TTC (Time to Collision) of the scenario, as depicted in Figure 10. Distracted CogMod agents generated scenarios where the TTC value decreased from the original scenario. This outcome stems from both the cognitive architecture and the vision module. Due to the serial nature of task processing, latency in information processing is inevitable. Moreover, the driver's field of perception is limited to the area within the gaze triangle due to the constraints of the vision module. This restriction can often cause drivers to miss viewing task-critical information, thereby contributing to an escalation in scenario criticality. On the other hand, IDM agents failed to achieve the TTC value of the original scenario due to the early braking, as the agent had perfect information about the surrounding.

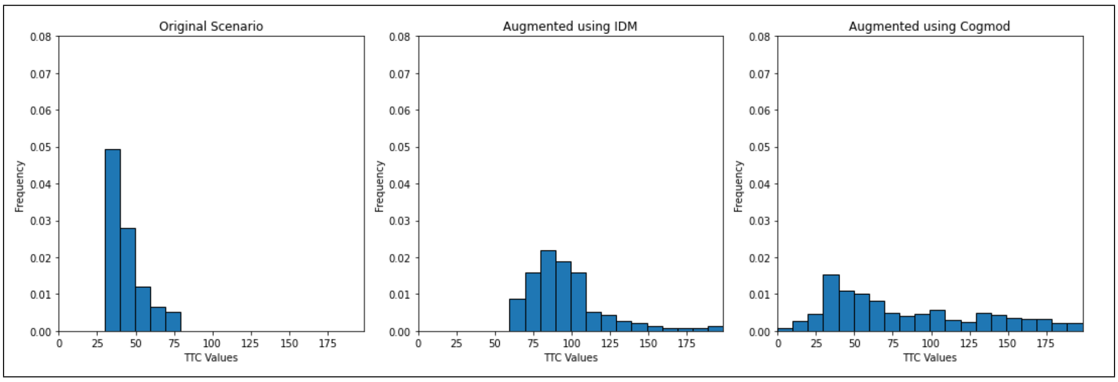

Figure 10: Distribution of TTC (left) Original scenario from HighD dataset, (mid) Augmented using IDM, (right) Augmented using CogMod

6 Conclusion

In this paper, we put forth a model of human driver behavior that is grounded in a hybrid cognitive architecture. Our approach drew upon theories from a diverse range of fields, including traffic modeling research, psychology, cognitive science, and behavior science, to create a unified process of driving. This model is capable of integrating multiple task-specific analytical driver models, particularly in the simulation of car-following scenarios, under a common cognitive process framework. Importantly, the model is able to reproduce scenarios wherein agents exhibit delayed decision-making due to an increased duration of information processing. Along with processing time limitations, human drivers also have a limited field of view and variable resolution of visual information due to focus and peripheral vision, forcing the driver to look into a selective portion of the available visual field. These limitations emerged in scenarios with variable driving behavior that we used to augment existing scenarios. The model can act reactively to changing AV behavior and can be used throughout the AV development process.

Bibliography

[1] I. R. Jenkins, L. O. Gee, A. Knauss, H. Yin, and J. Schroeder, "Accident scenario generation with recurrent neural networks," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 3340–3345, IEEE, 2018.

[2] Z. Xinxin, L. Fei, and W. Xiangbin, "Csg: Critical scenario generation from real traffic accidents," in *2020 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1330–1336, IEEE, 2020.

[3] F. Klück, Y. Li, M. Nica, J. Tao, and F. Wotawa, "Using ontologies for test suites generation for automated and autonomous driving functions," in *2018 IEEE International symposium on software reliability engineering workshops (ISSREW)*, pp. 118–123, IEEE, 2018.

[4] K. Rumar, "The basic driver error: late detection," *Ergonomics*, vol. 33, no. 10-11, pp. 1281–1290, 1990.

[5] J. E. Laird, *The Soar cognitive architecture.* MIT press, 2019.

[6] L.-Z. Bi and Y.-L. Liu, "Modeling driver car-following based on the queuing network

cognitive architecture," in *2009 International Conference on Machine Learning and Cybernetics*, vol. 2, pp. 895–900, 2009.

[7] Y. Liu and Z. Wu, "Multitasking driver cognitive behavior modeling," in *2006 3rd International IEEE Conference Intelligent Systems*, pp. 52–57, IEEE, 2006.

[8] A. Baddeley, G. Hitch, and R. Allen, "A multicomponent model of working memory," *Working memory: State of the science*, pp. 10–43, 2021.

[9] M. A. Arbib, *The handbook of brain theory and neural networks.* MIT press, 2003.

[10] G. J. Wilde, "Risk homeostasis theory and traffic accidents: propositions, deductions and discussion of dissension in recent reactions," *Ergonomics*, vol. 31, no. 4, pp. 441–468, 1988.

[11] L. Evans, "Comments on wilde's notes on" risk homeostasis theory and traffic accident data."," 1986.

[12] R. Fuller, "Driver control theory: From task difficulty homeostasis to risk allostasis," in *Handbook of traffic psychology*, pp. 13–26, Elsevier, 2011.

[13] R. Fuller, "Towards a general theory of driver behaviour," *Accident analysis & prevention*, vol. 37, no. 3, pp. 461–472, 2005.

[14] J. J. Gibson and L. E. Crooks, "A theoretical field-analysis of automobile-driving," *The American journal of psychology*, vol. 51, no. 3, pp. 453–471, 1938.

[15] H. Summala, "Accident risk and driver behaviour," *Safety Science*, vol. 22, no. 1-3, pp. 103–117, 1996.

[16] T. A. Ranney, "Models of driving behavior: a review of their evolution," *Accident analysis & prevention*, vol. 26, no. 6, pp. 733–750, 1994.

[17] C. D. Wickens, "Multiple resources and mental workload," *Human factors*, vol. 50, no. 3, pp. 449–455, 2008.

[18] D. De Waard and K. Brookhuis, "The measurement of drivers' mental workload," 1996.

[19] J. Paxion, E. Galy, and C. Berthelon, "Mental workload and driving," *Frontiers in psychology*, vol. 5, p. 1344, 2014.

[20] D. Kahneman, *Attention and effort*, vol. 1063. Citeseer, 1973.

[21] Y. Yeh and C. D. Wickens, "The dissociation of subjective measures of mental workload and performance," tech. rep., 1984.

[22] G. J. Wilde, "Target risk 3," *Risk Homeostasis in Everyday Life. Digital Edition. Version*, vol. 20, 2014.

[23] C. J. Patten, A. Kircher, J. Östlund, L. Nilsson, and O. Svenson, "Driver experience and cognitive workload in different traffic environments," *Accident Analysis & Prevention*, vol. 38, no. 5, pp. 887–894, 2006.

[24] C. Gabaude, B. Baracat, C. Jallais, M. Bonniaud, and A. Fort, "Cognitive load

measurement while driving. in: Human factors: a view from an integrative perspective," 2012.

[25] M. Treiber, A. Hennecke, and D. Helbing, "Congested traffic states in empirical observations and microscopic simulations," *Physical review E*, vol. 62, no. 2, p. 1805, 2000.

[26] D. C. Gazis, R. Herman, and R. B. Potts, "Car-following theory of steady-state traffic flow," *Operations research*, vol. 7, no. 4, pp. 499–505, 1959.

[27] P. G. Gipps, "A behavioral car-following model for computer simulation," *Transportation Research Part B: Methodological*, vol. 15, no. 2, pp. 105–111, 1981.

[28] K. I. Ahmed, *Modeling drivers' acceleration and lane changing behavior.* PhD thesis, Massachusetts Institute of Technology, 1999.

[29] G. F. Newell, "Nonlinear effects in the dynamics of car following," *Operations research*, vol. 9, no. 2, pp. 209–229, 1961.

[30] B. Higgs, M. Abbas, and A. Medina, "Analysis of the wiedemann car following model over different speeds using naturalistic data," in *Procedia of RSS Conference*, pp. 1–22, 2011.

[31] A. Kesting, M. Treiber, and D. Helbing, "General lane-changing model mobil for car-following models," *Transportation Research Record*, vol. 1999, no. 1, pp. 86–94, 2007.

[32] M. Treiber, A. Kesting, and D. Helbing, "Delays, inaccuracies and anticipation in microscopic traffic models," *Physica A: Statistical Mechanics and its Applications*, vol. 360, no. 1, pp. 71–88, 2006.

[33] M. Lindorfer, C. F. Mecklenbraeuker, and G. Ostermayer, "Modeling the imperfect driver: Incorporating human factors in a microscopic traffic model," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 9, pp. 2856–2870, 2017.

[34] J. R. Anderson, M. Matessa, and C. Lebiere, "Act-r: A theory of higher level cognition and its relation to visual attention," *Human–Computer Interaction*, vol. 12, no. 4, pp. 439–462, 1997.

[35] Y. Liu, R. Feyen, and O. Tsimhoni, "Queueing network-model human processor (QN-MHP) a computational architecture for multitask performance in human-machine systems," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 13, no. 1, pp. 37–70, 2006.

[36] D. D. Salvucci, "Modeling driver behavior in a cognitive architecture," *Human factors*, vol. 48, no. 2, pp. 362–380, 2006.

[37] L. Bi, G. Gan, and Y. Liu, "Using queuing network and logistic regression to model driving with a visual distraction task," *International journal of human-computer interaction*, vol. 30, no. 1, pp. 32–39, 2014.

[38] L.-Z. Bi, J.-X. Shang, and G.-D. Gan, "Modeling driver lane changing control with

the queuing network-model human processor," in *2012 International Conference on Machine Learning and Cybernetics*, vol. 3, pp. 830–834, IEEE, 2012.

[39] O. Tsimhoni and Y. Liu, "Modeling steering using the queueing network—model human processor (QN-MHP)," in *Proceedings of the human factors and ergonomics society annual meeting*, vol. 47, pp. 1875–1879, SAGE Publications Sage CA: Los Angeles, CA, 2003.

[40] J. R. Anderson, D. Bothell, M. D. Byrne, S. Douglass, C. Lebiere, and Y. Qin, "An integrated theory of the mind.," *Psychological review*, vol. 111, no. 4, p. 1036, 2004.

[41] F. C. Bartlett, *Psychology and primitive culture.* CUP Archive, 1928.

[42] R. C. Anderson, "Role of the reader's schema in comprehension, learning, and memory," in *Theoretical Models and Processes of Literacy*, pp. 136–145, Routledge, 2018.

[43] J. Sweller, J. J. Van Merrienboer, and F. G. Paas, "Cognitive architecture and instructional design," *Educational psychology review*, vol. 10, no. 3, pp. 251–296, 1998.

[44] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, "Carla: An open urban driving simulator," in *Conference on robot learning*, pp. 1–16, PMLR, 2017.

[45] ASAM OpenDRIVE, "Asam opendrive v1.8.0," 2022. [Online; accessed 5-May-2022].

[46] "Roadrunner," 2023. Accessed: June 12, 2023.

[47] D. Gettman and L. Head, "Surrogate safety measures from traffic simulation models," *Transportation Research Record*, vol. 1840, no. 1, pp. 104–115, 2003.

[48] R. Krajewski, J. Bock, L. Kloeker, and L. Eckstein, "The highd dataset: A drone dataset of naturalistic vehicle trajectories on german highways for validation of highly automated driving systems," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 2118–2125, IEEE, 2018.

[49] M. Green, "How long does it take to stop? Methodological analysis of driver perception-brake times," *Transportation human factors*, vol. 2, no. 3, pp. 195–216, 2000.