Modeling the concept of a Safety Tolerance Zone: State-of-the-art and proposed alternatives

Eva Michelaraki[1*], Christos Katrakazas[1], Amir Pooyan Afghari[2], Eleonora Papadimitriou[2], Christelle Al Haddad[3], Kui Yang[3], Constantinos Antoniou[3], Tom Brijs[4], George Yannis[1]

[1]*National Technical University of Athens, Department of Transportation Planning and Engineering, 5 Heroon Polytechniou str., 15773, Athens, Greece*
[2]*Delft University of Technology, Faculty of Technology, Policy and Management, Jaffalaan 5, 2628 BX, Delft, the Netherlands*
[3]*Technical University of Munich, Chair of Transportation Systems Engineering, Arcisstrasse 21, 80333, Munich, Germany*
[4]*UHasselt, School for Transportation Sciences, Transportation Research Institute (IMOB), Agoralaan, 3590 - Diepenbeek, Belgium*

1. Introduction

Within a transport system, a driver can be viewed as a (technology assisted) human operator, self-regulating control over a vehicle in the context of crash avoidance. Based on the Fuller's task capability model [2, 3], driving difficulty is inversely related to the difference between driving task demand and the driver's task capability. As a result, safe driving can be regarded as the practice of using driving strategies that minimize the risk on the road and thus help avoiding critical events (e.g. crashes) by predicting hazardous situations on the road. Conversely, dangerous driving is found when an individual's driving falls below the expected level of a careful and competent driver [1]. It can also be classed as dangerous driving scenarios where the vehicle being driven is in a dangerous condition and not suitable to be on public roads. It is worth noting that traffic safety conditions involve the quality of the road defined by the level of crashes and reflecting the degree of safety of traffic participants from road traffic crashes as well as their consequences. At the same time, road traffic safety can be understood as the result of the safe interaction of participants between themselves and the environment. Thus, when assessing the traffic safety on the road environment, driver's physiological and psychological capabilities should be taken into consideration.

The i-DREAMS project aims to establish a framework for the definition, development, testing and validation of a context-aware safety envelope for driving in a Safety Tolerance Zone (STZ), within a smart Driver, Vehicle and Environment Assessment and Monitoring System (i-DREAMS). Taking into account driver background factors and risk indicators associated with the driving performance as well as the driver state and driving task complexity parameters, a continuous real-time assessment will be made in order to monitor and determine if drivers are within acceptable boundaries of safe operation. Furthermore, delayed safety-oriented interventions and post-trip feedback aimed at enhancing the knowledge, attitudes and perceptions will be provided.

The concept of the STZ is the core concept of the i-DREAMS project[2] and attempts to describe the point at which self-regulated control is considered safe. It is based on Fuller's Task Capability Interface Model [2, 3] which states that loss of control occurs when the demand of a driving task outweighs the operator's capability. The STZ is subdivided in three levels of safety, namely: the 'Normal Driving phase', the 'Danger phase' and the 'Avoidable Accident phase'.

This study aims to explicitly describe the practical conceptualization of the STZ in order to transition from a theoretical framework to a practical implementation and a fully functional methodology. In order to fulfil the purpose of this research, the most suitable mathematical models to realize the STZ, applied in the i-DREAMS risk analyses, both from a real-time and post trip perspective are provided.

2. Methodology

To date, predicting driving behavior by employing mathematical driver models, obtained directly from the observed driving-behavior data, has gained much attention [4]. A few models have been used to address road safety and the estimation of driving behavior, many of which in the context of experimental studies, including

[1] Corresponding author. Tel.: +30-210-772-1265;
E-mail address: evamich@mail.ntua.gr

[2] Further general project information can be found on the website: https://idreamsproject.eu/

naturalistic driving or field operational trials and driving simulator studies. A review of safety models can be found in [5], where the authors noted inconsistency in the language of safety models and emphasized that additional factors should be investigated, such as the effect of organizational culture, emergency responses, the health system and economic influences on-road safety. In their opinions, there are models with potential to improve road safety, but yet to be applied.

In order to obtain the most suitable modeling approaches for the STZ, a thorough literature review of models dealing with driver behavior and collision risk, both in real-time and post-trip, was implemented. Several state-of-the-art methodological approaches that enable the modeling of crash risk were evaluated. The key output is expected to be the correlation of the explanatory variables and various indicators of task complexity and coping capacity with the dependent variable risk.

Figure 1 provides the flowchart of the proposed approach.

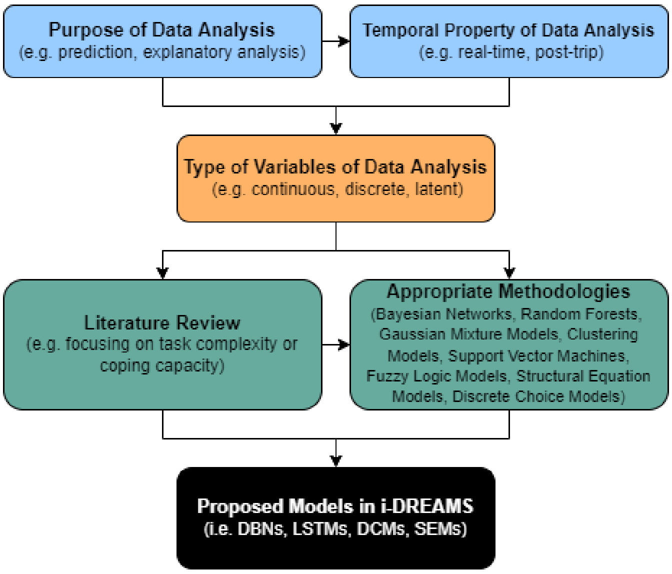

Figure 1: Flowchart of the proposed approach

3. Results

3.1 Dynamic Bayesian Networks (DBNs)

Dynamic Bayesian Networks (DBNs) are the most appropriate method to model discrete indicators of risk. A DBN is a directed acyclic graphical model that can express a joint probability distribution of a large set of variables [6]. Usually, DBNs are utilized for learning causal relationships and hence are ideal for investigating the effect of interventions by combining new and prior knowledge data. The core of DBNs is the attempt to infer a "hidden" state based on a group of available observations.

The variables monitored by the i-DREAMS platform concerning task complexity and coping capacity (i.e. driver and vehicle state); thus the raw sensor measurements are observed. By filtering these raw measurements, the Context-Operator-Vehicle (COV) indicators become available, so they are used to determine the coping capacity and task complexity at each time moment. Hence, the two layers of task complexity and coping capacity depend on the COV indicators. Finally, as the operator's capacity indicates the ability of the driver to operate safely with regards to the task imposed, the operator's capacity depends on the complexity of the task.

3.2 Long Short-Term Memory Networks (LSTMs)

Long Short-Term Memory Networks (LSTMs) are suitable for continuous indicators of risk. These models are a special kind of Recurrent Neural Network (RNN), capable of learning long-term dependencies [7]. They work tremendously well on a large variety of problems, and are now widely used. LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior and not something they struggle to learn. All recurrent LSTMs have the form of a chain of repeating modules of neural network.

LSTMs use “memory block” in the hidden unit to capture the long-term dependencies that may exist in the data [8]. This memorizing capability of LSTM has shown the best performance across many time-series tasks, such as activity recognition, video captioning and language translation. The cell state (memory block) of LSTM has one or more memory cells that are regulated by structures called gates, which control the addition of new sequential information and the removal of useless ones to and from memory, respectively. Gates are a combination of sigmoid activation functions and a dot (scalar) multiplication operation, and they are used to control information that passes through the network.

The problem of defining the STZ levels becomes more straightforward, since LSTMs as a sub-category of Deep Neural Networks act like “black-boxes” [9] and thus the only input that needs to be provided to the model are labelled time series data.

3.3 Discrete Choice Models (DCMs)

Discrete Choice Models (DCMs) are the most common statistical approaches to model discrete indicators of risk. These models rely on the maximum utilisation theory in economics [10] stating that among many alternatives, individuals select the alternative (i.e. discrete category) that maximises their utility. Thus, the first step in formulating DCMs is defining a utility for each discrete alternative.

This utility will not have a physical meaning but is rather an auxiliary term to determine the probability of selecting an alternative over the other alternatives. Depending on the nature of the discrete variable being nominal (e.g. occurrence of a rare event/no rare event) or ordered (i.e. STZ levels), DCMs can take the form of either unordered or ordered.

3.4 Structural Equation Models (SEMs)

Structural Equation Models (SEMs) are suitable for continuous indicators of risk. These models represent a natural extension of a measurement model and establish a mature statistical modelling framework [11]. In particular, they are designed to deal with several difficult modelling challenges, including cases in which some variables of interest to a researcher are unobservable or latent and are measured using one or more exogenous variables, endogeneity among variables, and complex underlying social phenomena. SEMs are widely used for modelling complex and multi-layered relationships between observed and unobserved variables. Observed variables are objectively measurable, whereas unobserved variables are latent constructs - analogous to components in a factor/principal component analysis. SEMs have two components: a measurement model and a structural model. The measurement model is used to determine how well various observable exogenous variables can measure (i.e. load on) the latent variables, as well as the related measurement errors. The structural model is used to explore how the model variables are inter-related, allowing for both direct and indirect relationships to be modelled. In this sense, SEMs differ from ordinary regression techniques in which relationships between variables are strictly.

According to the i-DREAMS concept of the STZ, it is hypothesized that latent risk is measured by a composite variable consisting of all risk factors (e.g. Y: fatigue, loss of sleep, hands on wheel or mobile phone use, speeding, harsh acceleration, harsh deceleration, harsh cornering, lane departure warning, illegal overtaking warning, forward collision warning, vulnerable road user warning), and latent task complexity and latent coping capacity predict the latent risk. Latent task complexity and latent coping capacity are also measured by observed indicators.

4. Discussion

A variety of analytical methods and potential modeling approaches has been reviewed, among which four methods have been selected to be used in i-DREAMS: Dynamic Bayesian Networks (DBNs), Long Short-Term Memory (LSTMs) deep neural networks, Discrete Choice Models (DCMs) and Structural Equation Models (SEMs). Each of the aforementioned methods has strengths and limitations, making it suitable for a certain purpose in the project. Based on the methodological background, an attempt was made to transform the model approach into a suitable structure. The key output is expected to be the correlation of the explanatory variables and various indicators of task complexity and coping capacity with the dependent variable risk.

While this literature review provided a good understanding of the potential modeling candidates in i-DREAMS and the selected models seem plausible, there are still some open issues that need to be considered for model selection. Specifically, the suggested models may be confronted with additional limitations considering the different types of data being collected in i-DREAMS. Additionally, several new limitations have been identified with additional deeper investigations into these models. For instance, it is noted that LSTM is not able to incorporate the inter-relationship between variables into real-time predictions (endogeneity) and SEM is not suitable for analyzing discrete dependent variables.

All in all, considering risk as a dependent variable in i-DREAMS, the type of mathematical model to be used for data analysis highly depends on the definition of risk adopted in each case. Figure 2 provides a schematic overview of the proposed mathematical models (DBN, LSTM, DCM and SEM) to be considered for the analysis.

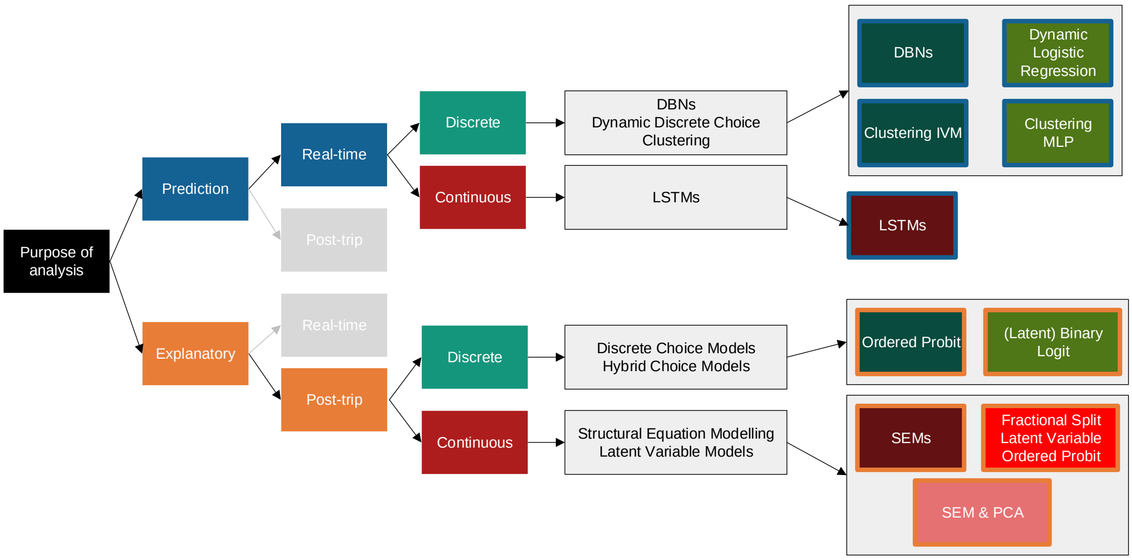

Figure 2: Schematic overview of modeling approaches considered for the analysis of risk factors

5. Conclusions

The aim of the current research is to present the practical conceptualization of the STZ in order to transition from a theoretical framework for operational design into a practical implementation and a fully functional methodology of the STZ concept.

To achieve this goal, four different methodological formulations were proposed to turn the available measurements into meaningful information on the level of driving safety. The most prominent approaches that can model driving behavior and recognize the three phases of the STZ were initially found to be Dynamic Bayesian Networks (DBNs; a probabilistic graphical time-series model) and Long Short-Term Memory networks (LSTMs; a deep neural network formulation), due to their efficiency and flexibility in real-time predictions. Furthermore, Discrete Choice Models (DCMs) and Structural Equation Models (SEMs) were also deemed suitable for the i-DREAMS concept, providing ‘static’ or post-trip predictions, in contrast with DBNs and LSTMs which work dynamically (i.e. in real-time).

The testing, calibration and enhancement of the mathematical models during the i-DREAMS simulation and on-road experiments can assure a sufficient and efficient data analysis, as well as timely initiation of the safety interventions. When preliminary results are available, the most crucial risk indicators of task complexity and coping capacity will be extracted, the proposed models will be tested and the suitable models will be selected for data analysis.

Acknowledgments

The research was funded by the European Union's Horizon 2020 i-DREAMS project (Project Number: 814761) funded by European Commission under the MG-2-1-2018 Research and Innovation Action (RIA).

References

1. Dula, C. S., & Geller, E. S. (2003). Risky, aggressive, or emotional driving: Addressing the need for consistent communication in research. Journal of safety research, 34(5), 559-566.
2. Fuller, R. (2005). Towards a general theory of driver behaviour. Accident analysis & prevention, 37(3), 461-472.

3. Fuller, R. (2011). Driver control theory: From task difficulty homeostasis to risk allostasis. In Handbook of traffic psychology (pp. 13-26). Academic Press.
4. Kanaan, D., Ayas, S., Donmez, B., Risteska, M., & Chakraborty, J. (2019). Using Naturalistic Vehicle-Based Data to Predict Distraction and Environmental Demand. International Journal of Mobile Human Computer Interaction (IJMHCI), 11(3), 59-70.
5. Hughes, B. P., Newstead, S., Anund, A., Shu, C. C., & Falkmer, T. (2015). A review of models relevant to road safety. Accident Analysis & Prevention, 74, 250-270.
6. Sun, J., & Sun, J. (2015). A dynamic Bayesian network model for real-time crash prediction using traffic speed conditions data. Transportation Research Part C: Emerging Technologies, 54, 176-186.
7. Gers, F. A., Schraudolph, N. N., & Schmidhuber, J. (2002). Learning precise timing with LSTM recurrent networks. Journal of machine learning research, 3(Aug), 115-143.
8. Girma, A., Yan, X., & Homaifar, A. (2019). Driver Identification Based on Vehicle Telematics Data using LSTM-Recurrent Neural Network. arXiv preprint arXiv:1911.08030.
9. Xu, C., Wang, W., Liu, P. (2013). A Genetic Programming Model for Real-Time Crash Prediction on Freeways. IEEE Trans. Intell. Transp. Syst. 14, 574–586.
10. Hensher, D. A., Rose, J. M., Rose, J. M., & Greene, W. H. (2005). Applied choice analysis: a primer. Cambridge university press.
11. Heck, R. H., & Thomas, S. L. (2020). An introduction to multilevel modeling techniques: MLM and SEM approaches. Routledge.