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BRIEF REPORT

Bayesian network approach to building an affective module for a driver behavioural model

[version 1; peer review: 2 approved with reservations]

Dorota Mlynarczyk[1], Gabriel Calvo[1], Francisco Palmi-Perales[1], Carmen Armero[1], Virgilio Gómez-Rubio[2], Ana de la Torre-García[3], Ricardo Bayona Salvador[3]

[1]Universitat de València, Valencia, Valencian Community, Spain
[2]Universidad de Castilla-La Mancha, Albacete, Castilla-La Mancha, Spain
[3]Instituto de Biomecánica de Valencia, Valencia, Valencian Community, Spain

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Abstract

This paper focuses on the affective component of a driver behavioural model (DBM). This component specifically models some drivers' mental states such as mental load and active fatigue, which may affect driving performance. We have used Bayesian networks (BNs) to explore the dependencies between various relevant random variables and assess the probability that a driver is in a particular mental state based on their physiological and demographic conditions. Through this approach, our goal is to improve our understanding of driver behaviour in dynamic environments, with potential applications in traffic safety and autonomous vehicle technologies.

Keywords

Directed acyclic graph, Mental states, Probability and uncertainty, Statistical modelling

HE This article is included in the Horizon Europe gateway.

Open Peer Review

Approval Status ? ?

	1	2
version 1 06 Jul 2026	? view	? view

1. **Johan Kwisthout**, Radboud University, Nijmegen, The Netherlands
Joost Vossers, Radboud University Donders Institute for Brain Cognition and Behaviour, Nijmegen, The Netherlands

2. **Henrick Haule**, The University of Alabama in Huntsville, Huntsville, USA

Any reports and responses or comments on the article can be found at the end of the article.

Corresponding author: Dorota Mlynarczyk (dorota.mlynarczyk@uv.es)

Author roles: Mlynarczyk D: Conceptualization, Data Curation, Investigation, Methodology, Software, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing; **Calvo G**: Conceptualization, Data Curation, Investigation, Methodology, Software, Writing – Original Draft Preparation, Writing – Review & Editing; **Palmi-Perales F**: Conceptualization, Investigation, Methodology, Writing – Review & Editing; **Armero C**: Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – Review & Editing; **Gómez-Rubio V**: Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – Review & Editing; **de la Torre-García A**: Data Curation, Investigation; **Bayona Salvador R**: Data Curation, Investigation

Competing interests: No competing interests were disclosed.

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1. Introduction

Understanding driver behaviour is a cornerstone of improving road safety, optimising traffic management, and developing autonomous vehicle systems. Human drivers exhibit complex decision-making processes influenced by numerous factors with a high degree of uncertainty, including environmental conditions, traffic scenarios, and psychological states among others. To reflect human behaviour, a probabilistic model is required that can both account for its complexity and capture the uncertainty associated with it. Bayesian networks (BNs) provide a robust framework to address this challenge.

A BN[1] is a probabilistic model within a graphical framework to represent stochastic relationships between random variables. These variables are shown as nodes, and the edges between them encode probabilistic conditional dependencies, allowing the BN to assess probabilities associated with different outcomes based on data. From a modelling perspective, BNs provide a flexible framework for inference and prediction, because as Pearl and Russell[2] state "they are direct representations of the world, not of reasoning processes". By incorporating probabilistic reasoning, BNs are powerful tools for modelling complex systems. This approach is particularly suitable for analysing driver behaviour, as it can effectively accommodate the unpredictability inherent in human decision-making processes.[3]

A driver behavioural model (DBM)[4] is a broad framework that integrates data from various sources, such as sensors, traffic systems, or driver profiles, to examine how different factors (such as speed, road conditions, and distractions) influence driver actions. This research is a part of the BERTHA EU project (BEhavioural ReplicaTion of Human drivers),[5] which aims to develop a comprehensive modular DBM capable of explaining and predicting human driving behaviour in a wide range of contexts relevant for connected, cooperative, and automated mobility (CCAM). The DBM proposed in BERTHA integrates multiple dimensions of human driving—including cognitive, affective, perceptual, and contextual factors—within a unified probabilistic framework. By combining empirical data from controlled experiments and real-world driving, BERTHA seeks to capture the inherent variability of human driving.

In this paper, we focus on a part of the affective module of the DBM of the BERTHA project, designed to capture and model the emotional and cognitive states that influence the behaviour of a driver. Specifically, we will discuss the intensity of some mental states, such as active fatigue and mental load, that significantly impact a driver's response in various scenarios. Furthermore, the model in this paper could easily be extended to explore how mental states influence driving actions, offering a more comprehensive understanding of driver behaviour under dynamic and uncertain conditions.

The remainder of this paper is organised as follows. Section 2 outlines the foundational principles of BNs in a Bayesian inferential context, details the database for the BN model and presents its structure. Section 3 presents the results in general terms, illustrating them with predictive assessments of active fatigue and mental load. Finally, Section 4 briefly discusses the extension of the model and areas for further research.

2. Methods

2.1 Bayesian networks and Bayesian inference

BNs are probabilistic models whose stochastic behaviour can be depicted graphically by using directed acyclic graphs (DAGs). Graphs are mathematical structures that can be used to connect pairs of nodes by edges. These elements are random variables and probability distributions in probabilistic DAGs, respectively. In addition, DAGs must adhere to two general properties: all edges must have a probabilistic direction, and the graph must be acyclic. In a DAG, the parents of a node are all those nodes in the network structure that have directed edges pointing to it. Figure 1 illustrates the DAG corresponding to the set of random variables $\{Y_1, Y_2, Y_3, Y_4\}$, where the random variables Y_1 and Y_2 are the parents of Y_3 ($\text{pa}(Y_3) = \{Y_1, Y_2\}$) and Y_3 is the only parent of Y_4 ($\text{pa}(Y_4) = \{Y_3\}$). The four variables are connected through three pointed edges that represent the probability distribution of Y_3 given its parents and that of Y_4 given Y_3. Nodes Y_1 and Y_2 have no parents.

Probabilistic models that depend on unknown parameters $\boldsymbol{\theta}$ need the statistic framework to estimate them. In this paper, this will be the Bayesian inferential methodology. This approach requires the full specification of a probability distribution for all random variables in the model, together with a prior distribution for all the unknown parameters. Formally, a BN[2] is a joint probability distribution $f(\boldsymbol{y}, \boldsymbol{\theta})$ over a set of random variables $\boldsymbol{Y} = \{Y_v : v = 1, \ldots, V\}$, representing the node set of the network, and a vector $\boldsymbol{\theta}$ of their subsequent parameters as follows:

$$f(\mathbf{y}, \boldsymbol{\theta}) = f(\mathbf{y}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}),$$

where $f(\mathbf{y}|\boldsymbol{\theta})$ is the conditional distribution of $\mathbf{Y}$ given $\boldsymbol{\theta}$ and $\pi(\boldsymbol{\theta})$ is a prior distribution for $\boldsymbol{\theta}$. The BN satisfies the

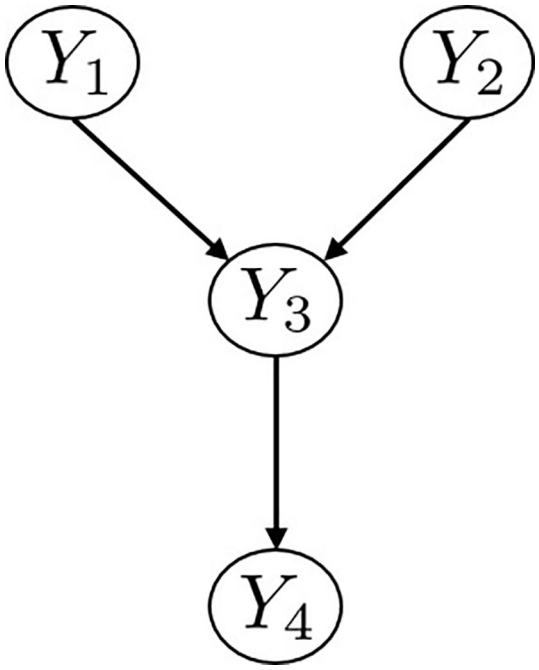


Figure 1. Basic direct acyclic graph example.

factorization property. This means that the conditional joint probability distribution $f(\mathbf{y}|\boldsymbol{\theta})$ decomposes in terms of the univariate conditional distributions

$$f(\mathbf{y}|\boldsymbol{\theta}) = \prod_{v=1}^{V} f\left(y_v|\mathbf{y}_{\text{pa}(Y_v)}, \boldsymbol{\theta}\right),$$

being $f\left(y_v|\mathbf{y}_{\text{pa}(Y_v)}, \boldsymbol{\theta}\right)$ the conditional distribution of node Y_v given its parents and $\boldsymbol{\theta}$. Data $\boldsymbol{\mathcal{D}}$ are the food of the statistical model that updates the information about $\boldsymbol{\theta}$ through Bayes' theorem to obtain its posterior distribution $\pi(\boldsymbol{\theta}|\boldsymbol{\mathcal{D}})$. The computation of this posterior distribution is approximated via Markov chain Monte Carlo (MCMC) simulation.[6] This results in a subsequent approximate random sample that allows to approximate the joint posterior predictive distribution

$$f(\mathbf{y}|\boldsymbol{\mathcal{D}}) = \int f(\mathbf{y}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}|\boldsymbol{\mathcal{D}})\, d\boldsymbol{\theta},$$

from which any posterior predictive marginal or conditional distribution of interest can be approximated.

2.2 Data structure and variables

Data for the construction of a BN for the affective module of the DBM came from Instituto de Biomecánica de València (IBV), the leading institution of the European BERTHA project. IBV performed an experimental study employing a driving simulator to characterise key mental states in car drivers. Mental workload and active fatigue were evaluated through a structured protocol combining subjective assessment with multimodal physiological monitoring. Participants completed validated mental workload and active fatigue scales at baseline and after each cognitive block, while physiological activity was recorded using ECG and respiratory signals via the PLUX Biosignals platform.

The resulting dataset encompasses a collection of demographic and physiological variables, together with responses to experimental questionnaires specifically designed to quantify mental load and active fatigue. The dataset comprises observations collected from 17 participants, with the following basic covariate information:

- Y_{Sex}: Sex; 8 women ($Y_{Sex} = 0$) and 9 men ($Y_{Sex} = 1$).
- Y_{Age}: Age, in years; ranging from 24 to 61 (mean: 44.59 years).

- Y_{BMI}: Body mass index; ranging from 17.65 to 35.16 (mean: 24.35).

Physiological information was assessed through variables related to heart and respiration function:

- Y_{SRT}: Standard Deviation of the Time elapsed between two successive normal heartbeats (RR intervals) in milliseconds (ms); ranging from 19.45 to 191.76 (mean: 63.07 ms).
- Y_{SDD}: Standard Deviation of the successive Differences between adjacent RR intervals in milliseconds (ms); ranging from 14.38 to 104.16 (mean: 53.17 ms).
- Y_{MHR}: Mean Heart Rate in beats per minute (bpm); ranging from 46.08 to 152.09 (mean: 73.94 bpm).
- Y_{RLH}: Ratio of the variance of the heart rate variability (HRV) in the Low-frequency to the High-frequency band; ranging from 0.17 to 29.91 (mean: 3.51).
- Y_{MNB}: Mean of the Number of Breaths per minute; ranging from 9.42 to 23.38 (mean: 15.26 breaths/min).

Following the experimental tasks, participants also completed a series of questionnaires regarding mental load, (Y_{ML}), and active fatigue, (Y_{AF}). Original responses were transformed into a binary format with two outcomes: 1, indicating that the participant entered the specified mental state, and 0 otherwise.

2.3 A Bayesian network for assessing active fatigue and mental load in drivers

The model was formulated as a BN representing the probabilistic relationships among mental states, physiological responses, covariates and parameters. Figure 2 presents the DAG of the analysed BN. It illustrates the relationships among mental load (Y_{ML}), active fatigue (Y_{AF}), and the set of physiological variables: Y_{SRT}, Y_{SDD}, Y_{MHR}, Y_{RLH}, and Y_{MNB}. For simplicity, covariates and parameters have been omitted from the graph. The nodes corresponding to the two variables of interest, Y_{ML} and Y_{AF}, have a direct influence on Y_{MHR}, Y_{SDD}, and Y_{RLH}. The node Y_{SDD} affects Y_{MHR}, and both Y_{SDD} and Y_{MHR} contribute to Y_{RLH}. These three variables Y_{MHR}, Y_{SDD}, and Y_{RLH} are parents of Y_{SRT}, which in turn is a parent of Y_{MNB}. These interdependencies illustrate the complex relationships within the network. In terms of interpreting these variables, it can be stated that, according to the model, mental states influence heart function, which in turn affects respiration. The subsequent conditional joint distribution of all nodes in the network given the set $\boldsymbol{\theta}$ of parameters factorizes as the product

$$\begin{aligned} f(y_{MNB}, y_{SRT}, y_{RLH}, y_{MHR}, y_{SDD}, y_{ML}, y_{AF}|\boldsymbol{\theta}) &= f(y_{MNB}|y_{SRT}, \boldsymbol{\theta}) \\ &\cdot f(y_{SRT}|y_{RLH}, y_{MHR}, y_{SDD}, y_{AF}, \boldsymbol{\theta}) \cdot f(y_{RLH}|y_{MHR}, y_{SDD}, y_{AF}, y_{ML}, \boldsymbol{\theta}) \\ &\cdot f(y_{MHR}|y_{SDD}, y_{AF}, y_{ML}, \boldsymbol{\theta}) \cdot f(y_{SDD}|y_{AF}, y_{ML}, \boldsymbol{\theta}) \\ &\cdot f(y_{AF}|\boldsymbol{\theta}) \cdot f(y_{ML}|\boldsymbol{\theta}). \end{aligned} \tag{1}$$

This decomposition allows each univariate conditional distribution in (1) to be modelled independently. Mental load (Y_{ML}) and active fatigue (Y_{AF}) are Bernoulli variables whose probability of success is modelled using Bayesian logistic regression (BLR). We analysed the conditional distribution of each of the continuous physiological measures, Y_{MNB}, Y_{SRT}, Y_{RLH}, Y_{MHR} and Y_{SDD} in (1) using a Bayesian regression model (BRM) with the subsequent conditional mean expressed as a linear function of the three base covariates and the parents variables of the response variable considered. For example, in the case of the modelling of $f(y_{MHR}|y_{SDD}, y_{AF}, y_{ML}, \boldsymbol{\theta})$ we assume a normal distribution with mean μ_{MHR} expressed as a linear function of the three base covariates, Y_{Sex}, Y_{Age}, and Y_{BMI}, as well as nodes Y_{SDD}, Y_{AF}, Y_{ML} as the parents of Y_{MHR}.

$$\mu_{MHR} = \beta_0 + \beta_W I_W + \beta_{Age} Y_{Age} + \beta_{BMI} Y_{BMI} + \beta_{SDD} Y_{SDD} + \beta_{AF} Y_{AF} + \beta_{ML} Y_{ML}, \tag{2}$$

where I_W is an indicator variable with value 1 if the observation comes from a man and zero otherwise and β's are the regression coefficients, parameters, associated with the covariates.

The prior distributions for the model parameters $\boldsymbol{\theta}$ assume prior independence in a non-informative environment that gives all inferential prominence to the data. All regression coefficients β's are assigned normal distributions with mean

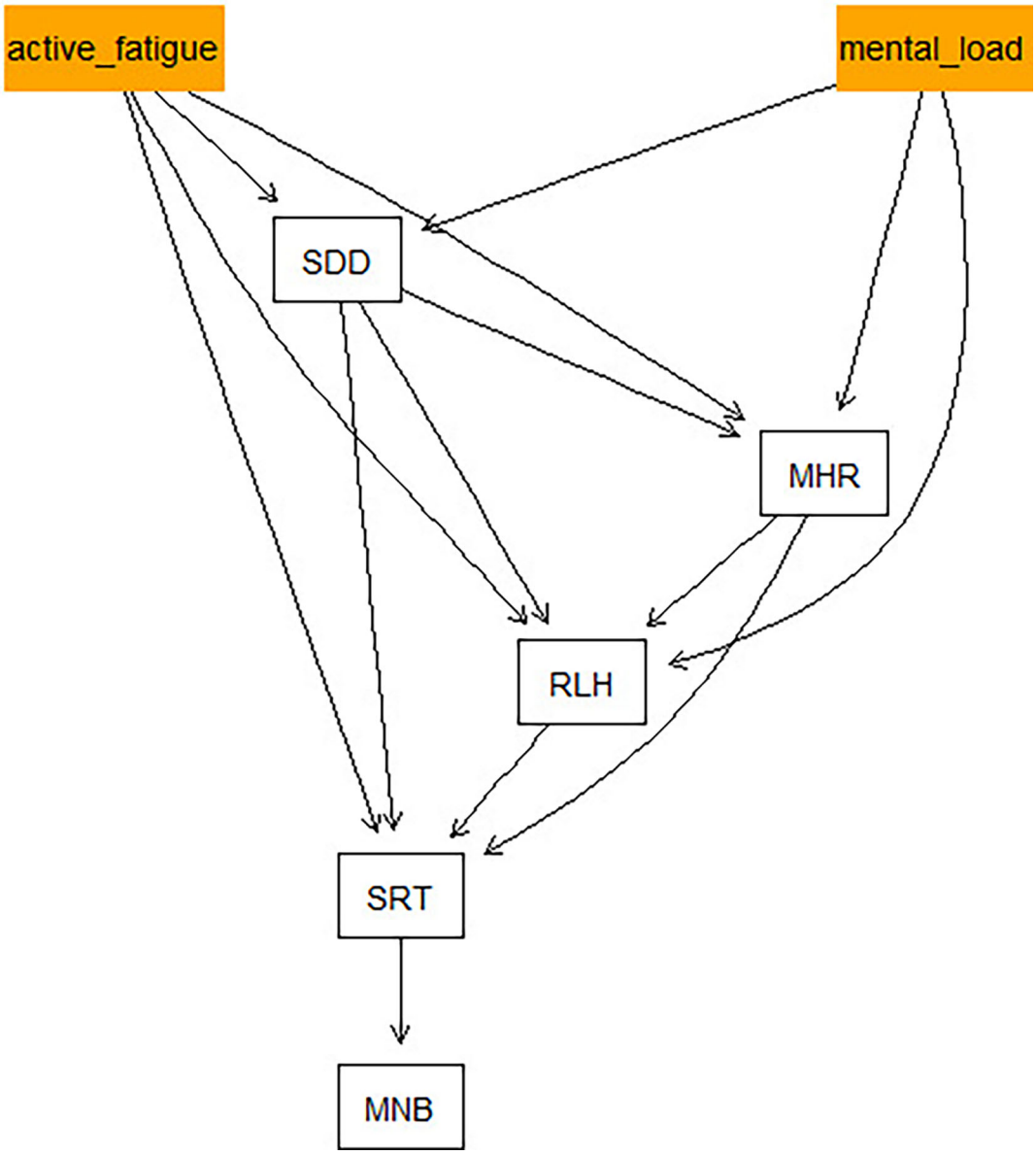


Figure 2. Bayesian Network for examining active fatigue and mental load. For clearer visualization, the nodes have been identified exclusively by the acronyms of their subindices.

0 and variance 25 in all BLR and BRM models. The standard deviation parameters of the BRM models are elicited as uniform distributions in the interval $(0, 30)$.

3. Results

The posterior distribution $\pi(\boldsymbol{\theta}|\mathcal{D})$ for all parameters of the BN was approximated by MCMC through JAGS software. The subsequent posterior MCMC sample was used to approximate the joint posterior predictive distribution. This results in a sample from which we can extract the behaviour of any predictive element of interest.

By way of illustration, Figure 3 shows the average posterior probability that a driver exhibits each of the four conditions defined by active fatigue and mental workload in relation to their gender, age, and BMI, and the range of possible values for the Y_{SRT} and Y_{MNB} nodes. In a real application, conditional posterior probabilities could be derived; for example, for a female driver aged 20 with a BMI of 22 and a mean breathing rate of 20 breaths per minute, the probability of experiencing mental workload is estimated to be approximately 0.72. Predictions seem to indicate that age has a protective effect against active fatigue and mental workload, but not gender, which does not appear to be relevant.

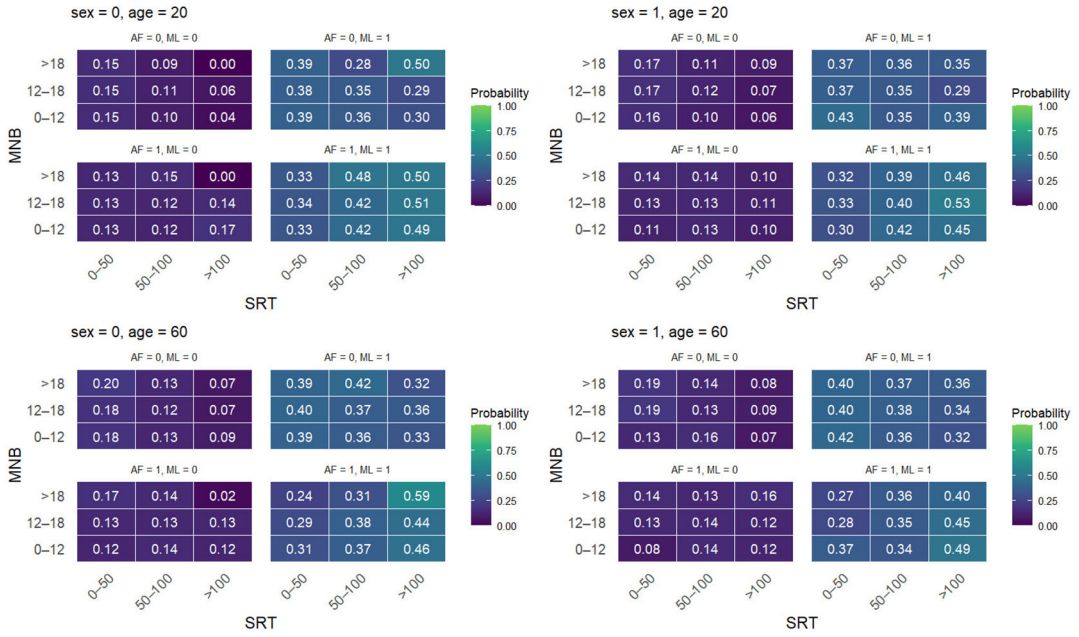


Figure 3. Average posterior probability of each joint state of active fatigue (AF) and mental workload (ML) as a function of driver gender and age, with BMI held constant at 22, shown across Y_{SRT} and Y_{MNB} values.

4. Discussion

The ability of BNs to estimate probabilities associated with specific mental states, such as mental load or active fatigue, under different physiological conditions of the driver is an important aspect of this study. This information would enable real-time assessments of the driver's mental state, with important implications for road safety.[7] For example, a vehicle could suggest a break to a driver showing signs of mental fatigue. This model could help optimize the design of systems to prevent accidents caused by cognitive fatigue or mental overload.

The results of this study show promising results, but the complexity of the subject requires further research and more data. They were obtained from a fairly small sample, and it would be desirable to work with larger samples that could provide greater power and predictive efficacy. It could be interesting to explore additional markers, such as facial expressions, which could provide additional information about the driver's mental state.

Analysis code

Analysis code available from:

https://github.com/dorotamlynarczyk/BN-Affective-Module-DBM

Archived analysis code as at time of publication:

https://doi.org/10.5281/zenodo.20531219

License: CC-BY 4.0.

Ethics and consent

Ethical approval for this study was obtained from the Research Ethics Committee of the Universitat Politècnica de València (Approval no. P01_28-05-2024 and P06_23-10-2024). All procedures involving human participants complied with the ethical standards of the institutional research committee and with the Declaration of Helsinki (https://www.wma.net/policies-post/wma-declaration-of-helsinki/). All participants were adults and provided written informed consent prior to their participation in the study.

Acknowledgments

Research activity under BERTHA project (GA101076360) funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure and Environment Executive Agency (CINEA). Neither the European Union nor the granting authority can be held responsible for them.

Data availability

Underlying data

Repository name:

BN-Affective-Module-DBM,

https://github.com/dorotamlynarczyk/BN-Affective-Module-DBM

https://doi.org/10.5281/zenodo.20531219

The project contains the following underlying data:

data_MW.Rdata (raw data).

License: CC-BY 4.0.

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Publisher Full Text

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Reference Source

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Reference Source

Open Peer Review

Current Peer Review Status: ? ?

Version 1

Reviewer Report 13 October 2026

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Henrick Haule
The University of Alabama in Huntsville, Huntsville, Alabama, USA

1. The article did not include a synthesis of previous studies on the subject that could indicate its position in the existing literature.

2. This paper aims to model an important aspect of a driver behavioral model. However, the chosen variables do not seem sufficient to explain drivers' mental state. Mental state is highly dependent on driving conditions, and individual characteristics can vary widely in ways the selected variables may not capture. Are there methodologies that could account for these unobserved factors and characteristics to effectively model drivers' mental load and active fatigue?

3. The number of participants included in the study does not seem sufficient to provide enough variability to support conclusions for the DBM model. The study should improve the recruitment process to increase the number of participants to more than 30. Why are the standard deviations of two successive RR intervals used, and why were the successive differences between adjacent RR intervals selected as the variables? It is critical for these variables to be explained and for the thinking behind their selection as measures to be explained. More details on the questionnaire should be provided, specifically what each question was intended to measure.

Is the work clearly and accurately presented and does it engage with the current literature?
No

Is the study design appropriate and is the work technically sound?
Partly

Are sufficient details of methods and analysis provided to allow replication by others?
Partly

Are all the source data and materials underlying the results available?

Yes

Are the conclusions drawn adequately supported by the results?
Partly

If applicable, is the statistical analysis and its interpretation appropriate?
I cannot comment. A qualified statistician is required.

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Traffic engineering

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Reviewer Report 12 October 2026

https://doi.org/10.21956/openreseurope.25055.r81890

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?

Johan Kwisthout
Radboud University, Nijmegen, The Netherlands
Joost Vossers
Radboud University Donders Institute for Brain Cognition and Behaviour, Nijmegen, Gelderland, The Netherlands

This article proposes and analyses a Bayesian network for modelling a driver's mental states, specifically mental load and active fatigue. The goal of the article is to improve understanding of driver behaviour in dynamic environments, with potential applications in traffic safety and autonomous vehicle technologies.

The authors introduce the topic of driver modelling clearly and include extensive background on Bayesian networks as a modelling technique. The analysis of the selected dataset is clear as well and includes a link to the codebase. The article is also well-written and easy to follow.

There are, however, a couple of revisions that are necessary for the article to better reflect the authors' contributions.

1. The main aspect I am missing in this work is *how* the proposed Bayesian network was constructed. The research that is used as groundwork for this model is not referenced and the selection of the nodes and edges between them is not addressed. Why are there specific connections between the nodes? Why are e.g. age and BMI not directly included in the model? These are substantial choices that require an explanation.

2. There is no specific Related Work or Background section while there is substantial work on modelling the mental states of drivers (either through BNs or other models). Including this would also make the movitation for the research clearer.
    - e.g. the work by Liu & Wang (2020) is cited in the conclusion but not discussed earlier which could be done to lay out the research already being done on this and to highlight the attribution of this paper.
3. The conclusion of the work is not very clear. The authors state some interesting ideas for future work, but do not really interpret the results or reflect on the process of constructing and/or analysing the Bayesian network.

Minor Points

- pg. 4 has an ambiguous sentence: "Data *D* are the food of the statistical model". Something like 'input' instead of 'food' is clearer.
- The IBV study mentioned on pg. 4 should be included as a reference (if published, I cannot find it myself).
- Formula 1 on pg. 5 includes a mistake or at least inconsistent notation. yML disappears on line 2 and yML and yAF switch places in the ordering.
- pg. 6's last sentence is structurally unclear. It now seems as if age has no protective effect against gender. I would suggest rephrasing to better reflect the intended meaning of the sentence.
- The mention of JAGS on pg. 6 would be more complete with a reference.
- Figures 1 (pg. 4) and 2 (pg. 6) are quite large in comparison to the text.
- Figure 2 is not consistent in naming convention. I would suggest to either follow the previous work and use the abbreviations *AF* and *ML*, or state why the choice was made for *active_fatigue* and *mental_load* instead.

Code Comments

- The README is not complete enough to allow for proper replication of the results. There are no running/setup instructions or data description and there are no requirements mentioned or no requirements.txt file.
- The comments in the code file itself are very clear.

Is the work clearly and accurately presented and does it engage with the current literature?
No

Is the study design appropriate and is the work technically sound?
Yes

Are sufficient details of methods and analysis provided to allow replication by others?
Partly

Are all the source data and materials underlying the results available?
Yes

Are the conclusions drawn adequately supported by the results?
Partly

If applicable, is the statistical analysis and its interpretation appropriate?

Not applicable

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Bayesian networks, uncertainty, explainable AI

We confirm that we have read this submission and believe that we have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however we have significant reservations, as outlined above.