Revisiting Interactions of Multiple Driver States in Heterogenous Population and Cognitive Tasks

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Statement of Significance: This paper decoupled and inferred the complex causal relationships between multiple types of drowsiness and cognitive load by first introducing double machine learning. Additionally, we identified key physiological and eye-tracking indicators in the presence of multiple driver states and under the influence of a single state, excluding the influence of other driver states, environmental factors, and individual characteristics. We believe our findings have significant implications for designing driver state monitoring systems, enhancing safety in both non-automated and conditionally automated vehicles.

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INTRODUCTION

Driver drowsiness and high cognitive load can both negatively impact driving safety. While autonomous technologies promise to reduce drivers' cognitive workload and drowsiness by relieving drivers from driving tasks (*1*), before fully autonomous vehicle comes, human drivers still must share control with driving automation systems. Particularly, with the Society of Automotive Engineers (SAE) Level-3 (L3) advanced driving systems (ADS) (*2*), the vehicle can control both steering and acceleration/deceleration but still requires the driver to remain actively engaged and ready to take over at any moment. Given that drivers are inclined to engage in non-driving-related tasks (NDRTs) with the assistance of driving automation (*3*), understanding the impact of NDRTs on the drivers' states is essential to the driving safety of SAE Level-3 vehicles.

Since the cognitive resource is multi-dimensional (*4*), different dimensions of NDRT tasks can bring disparities in the cognitive load states of drivers. However, during a drive, the effect of long-time driving and the high cognitive load as a result of NDRTs may co-exist, leading to compounded effects on drivers' readiness in driving and driving safety. However, though previous research tried to understand the relationships between NDRTs and specific driver states with specific variables controlled in experiments, isolating the effects of specific factors on a state is challenging. Specifically, statistical regression analysis is a classical method and has been widely used in previous works (*3*, *5*, *6*), but linear regression cannot eliminate the effect of uncontrolled confounders on the dependent variables. Thus, conclusions retrieved from previous studies may have been biased by these compound effects and whether specific NDRT affects cognitive load directly or through driving fatigue is unknown. In addition, past research has pointed out that individual heterogeneity (*7*) has a significant influence on a driver's cognitive state (*8*, *9*) and fatigue development (*10*, *11*) during driving. However, it is still difficult to tell whether one demographic feature impacts cognitive load and drowsiness directly or through affecting other states of drivers. Similarly, when measuring fatigue and cognitive workload through physiological and eye-tracking measures (*12–14*), linear correlation analyses may be insufficient to decouple the dual effect of the states. Hence, new approaches to isolate the co-effects of driver states are needed.

Inspired by the research in economics, a double/debiased machine learning (DML) (*15*) approach is introduced in our work. By specifying the confounding variable **W**, feature **X**, the treatment variable **T**, and outcome **Y**, the DML is able to precisely pinpoint the direct causal effect of concern and eliminate the spurious bias from confounders based on Neyman-orthogonal and K-fold cross-fitting (*16*). We propose four research questions: **RQ1**: How are states affected by NDRTs and the progress of the experiment (i.e., time) among the population? **RQ2**: Excluding the influence of NDRT and time, whether/how does individual heterogeneity affect cognitive load and drowsiness? **RQ3**: Excluding the influence of individual heterogeneity, what are the relationships between symbols and states? **RQ4**: Excluding the influence of individual heterogeneity and cross-effect between states, what are the relationships between symbols and a single state?

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METHODS

A driving simulation experiment with a within-subject design was adopted. By varying the types and difficulty levels of cognitive NDRTs, we aim to understand how these different demands can influence drives' physiological and eye movement responses. **Table 1** presents an overview of the three types of cognitive tasks (6 specific tasks) we adopted in this study plus a baseline without NDRT tasks. For each NDRT, each participant went through 3 drives, leading to 21 drives in total. A Latin-square design was adopted to minimize the effect of trail order, leading to 21 orders in total. In this study, a total of 42 drivers (24 males, and 18 females) were recruited.

All drives were on two-way six-lane highways with a speed limit of 120 kilometers per hour and a traffic density of 6 vehicles per kilometer per lane. However, the top speed of the driving automation was 110 kilometers per hour. In manual driving mode, drivers were required to drive in the middle lane. Each drive was approximately 7 kilometers long.

TABLE 1 Summary of Cognitive Load Tasks (NDRTs) Used in Our Study

Task Type	Description	Task Level(s)	Cognitive Resource
N-back Task (*17*)	A series of stimuli numbers are presented with a pause between each. Participants recall and verbally report the stimulus that is *n* positions earlier.	0-back (NB0), 1-back (NB1), 2-back (NB2) tasks.	Memory
Math Task (*18*)	Oral backward counting from 3,000 by increments of 3 or 5.	Counting backward by 3 (MT1) or 5 (MT2) from 3,000.	Calculation
Spatial Task (*19*)	Participants listen to an audio clip describing a route and identify the direction faced at the end, simulating cognitive task in navigation tasks.	"What direction is this person when he goes to the north station and moves two stations clockwise?" (Answer: East) (ST)	Spatial Processing

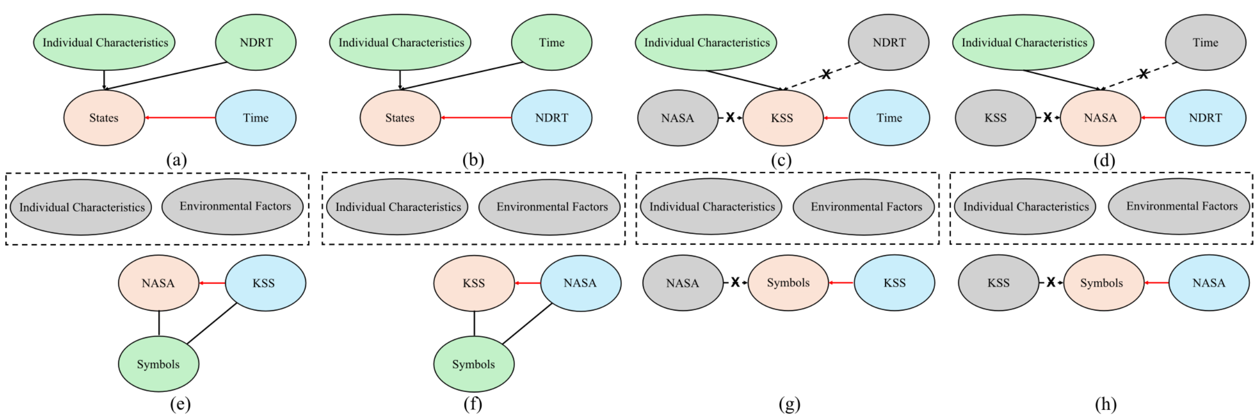

Figure 1 Brief illustration of constructed models. The green node indicates feature X; The orange node means outcome Y; The grey node means confounders W; and the blue node means treatment T. We are interested in the coefficients of the model of the black edge, and the treatment effect on the outcome for red edges.

DML was first proposed in (*15*) and widely used in econometrics (*20*, *21*). It integrates machine learning methods with traditional statistical inference to estimate causal effects. This approach ensures that the estimation of the causal effect remains robust and unbiased. The term "double" comes from the two-step process involved: 1) get residual from the outcome model predicting the relationship between outcome **Y** and features **X** and **W**; 2) get residual from the treatment model which models the effect of features **X** and **W** on the treatment **T**. Then, fit a new model targeting the residual of **Y** using **X** and residual of **T** to obtain unbiased estimation and control impacts of uncontrollable confounders **W**. Compared to statistical regression, DML also retains the explanatory power of statistical inference. Except for the better performance on high-dimensional data and avoiding over-fitting (*15*), DML can get the effect of applying **T** (i.e., Average Treatment Effect, ATE) by simulating an experimental-control group on the same batch of samples with **X** feature, and exclude the interference of **W**. Another advantage of DML is that it can obtain the Conditional Average Treatment Effect (CATE) of **T** for **X**, i.e., the difference in the average effect of **T** when it is applied to a specific group of samples (*22*). We adopted the "*LinearDML*" function in the 0.15.0 version of "*EconML"* package (*23*) in Python for modeling. Compared to other DML methods, *LinearDML* in *EconML* adopts the linear parametric method and enables the model to have interpretable model parameters. The two-step process was instantiated by gradient boost machines following previous work (*24*), and a 5-fold cross-fitting was used to avoid over-fitting. To better present the differences in the driver population due to individual heterogeneity, we used "*SingleTreeCateInterpreter*" function in *EconML* to interpret the model.

TABLE 2 Significant (*p* < .05) Coefficients of Models

Model	X	Y	T	Estimation	SE	Z Stat	*p*-value	95%CI-lower	95%CI-upper
(a)	Trust	NASA	Time	0.007	0.003	2.517	.01	0.002	0.011
	DriveD	KSS	Time	0.019	0.009	2.084	.04	0.004	0.035
(b)	Trust	NASA	NB1	0.182	0.063	2.884	.004	0.078	0.286
	Age	NASA	ST	0.315	0.078	4.021	<.0001	0.186	0.444
	Age	KSS	NB1	0.064	0.026	2.509	.01	0.022	0.107
	Age	KSS	NB2	0.052	0.025	2.112	.04	0.012	0.093
(d)	Trust	NASA	NB1	0.154	0.064	2.382	.02	0.048	0.260
	Age	NASA	ST	0.176	0.077	2.294	.02	0.050	0.303
(e)	SCR	NASA	KSS	-0.122	0.058	-2.098	.04	-0.218	-0.026
(f)	SCR	KSS	NASA	-0.015	0.007	-2.095	.04	-0.026	-0.003
	RMSSD	KSS	NASA	0.029	0.009	3.068	.002	0.013	0.045
	SDNN	KSS	NASA	-0.053	0.017	-3.073	.002	-0.081	-0.025
	HF	KSS	NASA	0.169	0.079	2.134	.03	0.039	0.299

Note: In this table, for the effect of discrete treatment NDRT on the association between X and Y, the baseline is the control group T0.

RESULTS

In total, 8 models were built to answer the four research questions. A brief illustration of models is provided in **Figure 1**. Specifically, Model (a)(b) is for RQ1, (c)(d) is for RQ2, (e)(f) is for RQ3, and (g)(h) is for RQ4. The coefficients between features (X) and the outcome (Y) of each model are presented in **Table 2**. The ATE and CATE are summarized in **Table 3**, respectively.

In response to RQ1, based on the results of Model (a) in **Table 2**, we found that considering the influence of Time on the variation of NASA and KSS, Trust and DriveD were still positively associated with NASA and KSS, respectively. At the same time, a significant effect of Time on KSS was identified, but not on NASA. We noticed that, for those with high Trust (Trust>38.5), with the increase of Time, their NASA and KSS scores all increased in general. Particularly, those who have low trust and longer driving distances (DriveD), and females with high trust present higher sensitivity to Time (i.e., larger CATE).

For Model (b), as shown in **Table 3**, we first found that when drivers were conducting specific NDRTs, their Age and Trust were positively correlated with NASA and KSS in most cases. Moreover, seeing **Table 3**, compared to Base, all NDRTs contributed to higher NASA and lower drowsiness scores. We found that conducting any NDRTs can significantly reduce the KSS score. This effect also varies across tasks: overall, those tasks that lead to higher NASA led to lower KSS, although there were some comparisons that failed to reach significance level ($p \geq .05$). It is worth noting that as there are interactions between KSS and NASA, the accuracy of current differences in ATE comparisons between tasks cannot be ensured.

Therefore, we next refer to the results of Model (c)(d). According to **Table 3**, after the impact from NASA was removed, we noticed there is no significant correlation between Individual Characteristics and KSS score in Model (c). Besides, there is also no significant ATE of Time on the KSS score. To further verify it, we constructed another model (X= Individual Characteristics; Y=KSS; T=Time;

W=NASA and NDRT) and we still found no significant ATE of NDRT on KSS, which is opposite to the results of Model (b). For Model (d), we excluded the effect from KSS to NASA. Then, we identified that, with the increase in Trust and Age, drivers who were conducting NB1 and ST would perceive a higher cognitive workload. This finding is close to Model (b). These results indicate the necessity to detangle the mutual influence of multiple driver states using the DML approach in order to better reveal the influential factors of drivers' states.

TABLE 3 Significant (*p* < .05) ATE of Discrete Treatment NDRT Analysis of Models

Model	***Y***	***T0***	***T1***	*Estimation*	*SE*	*Z Stat*	*p-value*	*95%CI-lower*	*95%CI-upper*
(b)	*NASA*	*Base*	*NB0*	*2.150*	*0.389*	*5.519*	*<.0001*	*1.509*	*2.790*
			NB1	*4.891*	*0.401*	*12.182*	*<.0001*	*4.230*	*5.551*
			NB2	*9.342*	*0.427*	*21.870*	*<.0001*	*8.639*	*10.044*
			MT1	*6.910*	*0.438*	*15.775*	*<.0001*	*6.190*	*7.631*
			MT2	*4.106*	*0.410*	*10.017*	*<.0001*	*3.431*	*4.780*
			ST	*8.487*	*0.456*	*8.615*	*<.0001*	*7.737*	*9.237*
		NB0	*NB1*	*2.741*	*0.386*	*7.093*	*<.0001*	*2.105*	*3.377*
			NB2	*7.192*	*0.413*	*17.410*	*<.0001*	*6.512*	*7.871*
			MT1	*4.760*	*0.424*	*11.225*	*<.0001*	*4.063*	*5.458*
			MT2	*1.956*	*0.395*	*4.946*	*<.0001*	*1.305*	*2.606*
			ST	*6.338*	*0.443*	*14.297*	*<.0001*	*5.608*	*7.067*
		NB1	*NB2*	*4.451*	*0.424*	*10.491*	*<.0001*	*3.753*	*5.149*
			MT1	*2.019*	*0.439*	*4.605*	*<.0001*	*1.298*	*2.741*
			ST	*3.597*	*0.456*	*7.893*	*<.0001*	*2.847*	*4.346*
		NB2	*MT1*	*-2.431*	*0.460*	*-5.288*	*<.0001*	*-3.188*	*-1.675*
			MT2	*-5.236*	*0.434*	*-12.074*	*<.0001*	*-5.949*	*-4.523*
		MT1	*MT2*	*-2.804*	*0.446*	*-6.288*	*<.0001*	*-3.538*	*-2.071*
			ST	*1.577*	*0.488*	*3.229*	*.001*	*0.774*	*2.381*
		MT2	*ST*	*4.382*	*0.463*	*9.456*	*<.0001*	*3.620*	*5.144*
	KSS	*Base*	*NB0*	*-0.334*	*0.140*	*-2.380*	*.02*	*-0.565*	*-0.103*
			NB1	*-0.410*	*0.147*	*-2.782*	*.005*	*-0.653*	*-0.168*
			NB2	*-0.713*	*0.149*	*-4.793*	*<.0001*	*-0.958*	*-0.469*
			MT1	*-0.625*	*0.140*	*-4.477*	*<.0001*	*-0.855*	*-0.396*
			MT2	*-0.344*	*0.146*	*-2.358*	*.02*	*-0.585*	*-0.104*
			ST	*-0.710*	*0.133*	*-5.354*	*<.0001*	*-0.928*	*-0.492*
		NB0	*NB2*	*-0.379*	*0.148*	*-2.563*	*.01*	*-0.622*	*-0.136*
			MT1	*-0.291*	*0.139*	*-2.091*	*.04*	*-0.520*	*-0.062*
			ST	*-0.376*	*0.132*	*-2.845*	*.004*	*-0.593*	*-0.159*
		NB1	*ST*	*-0.300*	*0.139*	*-2.152*	*.03*	*-0.529*	*-0.071*
		NB2	*MT2*	*0.369*	*0.154*	*2.404*	*.02*	*0.117*	*0.622*
		MT2	*ST*	*-0.366*	*0.138*	*-2.652*	*.008*	*-0.592*	*-0.139*
(d)	*NASA*	*Base*	*NB0*	*1.416*	*0.394*	*3.597*	*<.0001*	*0.768*	*2.063*
			NB1	*4.037*	*0.395*	*10.216*	*<.0001*	*3.387*	*4.687*
			NB2	*8.333*	*0.450*	*18.519*	*<.0001*	*7.593*	*9.073*
			MT1	*6.238*	*0.438*	*14.236*	*<.0001*	*5.517*	*6.958*
			MT2	*3.645*	*0.384*	*9.484*	*<.0001*	*3.013*	*4.278*
			ST	*7.310*	*0.445*	*16.418*	*<.0001*	*6.578*	*8.043*
		NB0	*NB1*	*2.622*	*0.377*	*6.952*	*<.0001*	*2.001*	*3.242*
			NB2	*6.917*	*0.429*	*16.136*	*<.0001*	*6.212*	*7.622*
			MT1	*4.822*	*0.417*	*11.564*	*<.0001*	*4.136*	*5.508*
			MT2	*2.230*	*0.364*	*6.120*	*<.0001*	*1.631*	*2.829*
			ST	*5.895*	*0.424*	*13.905*	*<.0001*	*5.197*	*6.592*
		NB1	*NB2*	*4.296*	*0.434*	*9.909*	*<.0001*	*3.583*	*5.009*
			MT1	*2.200*	*0.426*	*5.170*	*<.0001*	*1.500*	*2.901*

	ST	*3.273*	*0.431*	*7.586*	*<.0001*	*2.563*	*3.983*
NB2	*MT1*	*-2.095*	*0.471*	*0.471*	*<.0001*	*-2.869*	*-1.321*
	MT2	*-4.687*	*0.427*	*-10.990*	*<.0001*	*-5.389*	*-3.986*
	ST	*-1.023*	*0.477*	*-2.144*	*.03*	*-1.807*	*-0.238*
MT1	*MT2*	*-2.592*	*0.418*	*-6.206*	*<.0001*	*-3.279*	*-1.905*
	ST	*1.073*	*0.467*	*2.298*	*.02*	*0.305*	*1.840*
MT2	*ST*	*3.665*	*0.423*	*8.656*	*<.0001*	*2.968*	*4.361*

Note: In this table, for the effect of discrete treatment NDRT on the association between X and Y, the baseline is the control group T0.

CONCLUSIONS

In a real-world driving environment, multiple states often occur simultaneously, subject to individual differences and environmental factors. Although previous studies have noted a correlation between drowsiness and cognitive load, drowsiness has been categorized into several types depending on the inducing cause, the experimental design and method of analysis were limited. However, due to limitations in experimental design and analytical methods, the results reported in previous studies focusing on a single state were actually biased, as the effects from other states were not completely eliminated. Relationships between states have also been limited to correlations or theoretically derived causal relationships.

To address these problems, this paper first introduced the DML analysis method in the field of driver state analysis. Based on an L3 autonomous driving simulator experiment with 48 participants and eight DML models, we first analyzed the key individual and environmental factors (including multidimensional NDRTs and driving time) that affect the variation of driver states. Subsequently, by setting confounding factors, we separately investigated the changes in the influence of individual and environmental factors on drowsiness and cognitive workload, when the effects of other states were eliminated. Further, the complex causal relationship between multiple types of drowsiness and cognitive load was successfully decoupled and inferred to a specific pattern. In addition, we investigated key physiological and eye-tracking indicators in the presence of cross-effects between states, as well as under the influence of a single state.

In general, our findings not only empirically demonstrate the co-occurrence of multiple types of fatigue with cognitive load. Moreover, the causal relationship between states provides evidence for further theoretical studies of driver psychological and physiological states. The causal inference analytical framework introduced in this paper also provides insights for subsequent analytical work. At the same time, the state-related metrics identified in this paper will further assist in the development of objective measures of state and driver state monitoring systems.

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