ITM Web of Conferences **69**, 03005 (2024) https://doi.org/10.1051/itmconf/20246903005
MAIH2024

Towards artificial intelligence based rail driving assistance tool

Jean-Valentin Merlevede[1,3,*], *Simon* Enjalbert[1,3,**], *Frédéric* Vanderhaegen[1,2,3,***], and *Francesco* Flammini[4,****]

[1]LAMIH, UMR 8201 - CNRS
[2]INSA Hauts-de-France, Valenciennes, France
[3]Univ. Polytechnique Hauts-de-France, Valenciennes, France
[4]Dalle Molle Institute for Artificial Intelligence, SUPSI, Lugano, Switzerland

Abstract. This work proposes additional levels of progressive driver assistance expanding the traditional Grades Of Automation (GoA) in order to allow both higher level of automation and keeping the driver involved in driving task at the same time. The second contribution is the Digital Co-Driver which aims to bring the driver back in the train driving activity with the new GoA defined before, taking into account human involvement and driving skills. This framework is made up of several modules, each of which addresses a specific issue arising from the increased level of automation. The Driver State and Performance Monitoring Module monitors the driver's involvement, situation awareness and performance. The Digital Adviser Module improves driver's situational awareness, and the Digital Teacher Module improves his/her driving skills and knowledge of the system. Finally, the Safety Manager ensures the system's compatibility with safety standards.

1 Introduction

Railway driver interfaces have undergone profound changes to adapt to all the systems that have gradually been incorporated into trains. The CARBODIN project [1] proposed to redesign and rethink the organization of the cabin by integrating both new systems and new interactions from the earliest design stages. This approach has highlighted drivers' interest in innovative interfaces based on new technologies, such as haptic, gesture and voice, which currently have no place on trains. We are now looking to extend this work by studying how Artificial Intelligence (AI) can be integrated into train driving. Various definitions of AI exist in the literature; in this paper, we consider AI to be all technologies that enable the transition from an automated system to an autonomous system capable of adapting to its environment. The aim of Academics4Rail is to propose driver assistance systems for railway driving.
In the first section, degrees of automation in railways sector, in order to propose additional levels of progressive driver assistance, are detailed. A taxonomy of driving activities to extract the tasks that need to be automated is proposed. The possibilities offered by the integration of the concept of a Digital Co-Driver (DCD) is then studied in the context of rail driving assistance. The DCD is an assistance tool framework which is created with the aim of maintaining the driver in the loop of controlling highly automated vehicles. The DCD is structured into modules, each covering one of the requirements identified during the conceptual phase. The Driver State and Performance Monitoring Module monitors the driver's involvement, situation awareness and performance to tune the behavior of the DCD according to the driver. The Digital Adviser Module improves driver's situational awareness by providing him relevant information regarding to the driving condition. The Digital Teacher Module selects the combination of methodological approach and interface best suited by the driver depending on learning abilities. It improves driver's driving skills or, when the driver performs better than the system, updates the artificial agent driving abilities. Finally the Safety Manager ensures the system's compatibility with safety standards. In the last section, we present the development steps we planned do achieve the DCD implementation.

2 Automating rail operations

In a Human-Machine Systems, the shared control of tasks between the human operator and an automated agent has been the subject of numerous studies. The aim of these studies was not only to determine levels of assistance, but also to identify the consequences of these levels of assistance for the system and the operator. One of the main issues studied in the design of automated systems is the impact of the addition of assistance functions on driver involvement and workload. Grades of Automation (GoA) define the distribution of driving tasks between the driver and the system, based on the capabilities of the automated driving agent [2].

*e-mail: jeanvalentin.merlevede@uphf.fr
**e-mail: simon.enjalbert@uphf.fr
***e-mail: frederic.vanderhaegen@uphf.fr
****e-mail: francesco.flammini@supsi.ch

	Levels	Operational	Operational	Tactical	Tactical	Strategical
Grades of Automation	Driving tasks	Speed regulation	Departure / stopping at station	Monitoring of driving environment	Doors closure / opening	Detection and management of emergencies
GoA-0		Driver	Driver	Driver	Driver	Driver
GoA-1	ATP	Driver \ System	Driver	Driver	Driver	Driver
GoA-2	ATP+ATO	System \ Driver	Driver \ System	Driver	Driver	Driver
GoA-2.1		System \ Driver	Driver \ System	Driver \ System	Driver \ System	Driver
GoA-2.2		System \ Driver	System \ Driver	System \ Driver	System \ Driver	Driver
GoA-3	Driverless	System	System	System	Train attendant	Train attendant
GoA-4		System	System	System	System	System \ Operational Control Center

Figure 1. Proposed extension of Grades of Automation (GoA)

- **GoA-0:**Manual control only, without automatic protection device.
- **GoA-1:**Manual operation with automatic protection. The automated systems concern compliance with speed limits and danger signals (ATP), in-cab signal repetition (ERTMS) and VACMA.
- **GoA-2:**Semi-autonomous train : Semi-autonomous train: the driver retains final authority over all systems, while assistance tools can act only under the driver's supervision (ATO).
- **GoA-3:**Driverless train: no driver on board, the train attendant is responsible for opening and closing the doors, as well as detecting and managing emergencies.
- **GoA-4:**Autonomous train. The train is fully automated, under the supervision of the Central Control Station.

In the Figure 1, GoA-2 and GoA-3, systems take over part of the tactical and operational management. Between GoA-2 and GoA-3, there is a transfer of authority from human to machine. This transfer has an impact on user safety and legal accountability in the event of an accident. Furthermore, the first implementations of GoA-2 trains raise questions about the transformation of the driver's role. Driver has gone from being the locomotive's active controller to the supervisor of a highly automated system. In the literature, there is a great deal of research on the difficulty for operators to remain active in a supervisory task. Other scales exist in the literature to measure the level of automation of systems, for example the work of Endsley and Kaber[3], and Fereidunian[3]. Upgrading from GoA-2 to GoA-3 means replacing the driver on board with train attendants. This does not yet seem acceptable to some users and manufacturers. It is therefore necessary to propose additional GoA that allows us to increase the grade of automation while keeping a driver on board. These grades are intermediate between GoA-2 and GoA-3, to manage the transfer of authority and the increase in competence of the automated system. They also enable the development of a human-centered system to mitigate the negative effects of high grades of automation on driver attention. They enable a natural transition from GoA-2 to GoA-3. Strategic tasks remain the responsibility of the driver. In order to be acceptable to drivers,[1], the system must be designed in such a way that the driver retains final authority. In addition, the driver must understand the system [1]. At GoA-2.1, the system can act autonomously, for actions concerning its motion, but the driver remains active and retains authority over the supervision of the train's movement in its environment. The system enhances the driver's situational awareness, helping him to anticipate driving tasks. The system can then acquire the skills it needs for GoA2.2. At GoA-2.2, The controller's role undergoes a major transformation, moving from active participation to a supervisory role, so the driver becomes the system's supervisor for driving and handling environment supervision tasks that the system cannot handle alone. Final authority remains in the hands of the driver. This new grade can be used in situations where the driver does not have sufficient reaction time to complete the driving task while ensuring passenger safety. For example, if distances between trains are reduced to cope with increasing customer volumes on a network that has no room to grow. The main benefit of this new approach is that it makes it possible to develop a system that keeps the driver involved in the driving task. The driver can take control back any time, keeping skills up-to-date, and better disposed to react when the system needs help in a new situation.
Now that we've proposed two new grades, GoA-2.1 GoA-2.2 for railway driving, the question arises as to which tasks we're going to automate. To answer this question, we'll compare a taxonomy of driving tasks with the GoA. In Table 1, the operational and tactical tasks of the task taxonomy proposed as part of the CARBODIN project [1] are presented.

A correlation between task taxonomy from CARBODIN and decision making levels can be observed. Indeed, for GoA-1 only the operational task of speed regulation is automated, whereas from GoA-2 to GoA-4, the automated functions are at tactical decision making level. Strategic tasks are not covered before the GoA-4, out of the scope of our study. This correlation makes it possible to determine the grade at which the tasks in the different categories are available to be transferred to the system by the driver. The critical tasks of speed control and environmental monitoring need to be automated. These tasks have already been automated separately in previous work, particularly in the context of energy

Table 1. Driving tasks distribution regarding authors taxonomy and decision making levels

	Operational GoA-1	Tactical GoA-2 to GoA-4
CRITICAL	**Speed regulation**	**Doors closure / opening** **Monitoring driving environment**
AUXILIARY	Accessories Power management	**Departure / stopping at station**
SIDE	Lighting Comfort systems	

saving. Auxiliary tasks such as accessories and power supply are requested by drivers. [1]. They want a level of automation comparable to that of their car. The support tasks Lighting and Comfort Systems are part of the operational tasks of driving and are therefore within the scope of the study.

With the changes in the driver's role arising from the higher GoA implementation, the driver moves from an active role in controlling the vehicle to a role as supervisor of the automated system operating the train. This shift has been extensively studied in the literature, in view of the consequences it has on the human operator [4]. In the literature, researchers have argued that this transition negatively affects the human operator's workload [5], as well as situation awareness. This reduces involvement in the driving process and considerably increases reaction time [6]. In the worst case, this can even lead to drowsiness [7]. In order to maintain safety and enable the driver to regain control of the system in the event of an unforeseen event, it is therefore important to monitor the driver's involvement in the driving task, and to adapt the distribution of tasks to reduce the risk of the driver getting out of the loop. Despite its importance in railway driving, previous studies have pointed a negative impact of highly automated systems on situation awareness [8] and the operator's ability to rebuild his/her situational awareness in the event of loss of automated functions [9]. So, if we want to increase the grade of automation, we need to take the driver's situational awareness into account. Finally, according to studies on car driving, driving with ADAS when the driver is not properly informed and trained not only reduce drivers' driving skills [10], but also lead to counter-performance due to the driver's lack of knowledge of how the automated system works[11]. It is therefore appropriate for the automated system integrated into the train to monitor the driver's performance and train him/her to collaborate with or in the event of a skill loss. In light of these potential risks for the driver and/or train, the implementation of Artificial Intelligence in trains requires us to take into account human factors and the impact of our system on the driver, in order to optimize involvement and safety, as well as that of passengers and rolling stock.

3 Digital Co-Driver

In the literature, there are numerous studies of railway driver assistance systems, mainly aimed at improving network management [12, 13] and energy efficiency [14, 15]. However, the majority of these studies do not take the human factor into account, or merely check that the driver is able to apply the system's instructions with sufficient speed and precision for the system to be effective. In the same time, there are already articles highlighting the negative impact of these systems on the driver condition [5, 6, 8]. We therefore need to propose an assistance system that put human back in the loop. To counterbalance the potential undesirable effects of increasing levels of automation in the railway sector, the Digital Co-Driver(DCD) is designed to focus on keeping the driver active in the driving task. This approach is justified by recent work in the field of semi-autonomous vehicles [16], but also in industry, where operators interact with increasingly intelligent robots.In addition to improving the safety and performance of the Human-AI Team, the Digital Co-Driver also addresses the issues of operator well-being that are at the heart of the Industry 5.0 model [17]. One of the most important issues in achieving an AI-based system that is safe for both driver and user is the Black Box problem. This problem of artificial intelligence-based systems, which implies that the system has become so complex that even the designer cannot predict its behavior [11], makes Human-Artificial Intelligence cooperation unpredictable.

In order to build an efficient collaboration between the DCD and the driver, human is put back into the loop to ensure the DCD adaptation to various human behavior like cooperation, competition, or non collaboration. It should be able to achieve a better driver involvement in driving activities regardless of the driver's attitude towards the system. The Digital Co-Driver, presented in Figure 2, consists of 4 main modules, each of which is designed to address one of the bottlenecks slowing down the integration of artificial intelligence-based systems in trains. The Driver Monitoring System mainly addresses problems of driver involvement in the driving task. The Digital Co-Driver uses Hybrid Human-Artificial Intelligence approaches [18] to improve Human-Artificial Intelligence by implementing transparency and explainability [16].Neuro-Symbolic artificial intelligence seems a promising solution to enable artificial intelligence system collaboration with human. This field mixes logic programming and deep

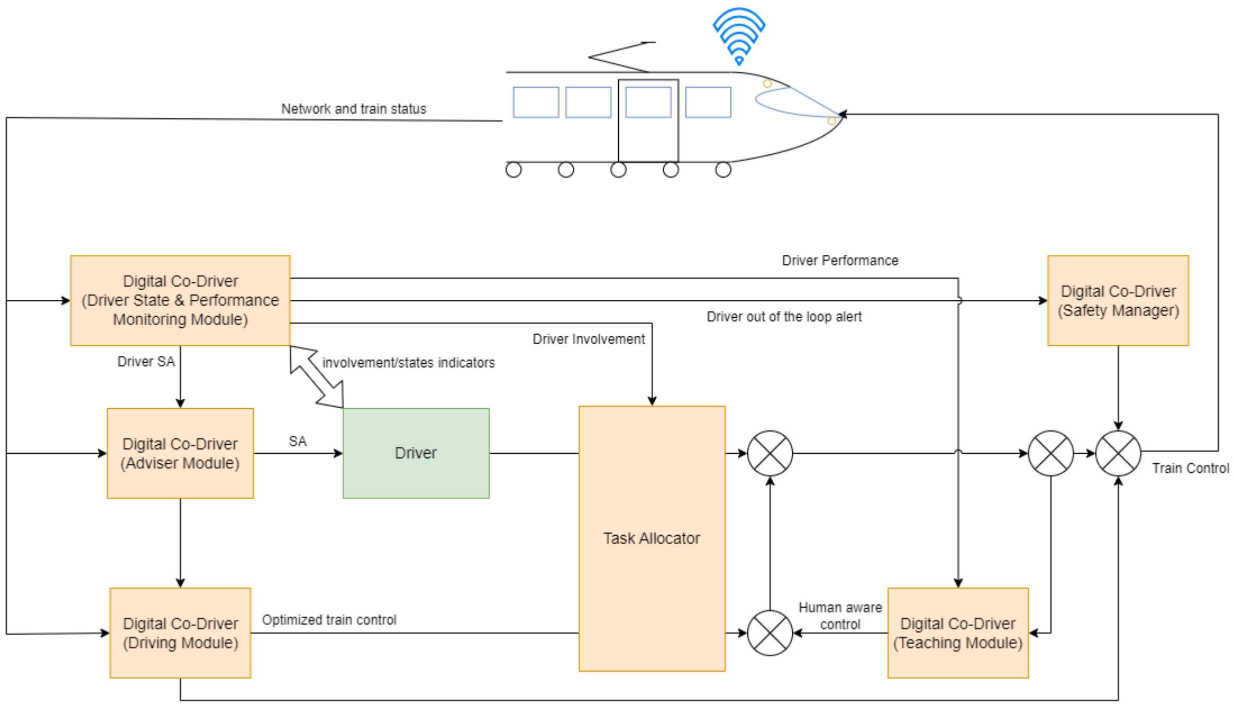

Figure 2. Digital Co-Driver operating diagram

learning methodology for a better human understanding of the artificial agent. A model proposed by Vanderhaegen [19] to divide tasks between a human actor and an assistance system, according to the triplet (Competence, Availability, Possibility-to-act (CAP)), is used by DCD at early learning stages to select the correct agent for the ongoing task. The Digital Advisor provides the driver with all the necessary and relevant information to enable him or her to perform according to energy efficiency and safety criteria. The Digital Teacher determines the most appropriate teaching method for the driver. And finally, the Safety Manager ensures that the decisions taken by the Human-AI team comply with safety standards, avoiding costly developments for manufacturers. To ensure the safety of the Digital Co-Driver, its actions on the train have to pass through a safety manager who is compatible with the standards that apply to railway safety and makes the implementation of artificial intelligence possible [20].

3.1 Driver State and Performance Monitoring Module

The task of the Driver State and Performance Monitoring Module is to assess the driver's involvement in driving the train, to prevent him or her from getting out of the loop, but also his or her driving skills (driving performance, reaction time) to personalize the operation of the Digital Co-Driver. The Driver State and Performance Monitoring Module must therefore be able to evaluate 3 aspects: the ability to perform the driving task, performance and situation awareness. Various factors, which are difficult to quantify, influence the driver's ability to drive, including concentration, workload, motivation, and fatigue. The measurements intended to assess the driver's condition is divided into 3 categories. The first category concerns the evaluation of the driver's cognitive availability through eye-tracking[21], Thermal imaging[22], heart rate variability, EMG, EGG, and IMU[23]. Another possible indicator is the interaction between the driver and the train, as in automotive vehicles, where the interaction between the driver and the steering wheel can be monitored. The second category is about the evaluation of driving skills[24] can be envisaged with indicators such as driving energy efficiency, adherence to schedules, material wear and tear, passenger comfort via the study of acceleration, braking and jerk variations, and finally safety, for example by taking into account the speed of approach to signals and danger zones. The third category is related to indicator about monitoring the driver's situational awareness, we are considering the possibility of the system asking the driver questions to check driver's perception, comprehension, projection based on the information extracted by the advisor module either by using tactile screen or voice interaction. The use of a connected watch would be interesting, as it would also provide information on the driver's general state.

The Driver State and Performance Monitoring Module studies the effect of varying grades of assistance on the driver's involvement in the supervision or driving task. Depending on the driver's degree of involvement, the Digital Co-Driver can decide to give tasks back to the driver to reduce boredom or drowsiness. The driver needs system approval to automate those tasks again. If the driver is deemed out of the loop by the system or if the system detect a significant drop in driver's competence, it forces the driver to go back in GoA-2.1 and the system acts only as a supervisor of driving. To reduce the risk of nodding off during long periods of inactivity, it is envisaged to share traction control to the driver, or to take advantage of this time to train a novice driver. In fact, a number of studies have shown encouraging results in terms of the ability to regain control of an automated system when the operator is busy with a secondary task[25, 26].

3.2 Digital Adviser Module

In line with researchers' findings on the need to improve drivers' situational awareness[27], and the contribution of improved situation awareness to rail drivers' efficiency and anticipation [24, 28, 29], the Digital Co-Driver's advisor module filters network state information (delay, trackside state, trackside maintenance operation), information from ground control, and train information to provide the driver relevant data regarding driving tasks and planned timetable. These information are available to optimize operations during rail driving. To simplify the driver's task, he can also choose to have a display of the speed and traction recommended by the system for an optimized driving behaviour. The use of artificial intelligence-based solutions enables the system to maintain user profiles to personalize recommendations. The Digital Co-Driver's advisor module is able to communicate with the driver via a visual interface (touch screen or Head up Display) as well as a voice interface, in line with driver requests but also with the theory of limited resources to avoid saturating the optical channel, which is already heavily used in rail driving [29].

3.3 Digital Teacher Module

Studies have been carried out into the possibility of using ADAS to train drivers in the field of private vehicles. The learning capabilities of ADAS have already been validated for parking[30, 31], and a previous paper has succeeded in improving drivers' skills in economic driving[32], with possible interesting results once applied to rail driving. In order to avoid any potential loss of skills caused by the use of a highly automated system, the Digital Co-Driver's Teacher module finds and applies the best learning strategy for the system's driver, based on the results communicated to it by the Driver State and Performance Monitoring Module. System determines the best task distribution for each individual and thus personalize the collaboration by adapting it to the limits of each driver. Studies have already demonstrated the ability of AIs to learn and reproduce the driving skills of human drivers in the railway sector, using deep learning approaches[33]. Once properly trained, these AIs can then serve as a reference for the digital teacher module. It's interesting to note that an AI can learn even from novice drivers and help them to drive efficiently[34]. It takes into account the Human-Machine interface best suited to the current driver (haptic or visual), the most effective teaching method with this driver, but also the driver's willingness to cooperate and receptiveness to advice, in order to determine the optimum strategy for the driver.

4 Future implementation

The next step will be the implementation of the Driver State and Performance Monitoring Module to monitor the drivers and test new task allocation proposed by the authors in order to test the process in simulation to validate the hypothesis about the positive impact of varying the task allocation based on driver state to bring the driver active in the loop. In order to access the situation awareness without the relevant information filtered by the Digital Adviser Module we will have to pick relevant information by hand when building the simulation scenario. Different algorithms are going to be compared, using different paradigm, some off them are going to use AI techniques.
The second step will be to implement the Digital Teacher Module to adapt the DCD's actions to personal preference of driver and take into account the willingness of driver to cooperate with the automated agent. This step will check possibility to use an artificial intelligence to train drivers. Since we have no database regarding to train driving, we will have to find a way to use no data AI or find a way to quickly build data.
The third step will be to finish the implementation of the Digital Adviser Module. The aim of this module is to use AI to filter relevant information about driving and choosing the right time and adapted mean of communication to give the information to the driver. This data will be used by the Driver State and Performance Monitoring Module to assess situation awareness.

5 Conclusion

We propose an innovative approach, in which the artificial system takes into account not only the strengths and weaknesses of the human operator, but also its impact on the human operator and the willingness of the operator to cooperate with the DCD. The two major contributions of Digital Co-Driver is the ability to monitor the driver's level of availability and involvement in order to adapt the task distribution. The second one is to assess driving skills and propose a training program based on learning the driving practices of expert drivers. DCD was enabled with the introduction of intermediate Grade of Automation allowing a task sharing between the automated agent (the DCD) and the train driver: These new grades give the system time to learn from the human, to build data, enabling a gradual transition from a train with a driver to one without. Artificial intelligence human teams seems a promising solution for the development of new driver-centered rail assistance system. However, it will be crucial to avoid problems related not only to the involvement of the human operator, but also to the operator's ability to retain his/her driving skills and manage unforeseen events. To make the Digital Co-Driver even more in line with the standards set by Industry 5.0, a special effort will be made to improve driver well-being.

6 Acknowledgements

This work was supported by the European Union's Horizon Europe research and innovation framework program, project Academics4Rail (HORIZON-ER-JU-2022-ExplR-04) No 101121842. This research is sponsored by RITMEA, the Hauts-de-France Region, the European Community, the Regional Delegation for Research and Technology, the Ministry of Higher Education, Research and Innovation, and the French National Center for Scientific Research (CNRS). The present research work has been supported by the Scientific Research Network on Integrated Automation and Human-Machine Systems (GRAISyHM), and by the Regional Council of "Hauts-de-France", project SACRe TIFSID (Technologie Innovante pour un Futur Solidaire, Inclusif, et Durable). The authors gratefully acknowledge the support of these institutions.

References

[1] J.V. Merlevede, S. Enjalbert, F. Henon, A.P. Baños, S. Ricci, F. Vanderhaegen, Expectations of train drivers for innovative driving cabin, IFAC-PapersOnLine **55**, 144 (2022). 10.1016/j.ifacol.2022.10.246

[2] L. Habib, O. Oukacha, S. Enjalbert, Towards Tramway Safety by Managing Advanced Driver Assistance Systems depending on Grades of Automation, IFAC-PapersOnLine **54**, 227 (2021). 10.1016/j.ifacol.2021.06.027

[3] M. Vagia, A.A. Transeth, S.A. Fjerdingen, A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed?, Applied Ergonomics **53**, 190 (2016). 10.1016/j.apergo.2015.09.013

[4] L. Bainbridge, in *Analysis, Design and Evaluation of Man–Machine Systems* (Elsevier, 1983), pp. 129–135, ISBN 978-0-08-029348-6, `https://linkinghub.elsevier.com/retrieve/pii/B9780080293486500269`

[5] N. Brandenburger, A. Naumann, On Track: A Series of Research about the Effects of Increasing Railway Automation on the Train Driver, IFAC-PapersOnLine **52**, 288 (2019). 10.1016/j.ifacol.2019.12.115

[6] N. Brandenburger, A. Naumann, M. Jipp, Task-induced fatigue when implementing high grades of railway automation, Cognition, Technology & Work **23**, 273 (2021). 10.1007/s10111-019-00613-z

[7] F. Naujoks, S. Höfling, C. Purucker, K. Zeeb, From partial and high automation to manual driving: Relationship between non-driving related tasks, drowsiness and take-over performance, Accident Analysis & Prevention **121**, 28 (2018). 10.1016/j.aap.2018.08.018

[8] M.A. Rad, L.M. Lefsrud, M. Hendry, D. Blais, Literature review on cognitive impacts of cab warning systems and train control technologies, Rail Research Conference (2021).

[9] C.D. Wickens, L. Onnasch, A. Sebok, D. Manzey, Absence of DOA Effect but No Proper Test of the Lumberjack Effect: A Reply to Jamieson and Skraaning (2019), Human Factors: The Journal of the Human Factors and Ergonomics Society **62**, 530 (2020). 10.1177/0018720820901957

[10] S. Nordhoff, J.D. Lee, S.C. Calvert, S. Berge, M. Hagenzieker, R. Happee, (Mis-)use of standard Autopilot and Full Self-Driving (FSD) Beta: Results from interviews with users of Tesla's FSD Beta, Frontiers in Psychology **14**, 1101520 (2023). 10.3389/fpsyg.2023.1101520

[11] M.R. Endsley, Ironies of artificial intelligence, Ergonomics **66**, 1656 (2023). 10.1080/00140139.2023.2243404

[12] G.M. Scheepmaker, R.M. Goverde, L.G. Kroon, Review of energy-efficient train control and timetabling, European Journal of Operational Research **257**, 355 (2017). 10.1016/j.ejor.2016.09.044

[13] Hainan Zhu, Xubin Sun, Lei Chen, Shigen Gao, Hairong Dong, Analysis and design of Driver Advisory System (DAS) for energy-efficient train operation with real-time information, in *2016 IEEE International Conference on Intelligent Rail Transportation (ICIRT)* (IEEE, Birmingham, United Kingdom, 2016), pp. 99–104, ISBN 978-1-5090-1555-9, `http://ieeexplore.ieee.org/document/7588717/`

[14] C. Fu, P. Sun, J. Zhang, K. Yan, Q. Wang, X. Feng, An energy-efficient train control approach with dynamic efficiency of the traction system, IET Intelligent Transport Systems **17**, 1182 (2023). 10.1049/itr2.12351

[15] Z. Yao, X. Sun, L. Yang, Z. Yu, X. Guo, W. Zhang, Driver Advisory System for Freight Train Based on Energy-saving Operation Optimization, in *2022 China Automation Congress (CAC)* (IEEE, Xiamen, China, 2022), pp. 1532–1537, ISBN 978-1-66546-533-5, `https://ieeexplore.ieee.org/document/10055694/`

[16] M.R. Endsley, Supporting Human-AI Teams:Transparency, explainability, and situation awareness, Computers in Human Behavior **140**, 107574 (2023). 10.1016/j.chb.2022.107574

[17] Y. Lu, H. Zheng, S. Chand, W. Xia, Z. Liu, X. Xu, L. Wang, Z. Qin, J. Bao, Outlook on human-centric manufacturing towards Industry 5.0, Journal of Manufacturing Systems **62**, 612 (2022). 10.1016/j.jmsy.2022.02.001

[18] H. Ning, R. Yin, A. Ullah, F. Shi, A Survey on Hybrid Human-Artificial Intelligence for Autonomous Driving, IEEE Transactions on Intelligent Transportation Systems **23**, 6011 (2022). 10.1109/TITS.2021.3074695

[19] F. Vanderhaegen, Heuristic-based method for conflict discovery of shared control between humans and autonomous systems - A driving automation case study, Robotics and Autonomous Systems **146**, 103867 (2021). 10.1016/j.robot.2021.103867

[20] F. Flammini, L. De Donato, A. Fantechi, V. Vittorini, in *Reliability, Safety, and Security of Railway Systems. Modelling, Analysis, Verification, and Certification*, edited by S. Collart-Dutilleul,

A.E. Haxthausen, T. Lecomte (Springer International Publishing, Cham, 2022), Vol. 13294, pp. 192–208, ISBN 978-3-031-05813-4 978-3-031-05814-1, series Title: Lecture Notes in Computer Science, https://link.springer.com/10.1007/978-3-031-05814-1_14

[21] T. Dang, S. Bhattacharya, J. Crumbley, A Review Study on the Use of Oculometry in the Assessment of Driver Cognitive States, in *SoutheastCon 2021* (IEEE, Atlanta, GA, USA, 2021), pp. 1–7, ISBN 978-1-66540-379-5, https://ieeexplore.ieee.org/document/9401905/

[22] Z. Zhou, Z. Fang, J. Wang, J. Chen, H. Li, L. Han, Z. Zhang, Driver vigilance detection based on deep learning with fused thermal image information for public transportation, Engineering Applications of Artificial Intelligence **124**, 106604 (2023). 10.1016/j.engappai.2023.106604

[23] A. Lambay, Y. Liu, P.L. Morgan, Z. Ji, Machine learning assisted human fatigue detection, monitoring, and recovery: Review, Digital Engineering p. 100004 (2024). 10.1016/j.dte.2024.100004

[24] V.J. Verstappen, E.N. Pikaar, R.G. Zon, Assessing the impact of driver advisory systems on train driver workload, attention allocation and safety performance, Applied Ergonomics **100**, 103645 (2022). 10.1016/j.apergo.2021.103645

[25] B. Wandtner, N. Schömig, G. Schmidt, Secondary task engagement and disengagement in the context of highly automated driving, Transportation Research Part F: Traffic Psychology and Behaviour **58**, 253 (2018). 10.1016/j.trf.2018.06.001

[26] G. Lu, J. Zhai, P. Li, F. Chen, L. Liang, Measuring drivers' takeover performance in varying levels of automation: Considering the influence of cognitive secondary task, Transportation Research Part F: Traffic Psychology and Behaviour **82**, 96 (2021). 10.1016/j.trf.2021.08.005

[27] N. Dadashi, A. Scott, J. Wilson, A. Mills, in *Rail Human Factors: Supporting reliability, safety and cost reduction* (Taylor & Francis, 2013), ISBN 978-1-138-00037-7 978-0-203-75972-1, http://www.crcnetbase.com/doi/book/10.1201/b13827

[28] K. Panou, P. Tzieropoulos, D. Emery, Railway driver advice systems: Evaluation of methods, tools and systems, Journal of Rail Transport Planning & Management **3**, 150 (2013). 10.1016/j.jrtpm.2013.10.005

[29] V. Verstappen, The impact of innovative devices in the train cab on train driver workload and distraction, in *Sixth International Human Factors Rail Conference. London, UK* (2017)

[30] T. Wada, Simultaneous achievement of driver assistance and skill development in shared and cooperative controls, Cognition, Technology & Work **21**, 631 (2019). 10.1007/s10111-018-0514-y

[31] S. Tada, K. Sonoda, T. Wada, Simultaneous Achievement of Workload Reduction and Skill Enhancement in Backward Parking by Haptic Guidance, IEEE Transactions on Intelligent Vehicles **1**, 292 (2016). 10.1109/TIV.2017.2686088

[32] T. Wada, K. Yoshimura, S.i. Doi, H. Youhata, K. Tomiyama, Proposal of an eco-driving assist system adaptive to driver's skill, in *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)* (IEEE, Washington, DC, USA, 2011), pp. 1880–1885, ISBN 978-1-4577-2197-7 978-1-4577-2198-4 978-1-4577-2196-0, http://ieeexplore.ieee.org/document/6083034/

[33] J. Huang, Y. Cai, J. Li, X. Chen, J. Fan, Toward Intelligent Train Driving through Learning Human Experience, in *2019 1st International Conference on Industrial Artificial Intelligence (IAI)* (IEEE, Shenyang, China, 2019), pp. 1–6, ISBN 978-1-72813-593-9, https://ieeexplore.ieee.org/document/8850749/

[34] F. Vanderhaegen, Pedagogical learning supports based on human–systems inclusion applied to rail flow control, Cognition, Technology & Work **23**, 193 (2021). 10.1007/s10111-019-00602-2