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Exploring the influence of job characteristics on the adoption of driver advisory systems for energy-efficient driving: Insights from a longitudinal field study in rail operations

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ABSTRACT

This study investigates the impact of Driver Advisory Systems (DAS) for eco-efficient driving on train drivers' job characteristics and job satisfaction, and their effects on acceptance and compliance with the system. Driving and questionnaire data from 16 drivers equipped with DAS were collected over a five-month period. Questionnaire data were compared to questionnaire data of a control group (n = 18). Contrary to expectations, DAS did not significantly alter job characteristics or occupational satisfaction. However, drivers with higher task identity and occupational satisfaction demonstrated greater acceptance of and compliance with DAS, highlighting the interplay between work design and technology adoption. Regression analyses indicated that perceived usefulness, task identity, and skill variety were key predictors of compliance. Despite our small sample size, our study provides first indications about the value of considering aspects of work design to understand drivers' willingness to drive more energy-efficiently with the support of DAS.

1. Introduction

1.1. Automation in rail operation

The transport sector contributes 25 % of greenhouse gas emissions in the European Union (European Commission, 2022), while demands for goods and passenger transport steadily rise (European Environment Agency, 2021). Rail, being the most energy-efficient and sustainable mode for long-distance transport (European Environment Agency, 2022a), is central to the EU's strategy to shift traffic from road and air to rail (European Environment Agency, 2022b). Consequently, European railways are under pressure to enhance capacity and energy efficiency while maintaining economic viability (Luijt et al., 2017; Yang et al., 2013). Technological innovation and automation are key to achieving these goals (European Environment Agency, 2023).

These advancements significantly impact train drivers as their tasks and work environments evolve with new technologies in and around the driver's cabin (Brandenburger et al., 2017a,b; Naumann et al., 2016a,b). Changes include the adoption of train protection systems (Giesemann, 2013), Driver Advisory systems (DAS) (Luijt et al., 2017), automated functions for braking and speed adjustment, and remote train supervision (Brandenburger and Naumann, 2019). Human factors research has examined the effects of automation on variables like task load, fatigue, situational awareness, attention allocation, workload, and performance (Brandenburger et al., 2017a,b; Naumann et al., 2016a,b; Giesemann, 2013). Although this research is crucial to make technologies in the railway domain safe, this strong cognitive focus may lead to a neglection of questions concerning general task- and work design and their consequences on technology adoption.

Additionally, there is limited knowledge about how these changes affect the qualitative aspects of operators' work and system acceptance. If such issues are not addressed during system design, operators may reject or fail to comply with these systems, undermining their potential benefits. To widen the concept of technology acceptance by including aspects of work design to predict technology adoption is therefore much needed.

To address this gap, this study explores how automation impacts train drivers' job characteristics and satisfaction, focusing on the implementation of a DAS for energy-efficient driving. We investigate how perceived changes in work characteristics influence system acceptance and compliance. To this end, we collected questionnaire data before and after DAS implementation in a German railway company. Additionally, driving data was collected over five months to examine interactions with the system.

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1.2. Energy-efficient driving and DAS in railways

Energy-efficient driving is increasingly vital for railway undertakings to enhance sustainability and reduce costs (Albrecht, 2013; Formato et al., 2023; Liu and Golovitcher, 2003). DAS offer a practical solution by providing real-time advice to optimize punctuality and energy consumption without requiring integration with train hardware or software (Albrecht, 2013; Meirich et al., 2020, 2023). Simulations have shown, that this way energy consumption can be decreased by up to 15 % (Hunscha and Geißler, 2018; Meirich et al., 2020). To do so, DAS integrate static (e.g. timetables, vehicle properties) and dynamic data (e.g. passenger boarding times, train crossings) to calculate optimal driving trajectories and the optimal point in time to transfer from cruising to coasting, during which the train does not consume any energy (Meirich et al., 2023; see Fig. 1).

DAS then provide a prompt to the driver, who then implements the driving advice by moving the master control lever to a neutral position (see Fig. 2). A driving advice is only given, when the system detects a sufficient buffer in the schedule as to not interfere with the train's punctuality.

An example of such a DAS is displayed in Fig. 3. This DAS was developed and piloted in the project "Fahrerassistenzsysteme adaptive Nachhaltigkeit" (Driver Advisory Systems Adaptive Sustainability; FASaN). The system was installed on drivers' mobile phones and displayed the current and next two stops, scheduled arrival times, and train delays. Driving advices to switch to coasting to save energy appeared as a yellow-framed pop-up for 5 s, with the phrase “Leistung abschalten” (“Switch off power”) and an icon indicating the required action, along with a reason for the advice (e.g., delayed train crossing). Driving advices were also given via voice audio, with the option to permanently mute the system.

For a DAS as a system that gives an operator advice for energy-efficient driving, DAS effectiveness depends on the drivers' compliance, which is primarily influenced by their acceptance of the system (Formato et al., 2023; Hunscha and Geißler, 2018; Yang et al., 2013).

1.3. Technology acceptance

Technological evolution has highlighted the need to understand the adoption and use of new technologies (Al-Emran and Granic, 2021; Regan et al., 2014). Technology acceptance is critical for a system to fulfill its intended purpose (Blut et al., 2022; F. D. Davis, 1985; Venkatesh et al., 2003). Numerous acceptance models have been proposed (for an overview, see Adell, 2009). One of the most influential models is the Technology Acceptance Model (TAM) (Fig. 4) developed by F. D. Davis (1985), which remains widely used in research today (King and He, 2006; Tarhini et al., 2016). Despite being developed nearly 40 years ago, TAM's application continues to expand (Al-Emran and Granic, 2021).

TAM explains how features of a new technology at the workplace influence its use (F. D. Davis and Venkatesh, 2004). It posits that an individual's behavioral intention to use a system predicts actual usage. This intention is shaped by perceived ease of use (the belief that the technology requires minimal effort) and perceived usefulness (the belief that the technology enhances job performance). Additionally, usefulness is influenced by ease of use, as systems that are easier to use tend to be seen as more useful (F. D. Davis, 1985).

The technological systems studied in the 1980s for acceptance research differ greatly from those train drivers encounter today. Meta-analyses show that the Technology Acceptance Model (TAM) was mainly applied to less complex technologies, such as text editors and e-mail programs (Legris et al., 2003). In contrast, modern technologies, like DAS in rail operations, integrate data from multiple sources in dynamic environments to provide concrete advices for train drivers.

These complex systems have the potential to significantly change train drivers' tasks and work environments. While it is known that new technologies in rail operations influence job characteristics and tasks (Brandenburger, 2022; Brandenburger et al., 2017a,b; Naweed, 2014), these factors are not yet fully considered in our understanding of technology acceptance and driver interaction with such systems. It is therefore necessary to expand the TAM to include occupational aspects like job characteristics as predictors for technology acceptance and use.

1.4. The influence of new technologies on perceived job characteristics

The implementation of new technology in the workplace changes tasks and organizational structures (Argote and Goodman, 1984; Bala and Venkatesh, 2013). Such changes can impact job attitudes, including

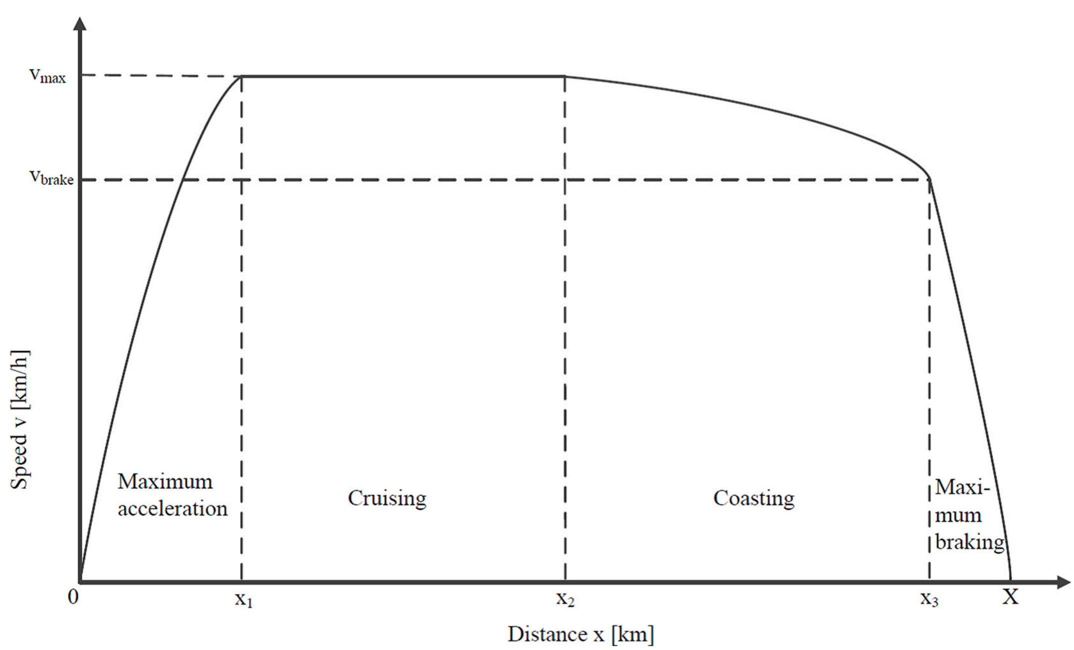

Fig. 1. Optimal driving regimes for a simple flat track (Scheepmaker and Goverde, 2015, p. 226).

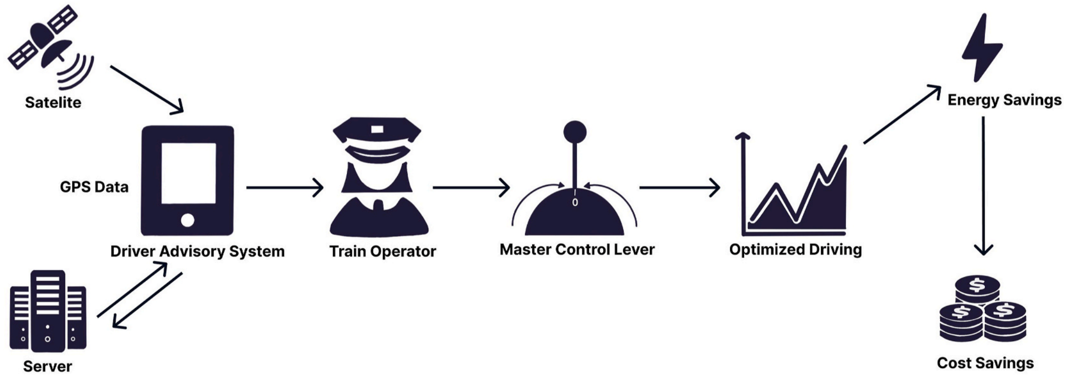

Fig. 2. Basic scheme of a DAS, its sources of information and its effects.

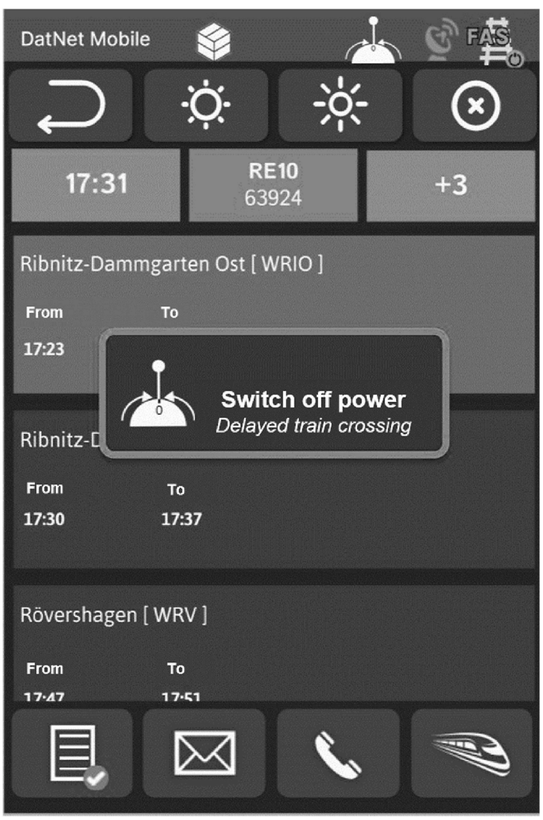

Fig. 3. DAS interface showing (among other things) current stop and next stops, scheduled arrival and departure times, driving advice and the reason for the advice. Interface was translated from German to English for this paper.

satisfaction and well-being (Ang and Slaughter, 2001; Morris and Venkatesh, 2010). Unfavorable changes in job characteristics may lead to negative reactions toward new systems (Bala and Venkatesh, 2013). Understanding how technology alters operator tasks is therefore essential to understanding technology adoption in the workplace.

While some researchers have called for a focus on how technologies influence work design (Ang and Slaughter, 2001; Cascio and Montealegre, 2016; Parker and Grote, 2022), more research is needed to better understand these changes and how operators directly perceive them (Barley, 2015; Cascio and Montealegre, 2016; Rieth, 2022).

The Job Characteristics Model (JCM; Hackman and Oldham, 1976) (Fig. 5) offers a framework for understanding how technological changes influence job characteristics and occupational satisfaction (Rieth, 2022). It is one of the most influential models for examining the

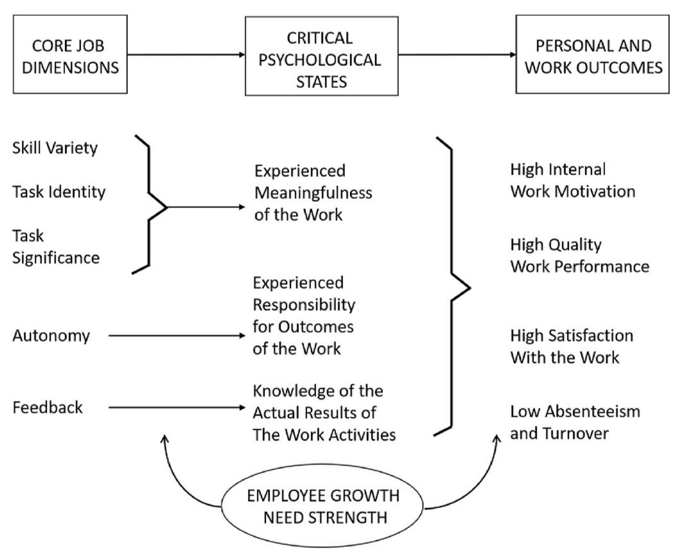

Fig. 5. The job characteristics model (Hackman and Oldham, 1976, p. 256).

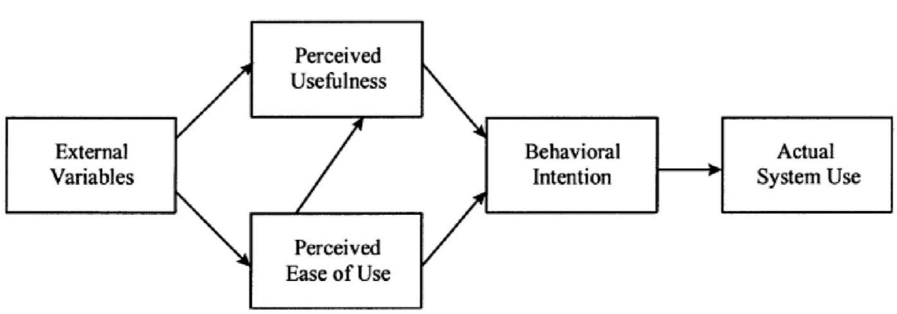

Fig. 4. The Technology Acceptance Model (F. D. Davis, 1985, p.24).

relationship between job characteristics, employee attitudes, and behavior (Boonzaier et al., 2001; Hogan and Martell, 1987).

The JCM specifies five key job characteristics essential for employees' satisfaction, motivation, and performance, that are described in Table 1.

The impact of job characteristics is moderated by employees' need for development and growth. Individuals with strong growth needs seek higher levels of these characteristics to find growth opportunities in their work environment. The JCM also suggests that job characteristics influence work-related outcomes through psychological states (see Fig. 4). However, this aspect has faced criticism, as some studies found psychological states mediate the relationship between job characteristics and work outcomes only partially (Renn and Vandenberg, 1995) or not at all (Fried and Ferris, 1987; Renn and Vandenberg, 1995). For instance, Fried and Ferris (1987) found no increase in explained variance in work-related outcomes when psychological states were included as mediators, while Wall et al. (1978) found that excluding psychological states from the model explained more variance in work outcomes than the original model.

In parallel to the JCM, Hackman and Oldham (1976) developed the Job Diagnostic Survey (JDS), which includes scales for all variables in the model (see Fig. 4). The results from the JDS are combined into the Motivation Potential Score (MPS), reflecting the extent to which the five core job characteristics are present in a job:

In addition to the multiplicative MPS index, an unweighted additive index is often used in studies. Evans and Ondrack (1991) found the additive index to be a better predictor of work outcomes in blue-collar workers than the MPS. Similar results were found by Fried and Ferris (1987) and Hinton and Boderman (1995). Based on these findings, Boonzaier et al. (2001) recommend using the additive index over the multiplicative index.

In the context of the JCM, the introduction of automated systems like DAS can be seen as a form of work redesign, impacting job characteristics and work-related outcomes such as occupational satisfaction (Ghani and Al-Meer, 1989).

Although Morris and Venkatesh (2010) note that system success often depends on job and process reengineering, there are currently no models of technology adoption that consider how changes in job characteristics influence technology acceptance.

Using the TAM and the JCM as theoretical frameworks, we therefore aim to answer the following research questions:

Q1: What influence does the introduction of a DAS for energy-efficient driving have on train drivers' perceived job characteristics and occupational satisfaction?

Q2: What influence does the change of drivers' perceived job characteristics have on the acceptance and use of the DAS?

Table 1
The five core dimensions of the JCM (Hackman and Oldham, 1976, p. 257–258).

JCM Scale	Definition
Autonomy	"The degree to which the job provides substantial freedom, independence, and discretion to the individual in scheduling the work and in determining the procedures to be used in carrying it out."
Feedback	"The degree to which carrying out the work activities required by the job results in the individual obtaining direct and clear information about the effectiveness of his or her performance."
Skill variety	"The degree to which a job requires a variety of different activities in carrying out the work, which involve the use of a number of different skills and talents of a person."
Task significance	"The degree to which a job has a substantial impact on the lives or work of other people, whether in the immediate organization or in the external environment."
Task identity	"The degree to which the job requires completion of a whole and identifiable piece of work; that is, doing a job from beginning to end with a visible outcome."

Previous studies on the influence of new technologies on job characteristics produced mixed findings. A study by C. J. Davis and Hufnagel (2007) examined the effects of an automated fingerprint identification system on 24 fingerprint technicians. The introduction of the system increased autonomy but decreased task identity, skill variety, and task significance. Similarly, Venkatesh et al. (2010) studied 1743 bank employees and found that the implementation of information and communication technology positively affected all five job characteristics. However, it had a negative impact on occupational satisfaction due to environmental barriers like unstable energy supply, which increased workload.

Millman and Hartwick (1987) investigated the impact of word processing, e-mail, and conference software on 75 middle managers. Most managers reported increased task significance and skill variety, but little change in autonomy and feedback. In contrast, an interview study by Rieth (2022) showed that air traffic controllers experienced a decrease in skill variety and task significance due to automation. A follow-up questionnaire study revealed that air traffic controllers in more automated work environments perceived lower autonomy compared to those in less automated environments.

Empirical findings on how new technologies affect job characteristics show that the direction of change (positive or negative) varies across technologies and work contexts (Cascio and Montealegre, 2016; Tausch and Kluge, 2022). For instance, a DAS which advises drivers on when to move the master control lever, could impact drivers' autonomy by reducing their control over driving decisions. Drivers may fear a loss of task variety or significance due to automation, which could negatively influence their attitudes toward the system (Brooks et al., 2017). On the other hand, it may increase skill variety by highlighting the goal of energy-efficient driving to their tasks.

Since there is no prior research on the impact of DAS in the railway domain regarding job characteristics, nor are there transferable empirical results from comparable domains or technologies, we adopted an exploratory approach. Our study investigates whether the introduction of DAS affects perceived autonomy, feedback, skill variety, task significance, task identity, and occupational satisfaction.

H1. Train drivers' perceptions of their job characteristics and occupational satisfaction change after the introduction of a DAS (see Fig. 6).

We suggest that a system that changes perceived job characteristics in a positive direction, aligns more with train drivers' needs for a job in which they are satisfied. This could lead to higher acceptance and compliance with the system then a system that has a negative or no influence on perceived job characteristics.

H2. The change in perceived job characteristics correlates positively with acceptance and use of the system. Specifically, the more positive the change in perceived job characteristics, the higher the acceptance of and compliance with the system.

To find the most suitable model to depict our variables and their relationships, we test the following hypotheses as depicted in Fig. 7:

H2a. Including the change in perceived job characteristics due to the introduction of a new technology to the original TAM will enhance the predictive value of the model.

H2b. The positive correlation between changes in perceived job characteristics and acceptance of and compliance with the system is mediated by the change in occupational satisfaction.

2. Method

2.1. Design

The study had a quasi-experimental design, with one between- (driving with DAS vs. driving without DAS) and one within-subjects factor (before vs. after the implementation of DAS) and acceptance and compliance as dependent variables.

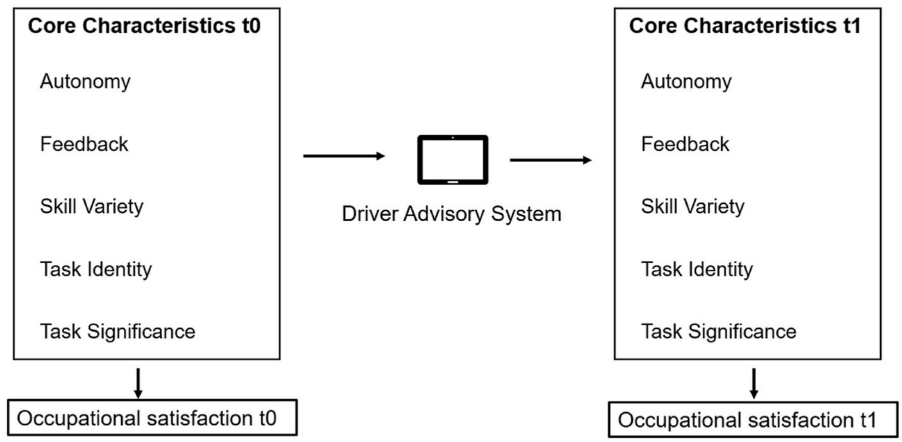

Fig. 6. The relationship between job characteristics and occupational satisfaction and their change due to the introduction of a DAS as hypothesized.

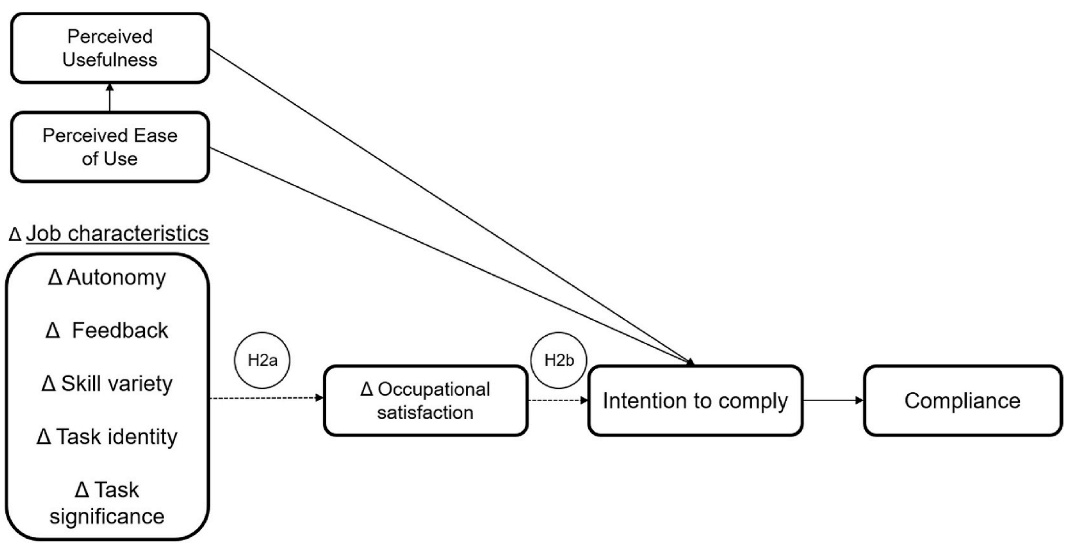

Fig. 7. Model for the relationship of JCM factors, technology acceptance and compliance.

2.2. Participants

Our sample consisted of train drivers from a German railway company. We recruited participants until three weeks before the study's end, aiming for $N = 30$. Due to a limited pool of drivers and a high dropout rate between the baseline questionnaire (t0), the data acquisition phase, and the follow-up questionnaire (t1), we ended up with a smaller sample. The intervention group was equipped with the DAS on their work phones, while the control group consisted of drivers from routes not equipped with DAS. Assignment to groups was based on the routes drivers were assigned to by their railway undertaking, not random.

In the intervention group, sixteen drivers completed all three phases. Our sample included 15 male drivers and 1 female driver, with a mean age of 43.46 years ($SD = 11.52$) and an average of 10.86 years of job experience ($SD = 13.47$). The control group consisted of 18 drivers (3 female), with a mean age of 41.5 years ($SD = 13.22$) and an average of 11.89 years of experience ($SD = 10.54$).

2.3. Material

2.3.1. Job characteristics and occupational satisfaction

We used the revised form of the *Job Diagnostic Survey (JDS)* (Idaszak and Drasgow, 1987) that contains 15 items overall for the scales *autonomy, feedback from the task, skill variety, task significance and task identity*, six items for the scale *growth need strength* and one item for *general occupational satisfaction* (cf. Spector, 2022; Nagy, 2002 on the advantages of using a single-item approach to measure occupational satisfaction). As discussed in section 1.4, we chose not to include the items covering the psychological states from Hackman's and Oldham's original model (1976), but worked with an additive index as an overall measure for all five job characteristics scales. We translated all items into German, based on the translation by van Dick and colleagues (2001). As the authors translated the *JDS* specifically for the context of education, we adapted some items to the context of train driving. We used the back-translation method recommended by Brislin (1970), with one English and one German native speaker, and one German native speaker who works as an English teacher.

2.3.2. Technology acceptance

Items to assess technology acceptance were based on the *TAM* questionnaire by F. D. Davis and Venkatesh (2004), consisting of the scales *perceived usefulness, perceived usability* and *intention to use*. The items were translated into German as described in section 2.2.1. As critical behavior in relation to DAS is not simply not using the system, the items of the scale *intention to use* were adapted to reflect this. The adaptation was based on an acceptance scale by Ghazizadeh and colleagues (2012) that includes drivers' intention to integrate a system's advices into their driving, and therefore better reflects the premises of this study.

2.3.3. Compliance with the DAS

Compliance with the system's driving advices was investigated based on behavioral driving data, as we expected biases in self-report measures concerning desirable behavior at the workplace from an employer's point of view.

The method to measure train drivers' compliance with the DAS, that was based on train position and time data is only briefly described here. For a detailed description see Appendix A and Schnücker et al. (2024).

Behavior in accordance with the driving advices was defined as follows: train drivers have to move the master control lever to a neutral position upon receiving an advice, which then initiates the coasting of the train. We used the train's speed profile as an indirect measure of compliance; with moderate deceleration indicating the implementation of the driving advice to coast. Speed data obtained via a GPS log (sampling rate 1 Hz) was processed with an Artificial Neural Network (ANN). This allowed us to automatically classify the driving regimes in a first step, and then ultimately to check for every driving advice if it was followed or not.

2.4. Procedure

Participation among train drivers working at our project railway undertaking was voluntary and advertised through internal events, e-mails, and the company intranet. Drivers in the intervention group (using DAS) received 80 Euros for activating the system on at least eight trips per week for a minimum of three weeks and completing a questionnaire twice. The control group (driving without DAS) completed the same questionnaire and had a chance to win one of five 50-Euro vouchers for an online marketplace or a German supermarket chain. All participating train drivers first completed an online questionnaire to assess baseline job satisfaction and perceived job characteristics (t0).

Train drivers from the intervention group were trained through an on-demand video uploaded to the company's internal information platform. They were instructed to follow the driving advices at their discretion, as the system should not interfere with safety-critical tasks. Drivers were allowed to choose not to follow advices due to safety-related operational and tacit knowledge, e.g. about wet leaves on the tracks, which could delay braking.

Once the DAS was installed, driving trajectories based on GPS data were collected for each trip where the driver activated the system. The driving data collection phase lasted for five months. Drivers in the intervention group completed a second questionnaire after at least eight rides with the DAS. This ensured that drivers already gained some experience with the DAS before assessing it. This second questionnaire assessed their job satisfaction, perceived job characteristics, and DAS acceptance (t1). Drivers from the intervention group were asked to keep on providing driving data after completing the second questionnaire until the data collection period ended after five months. The control group also completed the second questionnaire, such that a t1 measurement of occupational satisfaction and perceived job characteristics was obtained from both groups around the same time.

This approach ensured that the intervention and control groups assessed their experiences under similar conditions and allowed us to investigate the impact of DAS on perceived job characteristics and acceptance.

3. Results

3.1. Analyzed train rides and compliance

From the 16 drivers in the intervention group, 1049 train rides with DAS with an overall driving time of 1594 h over the course of five months were collected and analyzed. The average overall driving time per driver with DAS was 99.62 h (*Min.* = 8; *Max.* = 184). During this driving time, the DAS gave an average of 616 driving advices to each driver (*Min.* = 23; *Max.* = 1655). Using the ANN (see section 2.2.4.), every driving advice was categorized as followed or not followed, so that the compliance rate could be calculated for each driver. On average, the drivers followed 37.56 % of driving advices ($SD = 11.88$).

3.2. Effects of DAS on perceived job characteristics and occupational satisfaction

We conducted a two-way ANOVA with one between-subject factor (group) and one within-subject factor (time) to test hypothesis 1. All means and standard deviations can be found in Table 2. For overall job characteristics (additive index of all job characteristics scales, cf. 2.2.2), there was no main effect of group $F(1, 31) = 1.68$, $p = 0.2145$, or time $F(1, 31) = 1.22$, $p = 0.7298$, nor an interaction effect for group x time $F(1, 31) = 0.42$, $p = 0.5267$. The same was true for occupational satisfaction, as again neither a main effect of group $F(1, 31) = 1.53$, $p = 0.2351$, or time $F(1, 31) = 0.19$, $p = 0.669$, nor an interaction effect group x time $F(1, 31)$, $p = 0.5741$ proved to be significant. This means the introduction of DAS had no measurable effect on train drivers' perceived job characteristics or occupational satisfaction.

3.3. Correlations between changes in job characteristics and occupational satisfaction and acceptance and compliance

To test if changes in perceived job characteristics and occupational satisfaction correlate with the acceptance of and compliance with the system, we planned to compute Spearman correlations between the delta of the perceived job characteristics (e.g. the difference in autonomy before vs. after the introduction of DAS) with the respective TAM scales and the proportion of driving advice followed.

As we could not confirm hypothesis one, meaning we did not find indications that the DAS had an influence on job characteristics or occupational satisfaction, we discarded this approach. Instead, we exploratively examined the interrelations between the overall JCM score, the five JCM scales, acceptance, and compliance with the system. For the overall JCM score, the JCM scales, and occupational satisfaction, we used the mean of t0 and t1 for each participant.

We conducted multiple Spearman correlations with Bonferroni-Holm correction to adjust the significance level. The resulting correlation matrix is presented in Table 2.

For the TAM scales, we found a positive correlation between the system's perceived usefulness and the behavioral intention to comply with the system ($r = .80$, $p < .01$) as well as with compliance ($r = .64$; $p < .05$). Behavioral intention did not correlate with system compliance and ease of use did not correlate with usefulness, behavioral intention or system compliance.

Regarding the JCM, task identity correlated with compliance ($r = .57$, $p < .05$), and overall occupational satisfaction correlated positively with the perceived usefulness of the system ($r = .65$, $p < .05$). Furthermore, occupational satisfaction correlated positively with the overall JDS mean ($r = .56$, $p < .05$).

To proceed with the testing of H2a and H2b in the same manner as with the testing of H2, we examined the mean of t0 and t1 regarding the JCM and occupational satisfaction instead of the delta t0 – t1.

To examine if including job characteristics and occupational satisfaction enhances the predictive value of the TAM, we conducted a multiple regression analysis. As independent variables to predict system compliance, we included the original TAM variables perceived ease of use and usefulness into the model as well as the overall JCM mean, the five JCM scales and occupational satisfaction. This was to see, which factors from both models were best at predicting system compliance. The overall model was not significant $F(3,30) = 1.29$, $p = 0.2958$). Running a stepwise forward regression analysis instead, we found that the best fit for a model to predict system compliance was when adding usefulness, task identity and skill variety to the model $F(3, 31) = 7.96$, p

Table 2
Means, standard deviations, and correlations.

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Compliance	37.78	13.09										
2. Skill Variety	3.68	0.39	−.37									
3. Task identity	3.97	0.81	.57*	.30								
4. Task significance	4.09	0.68	−.41	.46	.28							
5. Autonomy	2.40	0.52	.35	−.09	−.11	−.42						
6. Feedback	2.93	0.68	.48	−.08	−.07	−.24	.65**					
7. JDS mean	3.41	0.31	−.24	.54*	.65**	.46	.35	.49				
8. Usefulness	5.21	1.31	.64*	.27	−.17	.08	.11	.42	.22			
9.Behavioral intention	5.71	0.95	.31	.50	−.09	.28	−.15	.24	.24	.80**		
10. Ease of use	6.37	0.55	.21	−.16	−.31	.28	−.24	.19	−.08	.20	.34	
11.Occupational satisfaction	4.53	0.83	.09	.44	.08	.45	.13	.38	.56*	.65*	.50	.21

Note. M and *SD* are used to represent mean and standard deviation, respectively. * indicates $p < .05$. ** indicates $p < .01$.

$< .05$., adjusted $R^2 = 0.63$.

Because when testing H2, we did not find any of the JCM dimensions to correlate with occupational satisfaction and at the same time with compliance or acceptance, we did not test, if a relationship between the JCM dimensions and compliance or acceptance was mediated by occupational satisfaction (H2).

4. Discussion

The aim of this study was to examine how advisory systems for eco-efficient driving impact train drivers' perceived job characteristics and occupational outcomes, and how these factors influence compliance with the system. We analyzed the driving behavior of 16 drivers using the DAS over five months, collected questionnaire data at two points in time from the DAS group, and compared results with a control group.

In general, the train drivers in our sample reported high levels of skill variety, task identity, task significance, and general occupational satisfaction, and low to medium autonomy and feedback, compared to the norm sample (Hackman and Oldham, 1975). Regarding technology acceptance, drivers perceived DAS as useful, easy to use, and intended to comply, though the actual compliance rate was relatively low with substantial variability.

Our study did not provide information on reasons why drivers did not follow the driving advices. As the system could be permanently muted, it could be, that drivers were not aware of the driving advices, if they relied on the audio cues only. Nevertheless, for the idea of this study, this would also be indicative for a lack of compliance with the system. Additionally, we do not know, if drivers may have had sufficient reason to not follow an advice such as the prioritization of safety or punctuality in a specific situation. Also due to the fact, that the DAS is programmed to only provide coasting advice when there is a sufficient time buffer, drivers might have not received advices for longer periods of time and therefore thought the system was not that relevant or not functioning. However, we can expect this margin of error in the estimation of the "true" compliance to be the same for all our participants as they all drove in the same railway sector and because of the large number of driving data we collected from each participant.

Correlations within the TAM only partly aligned with the model. While usefulness and behavioral intention and usefulness and compliance correlated, no correlation between behavioral intention and compliance was observed. Ease of use did not correlate with any other TAM variable. A direct link from usefulness to use was also observed by other authors (e.g. Lu and Gustafson (1994), and previous research has found usefulness to be a stronger predictor in the TAM then ease of use (F. D. Davis and Venkatesh, 2004).

We did not find support for the hypothesis 1, that train drivers' perceptions of their job characteristics and occupational satisfaction changes after the introduction of DAS. The premises to test hypothesis 2 was therefore not given and we adopted an exploratory approach to investigate whether drivers' current perceptions of their jobs were linked to their acceptance and compliance with DAS instead. The observed lack of impact of DAS on the JCM dimensions and occupational satisfaction may be explained by the voluntary use of the system. Had DAS use been mandatory, it is plausible that drivers would have perceived the system as more intrusive. This, in turn, could have led to a greater influence on their job characteristics.

The best model to predict system compliance, as determined by forward stepwise regression, included perceived usefulness, task identity, and skill variety.

This means, we were partly able to identify aspects of work design that are linked to system compliance. Drivers with higher task identity were more likely to integrate eco-efficient driving into their tasks. This could be due their recognition of broader organizational benefits, such as cost reduction. This would support findings from Schnücker et al. (2023), which indicated that operational cost savings motivated drivers to adopt energy-efficient driving. Similarly, the positive correlation between occupational satisfaction and perceived usefulness might be explained by more intrinsically motivated drivers who value tools like DAS to improve their driving efficiency. Furthermore, drivers who already perceived the variety of skills required for their jobs to be manifold, were more willing to integrate eco-efficiency into their driving.

Future research should continue to investigate a possible link between job characteristics and technology acceptance and compliance, as well as strive for sufficient sample sizes. It should also be investigated to what degree voluntariness impacts the influence on new technologies on job characteristics. While this study draws on the established JCM due to its strong applicability for job redesign, we acknowledge the emergence of more recent models to explain job satisfaction. We therefore see an opportunity for future research to investigate the relationship between occupational satisfaction and technology acceptance using these newer models. Additionally, it would be important to consider how other organizational factors, such as management support and incentives influence the adoption of technologies at the workplace.

In conclusion, this study provides a valuable contribution to a more holistic perspective of consequences of technology introduction by including job characteristics as factors to influence technology acceptance and compliance within the TAM. We found that the current status of job dimensions at least partly influences the adoption of DAS for energy-efficient driving. This provides new angles for strategies to improve technology adoption by considering aspects of work design. For a human centered future, technologies that enhance energy-efficiency should be designed and implemented in a way that is subjectively useful for operators and that aligns with their work characteristics. This will improve system adoption and therefore overall sustainability, especially in the railway domain.

CRediT authorship contribution statement

Gina N. Schnücker: Writing – original draft, Visualization,

Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Johannes Salge:** Visualization, Validation, Software. **Linda Onnasch:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Feature extraction, modeling, properties and performance of the artificial neural network for driving regime classification.

To achieve the optimal balance between precise timing of regime changes and stable classification despite noise, we employed a feature extraction procedure to extend the data set, followed by the use of an artificial neural network (ANN) model for regime classification. This classification was then used to assess compliance with driving advices using an automated rule-based rating. The process of feature extraction for the classification model, the performance of the model on regime classification and the procedure of compliance rating are described in the following section.

1. Feature extraction

To enhance the classification model's performance, we used a feature extraction technique incorporating variables denoted as Xi and Yi. These variables provide each data point with temporal context based on the velocity trajectory.

The Xi variables (X_1 to X_9) capture local changes in the velocity trajectory across different time scales. This involves segmenting the data into two consecutive windows of varying widths, performing linear regression within each window to estimate local slopes, and calculating the difference in slopes to measure velocity change over time. The window widths are iteratively increased from 2 to 512 data points, with X1 capturing the finest temporal changes and X_9 the broadest, enriching the feature set with detailed temporal dynamics.

The Y_i variables (Y_1 to Y_9) predict future velocity trends by capturing the forthcoming slope within a defined window. A regression is performed within a subsequent window, and the slope coefficient, indicating the expected velocity change, is assigned to the corresponding Yi variable. Window widths are expanded similarly to the X_i variables, embedding anticipatory characteristics into the feature set.

Unfiltered velocity, velocity smoothed using a Savitzky-Golay filter, and acceleration were also included as features. The resulting 21 variables (9 X_i, 9 Y_i, unfiltered velocity, filtered velocity, acceleration) comprised the final feature set that was used to classify driving regimes using an ANN.

These variables collectively enhance the model's ability to identify complex temporal patterns.

2. ANN modeling

For regime classification, we implemented an ANN using the neuralnet package in R. The network consists of an input layer with 21 nodes (representing the 21 variables from the feature enriched dataset), a first hidden layer with 21 neurons, a second hidden layer with 5 neurons, and an output layer with 5 nodes representing the classification regimes (standing, accelerating, cruising, coasting, and braking). Bias nodes in each layer improve the model's fit. This architecture was chosen to balance complexity and computational efficiency.

3. ANN regime classification performance

As a basis for training 9 rides with a total of 451 min of driving time were manually labeled. These rides comprised 46 driving advices. After feature extraction the enriched data were pooled together. From this pool, a learning set was constructed by randomly choosing 75 % of data points from the pool. The remaining 25 % of data points were used as a testing set.

Regime classification performance on the learning and testing set were 0.9415, 95 % CI [0.9381, 0.9447], and 0.9356, 95 % CI [0.9294, 0.9414], respectively. Fig. 1 shows the confusion matrices for the learning and testing set. Note the drop of sensitivity for the "standing" category for both sets.

Fig. 1. Left: confusion matrix learning set. Right: Confusion matrix testing set.

4. Rule-based compliance rating

Last, a rule-based rating was used to establish whether participants complied to the driving recommendation. A driving recommendation was rated as implemented when within a 40 s window after recommendation onset at least two regimes were found AND a non-coasting regime was followed by a coasting regime.

The performance of this final analysis step was accessed using the combined training and test data (Fig. 2).

Fig. 2. Confusion matrix of the compliance rating.

Figure A2 shows the confusion matrix for the compliance-rating procedure. The rule-based compliance-rating achieved an overall **accuracy of 80.43 % (95 % CI: 66.09–90.64).** The **Kappa coefficient was 0.6087**, indicating moderate to substantial agreement. The **sensitivity was 1.00**, while the **specificity was 0.6087**, showing that the ANN-classified regime data differed from the manually classified regime data in such a way that it prompted some false-alarms from the rule-based compliance-rating. This means that the procedure might consistently overestimate absolute compliance-rates over all participants. While absolute compliance rates should therefore be interpreted with caution, the consistent application of the two analysis steps across all participants allows for reliable relative comparisons between individuals or groups, assuming that classification errors are uniformly distributed.

References

Adell, E., 2009. *Driver Experience and Acceptance of Driver Support Systems - A Case of Speed Adaptation* [Doctoral Thesis]. Lund University, Lund. https://lucris.lub.lu.se/ws/portalfiles/portal/3577721/1511414.pdf.

Albrecht, T., 2013. Human factor challenges in the development of a Driver Advisory System for regional passenger trains. In: Dadashi, N., Scott, A., Wilson, J.R., Mills, A. (Eds.), Rail Human Factors. Taylor & Francis, pp. 129–138.

Al-Emran, M., Granic, A., 2021. Is it Still valid or outdated? A bibliometric analysis of the technology acceptance model and its applications from 2010 to 2020. In: Al-Emran, M., Shaalan, K. (Eds.), Recent Advances in Technology Acceptance Models and Theories. Springer International Publishing, pp. 1–12.

Ang, S., Slaughter, S.A., 2001. Work Outcomes and Job Design for Contract versus Permanent Information Systems Professionals on Software Development Teams. MIS Q. 25 (3), 321–350. https://doi.org/10.2307/3250920.

Argote, L., Goodman, P.S., 1984. Investigating the Implementation of Robotics. The Robotics Institute. https://www.ri.cmu.edu/pub_files/pub3/argote_linda_1984_1/argote_linda_1984_1.pdf.

Bala, H., Venkatesh, V., 2013. Changes in employees' job characteristics during an enterprise system implementation: a latent growth modeling perspective. MIS Q. 37 (4), 1113–1140. https://doi.org/10.25300/MISQ/2013/37.4.06.

Barley, S.R., 2015. Why the internet makes buying a car less loathsome: how technologies change role relations. Acad. Manag. Discov. 1 (1), 5–35. https://doi.org/10.5465/amd.2013.0016.

Blut, M., Chong, A.Y.L., Tsigna, Z., Venkatesh, V., 2022. Meta-analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT): challenging its validity and charting a research agenda in the red ocean. J. Assoc. Inf. Syst. Online 23 (1), 13–95. https://doi.org/10.17705/1jais.00719.

Boonzaier, Billy, Ficker, Bernhard, Rust, Braam, 2001. A review of research on the Job Characteristics Model and the attendant job diagnostic survey. S. Afr. J. Bus. Manag. 32 (1), 11–34. https://doi.org/10.4102/sajbm.v32i1.712.

Brandenburger, N., 2022. *The changing Role of Staff in automated railway Systems and why human Cognition is Here to stay.* European union agency for railways. ERTMS 2022 Conference, Valenciennes, France. https://elib.dlr.de/186335/1/Automation%20Myth%20Busting%20Paper%20%232_ERA-Version_published_online.pdf.

Brandenburger, N., Hörmann, H.-J., Stelling, D., Naumann, A., 2017a. Tasks, skills, and competencies of future high-speed train drivers. Proc. Inst. Mech. Eng. F J. Rail Rapid Transit 231 (10), 1115–1122. https://doi.org/10.1177/0954409716676509.

Brandenburger, N., Naumann, A., 2019. On track: a series of research about the effects of increasing railway automation on the train driver. IFAC-PapersOnLine 52 (19), 288–293. https://doi.org/10.1016/j.ifacol.2019.12.115.
Brandenburger, N., Naumann, A., Wittowski, M., 2017b. *Countering train driver Fatigue in automatic train operation.* Rail safety and standards board. Sixth International Human Factors Rail Conference. London, UK.
Brislin, R.W., 1970. Back-translation for cross-cultural research. J. Cross Cult. Psychol. 1 (3), 185–216. https://doi.org/10.1177/135910457000100301.
Brooks, J.D., Groshong, H., Liu, A., Houpt, P., Oman, C., 2017. Survey of future railroad operations and the role of automation. Transp. Res. Rec. 2608 (1), 10–18. https://doi.org/10.3141/2608-02.
Cascio, W.F., Montealegre, R., 2016. How technology is changing work and organizations. Ann. Rev. Organizational Psychol. Organizational Behav. 3 (1), 1171–1204. https://doi.org/10.1146/annurev-orgpsych-041015-062352.
Davis, C.J., Hufnagel, E.M., 2007. Through the eyes of experts: a socio-cognitive perspective on the automation of fingerprint work. MIS Q. 31 (4), 681–703. https://doi.org/10.2307/25148816.
Davis, F.D., 1985. *A technology acceptance model for empirically testing new end-user information systems: theory and results* [Doctoral thesis]. Massachusetts Institut of Technology, Massachusetts. https://dspace.mit.edu/bitstream/handle/1721.1/15192/14927137-MIT.pdf.
Davis, F.D., Venkatesh, V., 2004. Toward preprototype user acceptance testing of new information systems: implications for software project management. IEEE Trans. Eng. Manag. 51 (1), 31–46. https://doi.org/10.1109/TEM.2003.822468.
European Commission, 2022. ANNEX to the Commission Decision on the Submission of the Europe's Rail Joint Undertaking Master Plan for Adoption by Europe's Rail Governing Board. European Commission. https://rail-research.europa.eu/wp-content/uploads/2022/03/EURAIL_Master-Plan.pdf.
European Environment Agency, 2021. Passenger and freight transport demand in Europe. https://www.eea.europa.eu/data-and-maps/indicators/passenger-and-freight-transport-demand/assessment-1.
European Environment Agency, 2022a. Transport and environment report 2022: digitalisation in the mobility system: challenges and opportunities. EEA report 07/2022). https://www.eea.europa.eu/publications/transport-and-environment-report-2022/transport-and-environment-report/view.
European Environment Agency, 2022b. Transport and environment report 202: decarbonising road transport — the role of vehicles, fuels and transport demand. EEA report 02/2022. https://www.eea.europa.eu//publications/transport-and-environment-report-2021.
European Environment Agency, 2023. Transport and environment report 2022: digitalisation in the mobility system: challenges and opportunities. EEA report 07/2022. https://www.eea.europa.eu/publications/transport-and-environment-report-2022/transport-and-environment-report/view.
Evans, M.G., Ondrack, D.A., 1991. The motivational potential of jobs: is a multiplicative model necessary? Psychol. Rep. 69 (2), 659–672. https://doi.org/10.2466/PR0.69.6.659-672.
Formato, G., Carbone, L., Grassi, F., Divano, R., Segarich, P., 2023. Energy efficiency driving strategy with connected-driving advisory system (C-DAS). Transp. Res. Procedia 72, 263–270. https://doi.org/10.1016/j.trpro.2023.11.403.
Fried, Y., Ferris, G.R., 1987. The validity of the job characteristics model: a review and meta-analysis. Pers. Psychol. 40 (2), 287–322. https://doi.org/10.1111/j.1744-6570.1987.tb00605.x.
Ghani, J.A., Al-Meer, A.R., 1989. Effect of end-user computing on job satisfaction: an exploratory study. Inf. Manag. 17 (4), 191–195. https://doi.org/10.1016/0378-7206(89)90042-6.
Ghazizadeh, M., Peng, Y., Lee, J.D., Boyle, L.N., 2012. Augmenting the technology acceptance model with trust: commercial drivers' attitudes towards monitoring and feedback. Proc. Hum. Factors Ergon. Soc. Annu. Meet. 56 (1), 2286–2290. https://doi.org/10.1177/1071181312561481.
Giesemann, S., 2013. Automation effects in train driving with train protection systems - assessing person- and task-related factors. In: Dadashi, N., Scott, A., Wilson, J.R., Mills, A. (Eds.), Rail Human Factors. Taylor & Francis, pp. 139–150.
Hackman, J.R., Oldham, G.R., 1975. Development of the job diagnostic survey. J. Appl. Psychol. 60 (2), 159–170. https://doi.org/10.1037/h0076546.
Hackman, J.R., Oldham, G.R., 1976. Motivation through the design of work: test of a theory. Organ. Behav. Hum. Perform. (16), 250–279. https://doi.org/10.1016/0030-5073(76)90016-7.
Hinton, M., Boderman, M., 1995. Empirically derived job characteristics measures and the motivating potential score. J. Bus. Psychol. 9 (4), 355–364. https://doi.org/10.1007/BF02230975.
Hogan, E.A., Martell, D.A., 1987. A confirmatory structural equations analysis of the job characteristics model. Organ. Behav. Hum. Decis. Process. 39 (2), 242–263. https://doi.org/10.1016/0749-5978(87)90040-9.
Hunscha, U., Geißler, A., 2018. Fahr Umweltbewusst: Energieverbrauch im Schienenverkehr durch den Einsatz von Fahrerassistenzsystemen reduzieren. https://www.allianz-pro-schiene.de/wp-content/uploads/2019/03/Abschlussbericht_Fahr-umweltbewusst.pdf.
Idaszak, J., Drasgow, F., 1987. A revision of the job diagnostic survey: elimination of a measurement artifact. J. Appl. Psychol. 72 (1), 69. https://doi.org/10.1037/0021-9010.72.1.69.
King, W.R., He, J., 2006. A meta-analysis of the technology acceptance model. Inf. Manag. 43 (6), 740–755. https://doi.org/10.1016/j.im.2006.05.003.
Legris, P., Ingham, J., Collerette, P., 2003. Why do people use information technology? A critical review of the technology acceptance model. Inf. Manag. 40, 191–204. https://doi.org/10.1016/S0378-7206(01)00143-4.
Liu, R., Golovitcher, I.M., 2003. Energy-efficient operation of rail vehicles. Transport. Res. Pol. Pract. 37 (10), 917–932. https://doi.org/10.1016/j.tra.2003.07.001.
Lu, H.-P., Gustafson, D.H., 1994. An empirical study of perceived usefulness and perceived ease of use on computerized support system use over time. Int. J. Inf. Manag. 14 (5), 317–329. https://doi.org/10.1016/0268-4012(94)90070-1.
Luijt, R.S., van den Berge, M.P., Willeboordse, H.Y., Hoogenraad, J.H., 2017. 5 years of Dutch eco-driving: managing behavioural change. Transport. Res. Pol. Pract. 98, 46–63. https://doi.org/10.1016/j.tra.2017.01.019.
Meirich, C., Flamm, L., Krimmling, J., Jäger, B., 2020. Betriebliche Optimierung des Eisenbahnbetriebs mittels vernetzter Fahrerassistenzsysteme. ETR - Eisenbahntechnische Rundschau. Article 24-29. https://elib.dlr.de/130992/1/ETR_3_20_Meirich_ua_FA_vFAS.pdf.
Meirich, C., Ritzer, P., Reiher, P., Ullrich, G., Franz, A., 2023. FASaN - Fahrerassistenzsysteme adaptive Nachhaltigkeit im Bahnbetrieb. ETR - Eisenbahntechnische Rundschau, pp. 26–30. https://elib.dlr.de/191253/1/2023_ETR_FASaN_Meirich_FA.pdf.
Millman, Z., Hartwick, J., 1987. The impact of automated office systems on middle managers and their work. MIS Q. 11 (4), 479–491. https://doi.org/10.2307/248977.
Morris, M.G., Venkatesh, V., 2010. Job characteristics and job satisfaction: understanding the role of enterprise resource planning system implementation. MIS Q. 34 (1), 143–161. https://doi.org/10.2307/20721418.
Nagy, M.S., 2002. Using a single-item approach to measure facet job satisfaction. J. Occup. Organ. Psychol. 75 (1), 77–86. https://doi.org/10.1348/096317902167658.
Naumann, A., Grippenkoven, J., Lemmer, K., 2016a. Future information and assistance systems for train drivers and evaluation of their usability. International Union of Railways. 11th World Congress on Railway Research, Milan - Italy. https://elib.dlr.de/102426/1/WCRR2016_383_Naumann_Grippenkoven_Lemmer_final.pdf.
Naumann, A., Wörle, J., Dietsch, S., 2016b. The Effect of Train Protection Systems on Train Drivers' Visual Attention [Conference Poster]. HFES Europe Chapter Annual Meeting, Prague. https://elib.dlr.de/105466/1/Poster_Naumann_HFES_16_A4.pdf.
Naweed, A., 2014. Investigations into the skills of modern and traditional train driving. Appl. Ergon. 45 (3), 462–470. https://doi.org/10.1016/j.apergo.2013.06.006.
Parker, S.K., Grote, G., 2022. Automation, algorithms, and beyond: why work design matters more than ever in a digital world. Appl. Psychol. 71 (4), 1171–1204. https://doi.org/10.1111/apps.12241.
Regan, M.A., Horberry, T., Stevens, A. (Eds.), 2014. Human Factors in Road and Rail Transport. Driver Acceptance of New Technolgy. Ashgate Publishing Limited.
Renn, R.W., Vandenberg, R.J., 1995. The critical psychological states: an underrepresented component in job characteristics model research. J. Manag. 21 (2), 279–303. https://doi.org/10.1016/0149-2063(95)90059-4.
Rieth, M., 2022. Auswirkungen zunehemender Automatisierung auf Beschäftigte in High Reliability Organizations: Eine Analye der veränderten Arbeitsrolle und Anforderungen unter Berücksichtigung der Arbeitsgestaltung am Beispiel des Berufsbildes der Fluglots:innen. Pabst Science Publishers.
Scheepmaker, G.M., Goverde, R.M., 2015. The interplay between energy-efficient train control and scheduled running time supplements. J. Rail Trans. Plan. Manag. 5 (4), 225–239. https://doi.org/10.1016/j.jrtpm.2015.10.003.
Schnücker, G.N., Naumann, A., Salge, J., 2024. *A neural network to measure train operators' compliance with driver assistance systems* [Poster presentation]. HFES Europe Chapter: Annual Meeting, Lübeck, Germany. https://www.hfes-europe.org/wp-content/uploads/2024/04/Poster-HFES-Luebeck_Schnuecker.pdf.
Schnücker, G.N., Klencke, M., Naumann, A., 2023. *Requirements for advanced driver assistance systems in rail operations* [Poster presentation]. HFES Europe Chapter: Annual Meeting, Liverpool, United Kingdom. https://www.hfes-europe.org/wp-content/uploads/2023/04/Schnuecker2023.pdf.
Spector, P.E., 2022. Job Satisfaction: from Assessment to Intervention. Routledge. https://doi.org/10.4324/9781003250616.
Tarhini, A., Elyas, T., Akour, M.A., Al-Salti, Z., 2016. Technology, demographic characteristics and E-learning acceptance: a conceptual model based on extended technology acceptance model. High. Educ. Stud. 6 (3), 72. https://doi.org/10.5539/hes.v6n3p72.
Tausch, A., Kluge, A., 2022. The best task allocation process is to decide on one's own: effects of the allocation agent in human–robot interaction on perceived work characteristics and satisfaction. Cognit. Technol. Work 24 (1), 39–55. https://doi.org/10.1007/s10111-020-00656-7.
van Dick, R., Schnitger, C., Schwartzmann-Buchelt, C., Wagner, U., 2001. Der Job Diagnostic Survey im Bildungsbereich. Zeitschrift Für Arbeits- Und Organisationspsychologie A&O 45 (2), 74–92. https://doi.org/10.1026//0932-4089.45.2.74.
Venkatesh, V., Bala, H., Sykes, T.A., 2010. Impacts of information and communication technology implementations on employees' jobs in service organizations in India: a multi-method longitudanal field study. Prod. Oper. Manag. (19), 5. http://arxiv.org/pdf/2010.01148v1.
Venkatesh, V., Morris, M.G., Davis, F.D., Davis, G.B., 2003. User acceptance of information technology: toward a unified view. MIS Q. 27 (3), 425–478. https://doi.org/10.2307/30036540.
Wall, T.D., Clegg, C.W., Jackson, P.R., 1978. An evaluation of the job characteristics model. J. Occup. Psychol. (51), 183–196. https://doi.org/10.1111/j.2044-8325.1978.tb00413.x.
Yang, L., Liden, T., Leander, P., 2013. Achieving energy-efficiency and on-time performance with driver advisory systems. In: 2013 IEEE International Conference on Intelligent Rail Transportation Proceedings. IEEE, pp. 13–18. https://doi.org/10.1109/ICIRT.2013.6696260.