Breaking the ICE? Examining the Cognitive, Social, and Psychological Determinants of User Resistance to Electric Non-Road Work Vehicle Adoption

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The success of organizationally mandated technology adoption often hinges on whether employees are receptive or resistant to the new technology. This study examines non-road work vehicle operators' attitudes toward switching to using electric work vehicles. A research model investigating the impact of cognitive evaluations of vehicle attributes, organizational social context, and psychological antecedents on resistance was tested using survey data from 1460 respondents collected via an online panel. Results from hierarchical multiple regression analysis show that beneficial vehicle attributes (perceived sustainability and quietness of electric work vehicles) and positive social context (colleague opinions and organizational adoption intentions) lower resistance. In contrast, psychological attitudes related to technostress and disrupting the status quo (techno-overload and inertia) significantly increase resistance. Theoretical contributions and practical implications of these findings are discussed.

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1 Introduction

Employees often face situations where they are mandated to adopt technologies or information systems by their organization (Heath et al., 2022; Ilie & Turel, 2020; Klaus et al., 2010). Although new technologies often bring benefits to employees, resistance stemming from various sources, such as inertia (Polites & Karahanna, 2012), is a common reaction because people typically prefer to maintain the status quo (Kim & Kankanhalli, 2009). However, the dynamics and relative strength of these drivers and inhibitors of resistance are still not well understood. This is a critical concern, as user resistance may lead to underutilization of the new technology (Ilie & Turel, 2020) or even employee turnover (Califf et al., 2020; Lapointe & Rivard, 2005), resulting in the loss of institutional knowledge and necessitating additional training investments for new hires. With the pace of technological development and adoption increasing, a better understanding of how these factors influence user resistance is needed.

Electric vehicles (EVs) are being increasingly adopted by consumers, and organizations are now turning their attention to electrifying work fleets—especially non-road work vehicles—due to potential operational and employee benefits (Dehkordi et al., 2024; McKinsey & Company, 2023). These benefits include improved air quality in indoor and urban work environments and reduced greenhouse emissions (Lajunen et al., 2016, 2018). For instance, in 2019 non-road work vehicles accounted for an estimated 2% of total greenhouse emissions and up to 11% in certain EU industry sectors (Lončarević et al., 2022). However, adopting such vehicles can be challenging for companies because employees often vary in their receptiveness. The added complexity of operating the more digitalized control systems of the vehicles (Strayer et al., 2019) may, for instance, require employees to learn new operating procedures and disrupt established routines. Identifying the factors that contribute to resistance is crucial for organizations to proactively mitigate its emergence. Otherwise, resistance behaviors may spread and become entrenched (Jalo & Pirkkalainen, 2024; Lapointe & Rivard, 2005), making them particularly difficult to overcome (Selander & Henfridsson, 2012).

This paper examines how beneficial vehicle characteristics, an organization's social context, and employees' psychological attitudes toward change impact their resistance to adopting battery electric non-road vehicles (BENVs). The research model is tested using hierarchical multiple-regression analysis based on a sample of 1460 current non-road work vehicle operators collected via the Prolific online survey panel. The results show that although the perceived benefits of BENVs, namely their higher perceived environmental sustainability and lower noise, and an adoption-supportive social environment can dampen resistance attitudes, users' psychological predispositions toward switching to BENVs, specifically inertia and fear of techno-overload, are on balance more strongly related to resistance. We contribute to the innovation adoption and resistance literatures by empirically validating the relevance of the proposed resistance antecedents through a large survey study.

The rest of the paper is structured as follows. In Section 2, the theoretical background and the research model are presented. Section 3 describes the survey development and data collection. Section 4 presents the hierarchical multiple-regression analysis results. The results are discussed in Section 5, along with the study's limitations and suggestions for future research.

2 Theoretical background

EV adoption has received substantial attention in the innovation adoption literature (Kumar & Alok, 2020); however, the enterprise adoption context remains less studied. Switching entire vehicle fleets from internal combustion engine (ICE) vehicles to electric motor vehicles represents a significant investment for companies. Beyond the business case and larger ecosystem concerns (Dehkordi et al., 2024), it is also essential for companies' employees to be receptive toward the use BENVs, as resistance is one of the leading causes for failed technology adoptions (Cieslak & Valor, 2025). We ground our examination of employee resistance attitudes in the perceived beneficial *characteristics* of BENVs, the organization’s *social context*, and employees' *psychological attitudes* related to disrupting the status quo (Kim & Kankanhalli, 2009; Tarafdar et al., 2007).

When employees evaluate a technology, they often consider its technological or functional benefits, including a cognitive assessment of both switching benefits and switching costs (Kim & Kankanhalli, 2009). In the context of EVs, their perceived superior environmental impact compared to ICE vehicles has been identified as a key determinant of adoption in the consumer context (Kumar & Alok, 2020). Although employees might not conduct formal financial cost-benefit analyses of company investments, they may still evaluate the sustainability of BENVs similarly, potentially reducing resistance due to a personal preference for more environmentally friendly vehicles. EV users have also been shown to appreciate the lower noise levels produced by electric vehicles (Schmalfuß et al., 2017). The relevance of reduced noise may be particularly salient in work settings, where vehicles are typically operated for several hours a day. We therefore operationalize the *sustainability of BENVs* and employees' *low-noise preference* as key vehicle characteristics in our research model.

In the context of mandated technology adoption, the user's social context plays a central role (Khechine et al., 2023), as it shapes user attitudes through social pressure and the need to align with organizational objectives. When users are initially resistant to using the new technology, pressure from their immediate social environment (i.e., co-workers) can reduce resistance (Kim & Kankanhalli, 2009). However, social pressure can also increase resistance if employees discourage others from using the new solution (Lapointe & Rivard, 2005). However, the impact of employees' perceptions of their organization's adoption intentions on resistance remains less well understood, although an inverse relationship has been established from the organizational perspective—namely, that expected employee resistance can lower organizational adoption intentions (Jalo & Pirkkalainen, 2024). Accordingly, we operationalize the social context to include *colleague opinion* and *perceived organizational adoption intention*.

Employees typically favor the status quo (Kim & Kankanhalli, 2009). New technologies introduce uncertainty and require changes to established routines, which can engender resistance (Polites & Karahanna, 2012). Moreover, complex technologies often cause technostress, as employees may fear increased workloads—especially during the learning phase (Tarafdar et al., 2007). In addition to their power generation, BENVs differ from ICE vehicles through their heavier reliance on digital control systems, display interfaces, and integration with various information systems (Strayer et al., 2019). This adds a new layer of complexity for end users, who must adapt to digital interfaces that may differ substantially from the more analog controls of ICE work vehicles. Such shifts can trigger perceptions of added workload and feelings of techno-overload (Tarafdar et al., 2007), driven by anticipated complexity of BENV operation. These psychological responses have been linked to negative employee outcomes, such as lowered employee satisfaction, as well as increased attrition and turnover intentions (Califf et al., 2020). As a psychological coping mechanism, employees may prefer to continue using their current vehicles, which are more familiar and aligned with their existing expertise. Routine-seeking and cognitive rigidity also contribute to inertia, both of which have been linked to resistance attitudes (Laumer et al., 2016). Organizations must therefore account for employee inertia when implementing new technologies (Polites & Karahanna, 2012). Accordingly, the psychological dimension of our research model is operationalized through *techno-overload* and *inertia*.

As control variables, we included age, gender, and prior experience with EVs in non-work contexts. These variables are commonly included in technology adoption models (Venkatesh et al., 2003). Controlling for prior experience is particularly important, as users with limited exposure may hold inaccurate perceptions about EV performance (Burgess et al., 2013).

3 Methodology

The survey data were collected between November and December 2024 using the Prolific online survey panel and the Alchemer survey tool. The target group comprised operational employees and lower- and middle-level managers expected to be closely involved in vehicle operation. A total of 1573 responses were gathered. After removing 111 responses due to incorrect answers to one of the two attention trap questions, 1462 responses remained. Further examination identified six responses with a standard deviation of less than 0.7. Two of these were completed in under five minutes, suggesting potential inattentiveness, given that the estimated completion time for the survey was 15 minutes. These two responses were removed, resulting in a final sample size of 1460. Demographic and background information of the respondents is reported in Table 1. The respondents' companies were located in the United States (554), United Kingdom (458), Canada (94), Poland (74), Germany (50), Spain (25), Australia (25), Netherlands, (25), and 155 in other countries. The primary industries of the respondents were Manufacturing or Industrial (331), Warehousing and Distribution (275), Construction and Architecture (234), Consumer Goods (133), Agriculture (76), Aerospace or Aviation (65), and 346 worked in other industries.

Table 1: Sample demographics and background information

	Frequency	%
Gender		
Male	1073	73.5
Female	387	26.5
Age (years)		
18 to 29	530	36.3
30 to 39	504	34.5
40 to 49	237	16.2
50 to 59	148	10.1
60 to 76	41	2.8
Organizational position		
Operational level employee (e.g., forklift driver)	591	40.5
Lower-level manager (e.g., team supervisor)	384	26.3
Middle manager (e.g., worksite manager)	485	33.2
Non-work EV experience		
Not familiar with electric vehicles outside of work	214	14.7
Familiar with electric vehicles, but haven't driven one	382	26.2
Ridden as a passenger, but haven't driven one	273	18.7
Have driven an electric vehicle before	485	33.2
I own an electric vehicle	106	7.3

The constructs, item wordings, means, standard deviations, Cronbach's alpha values, and standardized item loadings are reported in Table 2. All scales were measured using 7-point Likert items ranging from Strongly disagree to Strongly agree. The BENV sustainability scale was adapted from Fang and Li's (2022) sustainability scale, which was originally based on Möhlmann's (2015) environmental impact scale. The low-noise enjoyability scale (Schmalfuß et al., 2017) was adapted to focus on preference for low vehicle noise rather than driving style adaptations. The colleague opinion scale (Kim & Kankanhalli, 2009) was slightly reworded to focus specifically on BENVs. The behavioral intention to use scale (Venkatesh et al., 2003) was adapted to assess employees' perceptions of organizational-level adoption intention, reflecting the mandatory adoption context. The inertia scale (Polites & Karahanna, 2012) was adapted to examine employee preferences for their current vehicles rather than their use continuance intention. The techno-overload scale (Tarafdar et al., 2007) was modified to assess perceptions of whether the complexity of BENV adoption would increase workload. Finally, the dependent variable of resistance was adapted from Kim and Kankanhalli (2009) to capture attitudinal rather than active resistance.

Table 2: Survey constructs and items (* p < 0.001)**

Construct	Item wording	Loading
Sustainability of BENVs (Fang & Li, 2022; Möhlmann, 2015) α = 0.872 Mean = 5.22 SD = 1.19	SUST1: Using electric work vehicles helps conserve more resources than traditional vehicles	0.823***
	SUST2: Using electric work vehicles is more sustainable than traditional vehicles	0.788***
	SUST3: Using electric work vehicles is more efficient in terms of resource utilization than traditional vehicles	0.781***
	SUST4: Using electric work vehicles is more environmentally friendly than using traditional vehicles	0.786***
Low-noise preference (Schmalfuß et al., 2017) α = 0.842 Mean = 5.47 SD = 1.17	LONO1: The low noise level of electric work vehicles would make driving more enjoyable	0.775***
	LONO2: I would like the quietness of electric work vehicles	0.815***
	LONO3: I would perceive the low noise level of electric work vehicles as pleasant	0.815***
Colleague opinion (Kim & Kankanhalli, 2009) α = 0.897 Mean = 4.59 SD = 1.34	COOP1: Most of my colleagues think switching to electric work vehicles is a good idea	0.879***
	COOP2: My peers support switching to electric work vehicles	0.854***
	COOP3: Most people I work with encourage switching to electric work vehicles	0.857***
Organizational future use intention (Venkatesh et al., 2003) α = 0.913 Mean = 5.20 SD = 1.35	OFUS1: I predict that our organization will use electric work vehicles in the future	0.826***
	OFUS2: Our organization plans to use electric work vehicles in the future	0.909***
	OFUS3: Our organization intends to use electric work vehicles in the future	0.916***
Inertia (Polites & Karahanna, 2012; Shi et al., 2018) α = 0.907 Mean = 3.62 SD = 1.47	INER1: I prefer traditional work vehicles because they are stress-free	0.802***
	INER2: I prefer traditional work vehicles because using them is more comfortable for me	0.862***
	INER3: I prefer traditional work vehicles because I have been working with them for so long	0.859***
	INER4: I prefer traditional work vehicles because I have used them regularly in the past	0.850***
Technology-overload (Tarafdar et al., 2007) α = 0.843 Mean = 2.96 SD = 1.38	OVLO1: The complexity of using electric vehicles would force me to do more work than I can handle	0.787***
	OVLO1: The complexity of using electric vehicles would leave me less time to focus on my actual work	0.821***
	OVLO1: I would have a higher workload because of the complexity of electric vehicles	0.793***
Resistance (Kim & Kankanhalli, 2009) α = 0.861 Mean = 2.68 SD = 1.44	RESI1: I am reluctant to switch to using electric work vehicles	0.800***
	RESI2: I am unwilling to switch to using electric work vehicles	0.839***
	RESI3: I oppose switching to using electric work vehicles	0.828***

4 Results

4.1 Reliability and discriminant and convergent validity

IBM SPSS version 29 was used to conduct an exploratory factor analysis (EFA) to examine the factor structure by assessing item cross-loadings. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.935, exceeding the recommended threshold of 0.8, and Bartlett's test of sphericity was significant ($\chi 2(276) = 23390.377$; $p < 0.001$), indicating sufficient inter-item correlations for factor analysis (Hair et al., 2014). EFA was performed using principal axis factoring with promax rotation (Costello & Osborne, 2019; Matsunaga, 2010). The seven-factor solution explained 68.5% of the total variance. All items loaded onto their expected constructs with adequate to strong loadings ranging from 0.627 to 0.950, and no strong cross-loadings (> 0.32) were identified (Costello & Osborne, 2019).

Next, we conducted confirmatory factor analysis (CFA) using IBM Amos version 28. We began by examining the standardized factor loadings. One resistance item had a loading of 0.64, below the commonly accepted threshold of 0.707 (Hair et al., 2014), indicating it explained less than 50% of the variance in the latent construct. This item was therefore dropped from subsequent analyses, resulting in three items measuring resistance.

We then assessed convergent and discriminant validity using average variance extracted (AVE), maximum shared variance (MSV), and composite reliability (CR) (Fornell & Larcker, 1981), as well as the heterotrait-monotrait (HTMT) ratio of correlations (Henseler et al., 2015; Voorhees et al., 2016). The Fornell-Larcker and HTMT results, obtained using the Master Validity tool by Gaskin et al. (2019), are shown in Table 3. Following the guidelines of Hair et al. (2014) and Henseler et al. (2015) (CR > 0.7; AVE > 0.5; MSV < AVE; square root of AVE greater than inter-construct correlations; HTMT < 0.85), the measurement model demonstrated adequate convergent and discriminant validity.

Table 3: Fornell-Larcker (lower triangle) and HTMT (upper triangle) results

	CR	AVE	MSV	INER	SUST	OFUS	OVLO	COOP	RESI	LONO
INER	0.908	0.712	0.535	**0.844**	0.435	0.373	0.583	0.360	0.653	0.380
SUST	0.873	0.632	0.371	-0.485	**0.795**	0.441	0.231	0.540	0.518	0.523
OFUS	0.915	0.782	0.458	-0.403	0.478	**0.885**	0.193	0.618	0.444	0.342
OVLO	0.843	0.641	0.472	0.660	-0.268	-0.207	**0.801**	0.058	0.585	0.267
COOP	0.898	0.745	0.458	-0.404	0.608	0.677	-0.072	**0.863**	0.406	0.353
RESI	0.863	0.677	0.535	0.732	-0.595	-0.481	0.687	-0.463	**0.823**	0.443
LONO	0.844	0.643	0.371	-0.430	0.609	0.379	-0.321	0.407	-0.524	**0.802**

4.2 Common method variance

We assessed common method variance (CMV) using Harman's single factor test with principal axis factoring and no rotation (Fuller et al., 2016). The single factor explained only 36.997% of the variance, well below the suggested 50% threshold. We also examined the correlations between a marker variable (MV, measuring attitude toward the color blue) and the theoretical variables (Miller & Simmering, 2023; Williams et al., 2010) during CFA. The absolute mean correlation between the MV and the theoretical constructs was 0.09, indicating minimal CMV (Malhotra et al., 2006). Having established the suitability of the measurement model, we calculated mean scores for each construct in SPSS for use in hierarchical regression analysis. Lastly, we checked variance inflation factors (VIF) during the regression analysis, with the highest VIF value being 2.008, well below the more stringent cutoff of 3 (Hair et al., 2014). Thus, CMV is not a threat to the validity of the results.

4.3 Hierarchical multiple-regression analysis results

Table 4 presents the four hierarchical multiple-regression models predicting resistance. Model 1 (control variables) explains 1.4% of the variance (R^2 = 0.014). Age (β = -0.108***) and prior EV experience (β = -0.066*) are both negatively associated with resistance.

Model 2 adds vehicle characteristics, increasing R^2 to 0.313. Perceived BENV sustainability (β = -0.395***) and low-noise preference (β = -0.230***) both reduce resistance; prior EV experience is no longer significant.

Model 3 adds social-context variables, slightly increasing R^2 to 0.355. Organizational adoption intention (β = -0.214***) is negatively associated with resistance, whereas colleague opinion is not. Vehicle characteristic effects remain statistically significant ($p < 0.001$), although their coefficients are slightly smaller.

Model 4 introduces psychological predictors, boosting R^2 to 0.589. Inertia (β = 0.274***) and techno-overload (β = 0.336***) show the strongest positive relations with resistance. All vehicle- and social-context predictors remain negative and significant, albeit with substantially lower coefficients. Age is no longer significant, while colleague opinion attains significance (β = -0.091***).

Table 4: Hierarchical regression analysis results (* p < 0.001, ** p < 0.01, * p < 0.05)**

	Model 1	Model 2	Model 3	Model 4
	Beta (sig.)	Beta (sig.)	Beta (sig.)	Beta (sig.)
Demographic and background characteristics				
Age	**-0.108*** **	**-0.78*** **	**-0.066** **	-0.025
Gender	-0.011	0.031	0.020	-0.021
Non-work EV experience	**-0.066* **	-0.018	0.011	-0.017
Vehicle characteristics				
Sustainability of BENVs		**-0.395*** **	**-0.299*** **	**-0.173*** **
Low-noise preference		**-0.230*** **	**-0.194*** **	**-0.107*** **
Organizational social context				
Colleague opinion			-0.042	**-0.091*** **
Organizational adoption intention			**-0.214*** **	**-0.109*** **
Psychological attitudes				
Inertia				**0.274*** **
Techno-overload				**0.336*** **
Adjusted R^2	0.014	0.313	0.355	0.589
ΔR^2	-	0.299	0.042	0.234
F change	F(3, 1456)= 7.945***	F(2, 1454)= 317.542***	F(2, 1452)= 48.374***	F(2, 1450)= 415.604***

5 Discussion

Companies need to consider employee attitudes when mandating the use of new technologies to ensure smooth roll-outs (Heath et al., 2022; Klaus et al., 2010). Our study examined how employees' perceptions of BENVs shape resistance to replacing ICE vehicles. The hierarchical regression results reveal a clear pattern. In the first step, age and prior non-work EV experience showed small negative links to resistance. However, once perceived BENV sustainability and low-noise preference were added, prior experience lost its influence. This shift indicates that employees are influenced less by mere familiarity with EVs than by conviction that BENVs deliver concrete environmental and noise-related advantages.

Adding social-context variables produced only a modest gain in explained variance, yet perceptions of the organization's intention to adopt BENVs still lowered resistance. Colleague opinion was insignificant until the final step, when techno-overload and inertia were included. Evidently, employees who feel overwhelmed by the technology or are strongly attached to their current vehicles discount peer enthusiasm for BENVs. Once those psychological barriers are accounted for, positive peer sentiment emerges as a distinct force that dampens resistance.

Psychological attitudes clearly dominate the story. Inertia and techno-overload not only have the largest coefficients but also suppress the age effect observed in earlier models. Although older employees appeared less resistant at first, their stance is better explained by lower perceived overload and weaker inertia rather than by age itself. Overall, potential losses in terms of extra workload and disruption of routines loom larger than potential gains, a finding consistent with the status-quo-bias perspective (Kim & Kankanhalli, 2009). Yet when employees clearly perceive BENVs' sustainability and noise advantages, those benefits can overcome default reluctance, provided that overload and inertia are addressed.

5.1 Theoretical contributions

This study contributes to theory in several ways. First, by demonstrating that techno-overload is a direct antecedent of resistance, it bridges the technostress and user-resistance literatures and extends prior work that linked overload mainly to employee satisfaction and turnover intentions (Califf et al., 2020; Tarafdar et al., 2007). Second, the findings refine status-quo-bias theory by indicating that demographic attributes such as age influence resistance mainly through their association with psychological factors—specifically inertia and techno-overload—rather than exerting an independent effect. Third, the study reveals a multi-level social-influence dynamic, indicating that an organization's declared adoption intention exerts a more consistent downward pressure on resistance than informal colleague opinion. This is noteworthy because most employee-level resistance models include only peer opinion as a social antecedent (e.g., Kim & Kankanhalli, 2009), whereas organizational-level adoption research has shown a negative link between anticipated employee resistance and organizational adoption intention (Jalo & Pirkkalainen, 2024). Collectively, these insights deepen our understanding of why employees resist or embrace mandatory sustainable technologies.

5.2 Practical implications

Our results have several implications for companies. First, companies should prioritize alleviating employees' fears about the extra work they may associate with BENV adoption. Before full deployment, small-scale pilot projects could be conducted to provide hands-on experience and allow employees to explore the vehicles' interfaces in a low-stakes environment. Such experiential learning can build competence and may help reduce techno-overload. To ease the switch from the status quo, professional inertia related to employees' preference for ICE vehicles must be addressed. Highlighting the benefits of BENVs can help mitigate these issues, but companies should also leverage peer influence to foster more positive attitudes toward adoption. Finally, communicating the organization's adoption plans well in advance may help prevent the emergence of resistance.

5.3 Limitations and future research

Our study has a few limitations. First, the data were collected using a cross-sectional design, which restricts our ability to infer causality between the antecedents and resistance (Maier et al., 2023). Longitudinal research that tracks pre- and post-adoption attitudes could clarify how resistance evolves over time in mandatory adoption settings. Second, the hierarchical regression model examined only direct relationships between the predictor and dependent variables. Future research might utilize structural equation modeling to examine whether some of the predictors mediate the influence of the antecedents or employ fuzzy-set qualitative comparative analysis to explore causal asymmetry and identify distinct resistance profiles (Pappas & Woodside, 2021). Third, our sample is mainly drawn from industrial, construction, and logistics contexts in which employees operate non-road work vehicles. Although the underlying mechanisms—status-quo bias, techno-overload, and multi-level social influence—should be broadly generalizable, sector-specific factors such as regulatory intensity or task complexity may moderate their effects. Replicating the model in other sectors, such as healthcare or public services, would help clarify boundary conditions and enhance external validity.

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