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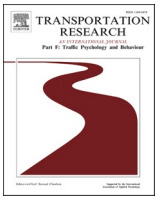

Understanding the charging behavior of electric vehicle drivers on long-distance trips – The roles of range regulation and human-automation cooperation

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ABSTRACT

Advances in battery technology and charging infrastructure have improved long-distance electric vehicle (EV) travel. However, effective trip planning can be challenging. EV trip planners (EVTs) can support drivers in range regulation, yet their effectiveness and acceptance depend on how drivers experience the interaction. In this context, we introduce Driver Electric Vehicle Trip Planner Interaction Style (DEVTIS), which captures individual differences in reliance on or modification of system-generated recommendations. DEVTIS is assumed to be shaped by driver characteristics, experience, and perceived system cooperativity. The objective of the present study was to examine EV drivers' interaction with EVTs for range regulation on long distances and its underlying psychological dynamics. Through a correlational online study with 133 EV drivers, we assessed affinity for technology interaction and subjective range competence as personal characteristics variables, perceived cooperativity and DEVTIS as core interaction-related variables, trust and system acceptance as evaluative user experience measures and range stress and range utilization as EV range-regulation-related variables. Findings revealed that perceived cooperativity negatively predicted DEVTIS, indicating that higher perceived cooperativity was associated with less frequent modification of system recommendations. Moreover, perceived cooperativity positively predicted trust and system acceptance, while DEVTIS negatively predicted both. Subjective range competence showed a slight negative association with range stress. These findings underscore the importance of understanding human-automation cooperation in EVT usage. Considering perceived cooperativity and individual interaction tendencies supports the design of adaptive, driver-centered EVTs, facilitating a seamless transition to EV-based mobility. Promoting perceived cooperativity may enhance trust and system acceptance, while excessive modification of EVT recommendations could undermine these factors.

1. Introduction

The transition to sustainable transportation is crucial for reducing greenhouse gas emissions and mitigating climate change.

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Electric vehicles (EVs) play a central role in the shift towards climate neutrality, particularly when connected to a smart grid (Castle & Hendry, 2024). While range limitations and charging availability were once major barriers to EV adoption, these challenges have been mitigated by improvements in battery range and the expansion of charging infrastructure (Egbue & Long, 2012). As a result, long-distance EV travel has become increasingly feasible, yet efficient range regulation remains cognitively demanding, particularly with regard to the integration of charging stops (Thorhauge et al., 2024; Wang, Yao, & Yang, 2024).

With increasing EV driving experience, range management progresses from dealing with range limitations (BDEW, 2023) to a more strategic and adaptive decision-making process (Franke & Krems, 2013; Rauh et al., 2017). This process involves the continuous monitoring of energy consumption, estimating charging needs, and selecting optimal charging stops, thus ultimately balancing complex cognitive efforts. This capability aligns with drivers' subjective range competence (SRC), which refers to their perceived ability to assess energy consumption and effectively manage charging needs (Franke, Neumann, et al., 2012). Prior research suggests that higher SRC is associated with greater confidence in range-related decisions, potentially reducing range concerns (Franke & Krems, 2013; Zatsarnaja et al., 2025).

In order to assist drivers in meeting these aforementioned complex demands, automated solutions have been developed, facilitating efficient long-distance EV trip planning. In the present study, the term Electric Vehicle Trip Planner (EVT) refers to automated route and charging assistants for EVs, providing real-time recommendations based on factors such as energy consumption, charging station availability, and route constraints (Wu et al., 2020). Ideally, these systems optimize decision-making by integrating relevant data while aligning with drivers' goals and preferences.

However, EVT's effectiveness depends not only on technical features but also on how drivers utilize them. If drivers do not experience the system as beneficial and aligned with their requirements, they may override suitable recommendations or disengage from them entirely. Research suggests that perceived cooperativity, defined as the extent to which a system is seen as working collaboratively with the user towards a shared goal (Attig et al., 2024), might play a key role in fostering user acceptance and adherence to system recommendations. In addition, drivers exhibit individual differences in how they engage with EVTs. Some drivers might rely on system-generated recommendations, while others may actively modify them based on personal preferences.

A core assumption in the present study is that EV drivers develop relatively temporally constant interaction styles with these systems over time, reflecting habitual ways of engaging with automated support tools. Such interaction styles may be closely linked to system acceptance and effective utilization. To capture these tendencies, we introduce Driver Electric Vehicle Trip Planner Interaction Style (DEVTIS), a construct that describes individual differences in how drivers interact with EVTs, ranging from closely adhering to system-generated recommendations to frequently modifying them. DEVTIS is assumed to be shaped by individual driver characteristics and perceptions of system cooperativity, potentially influencing drivers' reliance on EVT recommendations.

Prior research on human-automation interaction suggests that interaction styles influence the extent to which automated support is utilized (Franke & Krems, 2013). Additionally, affinity for technology interaction (ATI) reflects a general disposition towards active technology engagement (Franke et al., 2019). Drivers with high ATI are assumed to engage with EV technology, such as EVTs, in a more proactive manner, whereas those with lower ATI may prefer passive use. Similarly, SRC may shape how drivers interact with EVTs, as those with greater confidence in their range management abilities might be more selective in following system guidance.

The objective of the present study was to provide deeper insights into human-automation interaction in the context of optimizing range regulation through EVTs during long-distance trips. To this end, we conducted an online study with 133 EV drivers, assessing their EVT interactions and key psychological factors related to automation use. We conceptualized and measured DEVTIS to characterize human-automation interaction in the context of long-distance EV range regulation. Specifically, we examined DEVTIS in relation to its antecedents and outcomes, investigating how individual differences shape interaction. In this context, we explored the roles of ATI, SRC, and perceived cooperativity, as well as how perceived cooperativity and DEVTIS relate to the outcome measures trust and system acceptance. Additionally, we assessed SRC as a potential protective factor against range stress.

2. Background

This section outlines the theoretical foundations underlying the present study. It introduces relevant concepts from human-automation cooperation and EV range regulation and positions the central constructs examined in the empirical analyses.

2.1. Range regulation in long-distance EV driving

Limited vehicle range and the availability of charging infrastructure were previously seen as major barriers to EV adoption (Egbue & Long, 2012; Wang, Yao, & Yang, 2024), but technological advancements have significantly improved long-distance feasibility of EVs. Moreover, findings suggest that experienced EV drivers tend not to perceive range management as a source of anxiety or stress (BDEW, 2023; Franke, Cocron, et al., 2012), but rather as a strategic task that requires adaptive decision-making (Jensen et al., 2013; Pichelmann et al., 2013): Instead of focusing on overcoming range limitations, they engage in proactive planning and continuously optimizing charging strategies based on situational factors and personal preferences (Franke et al., 2017; Rauh et al., 2015; Summala, 2007).

Long-distance EV travel requires complex action regulation, as drivers must monitor battery levels, anticipate consumption, and adjust strategies dynamically (Fuller, 2005; Wang, Zhang, et al., 2024). According to action regulation theory, EV driving can be understood as an adaptive control loop in which drivers compare their status to predefined goals, identify deviations, and make necessary adjustments (Fuller, 2011; Summala, 2007; Zacher & Frese, 2018). Thus, range-related decision-making is not just a rational optimization process but also a dynamic psychological regulation task, balancing efficiency, risk, and cognitive effort.

Several psychological factors influence how effectively drivers regulate their battery range (Franke et al., 2016; Khaleghikarahrodi & Macht, 2024; Tamis et al., 2024). In the following, we discuss three factors which have been identified as crucial for effective EV range management in past research, in more detail: SRC, range stress, and range utilization. First, SRC refers to drivers' perceived ability to estimate range, plan charging stops, and optimize battery efficiency (Franke et al., 2016). Higher SRC is associated with greater confidence in energy management, allowing drivers to rely less on external guidance and make more autonomous decisions. Research suggests that individuals with higher competence in a domain are better able to self-regulate, experience lower stress, and adjust their strategies more effectively when making complex decisions (Frese & Zapf, 1994). Accordingly, drivers with higher SRC tend to approach range management more proactively, whereas those with lower SRC may experience greater uncertainty and depend more heavily on system-generated recommendations (Wang, Huang, Tu, & He, 2023).

Second, range stress, described as the emotional strain arising from perceived range limitations (Franke, Neumann, et al., 2012; Thorhauge et al., 2024), can influence charging behavior. Elevated range stress may lead to overly cautious charging decisions, potentially reducing overall efficiency (Rauh et al., 2017). Previous research has shown that higher range stress is linked to increased cognitive load, as drivers devote more mental resources to anticipating and mitigating range-related risks (Wang, Huang, He, & Tu, 2023). However, individuals with higher SRC are more likely to feel in control of their energy management, reducing anxiety and promoting more efficient range regulation (Franke et al., 2016).

This relation could be explained by drivers' greater confidence in estimating energy consumption and in strategically using available charging infrastructure, which can provide clearer internal reference points for evaluating system information and thereby reduce subjective uncertainty during range-related appraisals. For example, drivers with higher SRC may feel able to continue with a low remaining state of charge (SOC) when they judge remaining range and nearby charging options to be manageable, whereas drivers with lower SRC may experience greater uncertainty and stress in comparable situations.

Third, range utilization, which reflects how effectively drivers use their available battery capacity before recharging, is considered an indicator of range-related decision-making. Higher utilization might be associated with greater confidence in range estimation and energy optimization (Wang, Huang, He, & Tu, 2023; Wang, Zhang, et al., 2024). Drivers with high SRC are more likely to strategically delay charging rather than recharging prematurely out of caution, leading to a more efficient use of battery capacity (Rauh et al., 2017). This aligns with findings in self-regulation research, which indicate that individuals with greater competence in a given domain tend to set more precise goals and adjust their strategies dynamically to achieve optimal outcomes (Carver & Scheier, 2001).

While EV drivers develop personal range regulation strategies, automated route and charging planners are being developed and enhanced in supporting their decision-making (Neuhuber et al., 2022; Wu et al., 2020). These systems integrate real-time data on traffic, energy consumption, and charging station availability to provide dynamic recommendations for long-distance travel. However, their effectiveness depends on how well they align with drivers' regulatory strategies and expectations. Automation should enhance rather than replace drivers' regulatory strategies by providing targeted and adaptive assistance. If system recommendations do not align with drivers' strategies or situational understanding, drivers may override them, reducing system effectiveness.

In sum, EV drivers integrate multiple information sources into their decision-making process (Wang, Zhang, et al., 2024), including personal experience, situational constraints, and system-generated recommendations. While EVTs have the potential to enhance efficiency and reduce cognitive effort, their effectiveness relies on alignment with drivers' strategies rather than replacing them. The following section summarizes findings from human-automation interaction research to explore how an optimal human-automation coupling can be achieved in the context of long-distance EV driving.

2.2. Human-automation cooperation in EVT usage

EVTs optimize routes and charging strategies by integrating dynamic factors such as grid congestion, charging station availability, and weather. Calculated trip suggestions, including charging stops, are then visually presented to drivers. The optimal interaction would be for drivers to accept the first suggestion because they are confident that all important route, infrastructure, and vehicle-related information has been included in the calculation and that their individual goals and preferences have been taken into account by the EVT. In other words, an ideal EVT resembles shared decision-making by enabling informed decisions adapted to individual drivers' reference values as well as all relevant context variables.

However, the “black box” nature of many automated systems makes it difficult for users to understand how recommendations are generated. Thus, a system that lacks transparency might limit understanding of the system and be perceived as less than optimally trustworthy (Thill et al., 2018), limiting its effectiveness in managing resources (Kühne et al., 2023; Neuhuber et al., 2022). Consequently, to predict and optimize shared decision-making and ultimately system acceptance, it is of crucial importance to understand drivers' subjective perception of system functioning.

Drivers must be able to interpret and evaluate the rationale behind EVT-generated recommendations to integrate them effectively into their range management strategies (Wang, Yao, & Yang, 2024). To better understand how drivers form these perceptions, we refer to joint activity theory (Bradshaw et al., 2017; Klein et al., 2005), which postulates that successful human-automation teamwork requires mutual management of knowledge, beliefs, and goals. Effective collaboration depends on predictability (the ability to anticipate the system's actions) and directability (the ability to influence the system's behavior; Klein et al., 2005). More broadly, these cooperative automation principles have been discussed in the human-automation literature beyond recent AI contexts; in the present study, perceived cooperativity captures drivers' appraisal of such cooperative qualities in EVT decision support (Klein et al., 2005).

While drivers cannot verify directly whether an EVT meets these criteria, they can assess its cooperative qualities based on system behavior. If the EVT appears responsive to driver input and supports joint goal attainment (e.g., by allowing meaningful adjustments and providing interpretable feedback), drivers might be more likely to perceive the system as cooperative. Conversely, if

recommendations seem difficult to adapt, insufficiently responsive, or poorly aligned with the driver's current goals, drivers may disengage or override suggestions. This subjective perception of an EVT's cooperative qualities has been termed perceived cooperativity (Attig et al., 2024). Prior findings suggest that perceived cooperativity may play a critical role in fostering positive user experience, for instance, regarding trust and system acceptance (Attig et al., 2024).

In particular, trust serves as a key mechanism in human-automation interaction, shaping how users engage with system recommendations.

Following Lee and See (2004), trust in automation is understood as attitude reflecting the expectation that an automated system will help users achieve their goals in situations characterized by uncertainty and vulnerability. Within this perspective, perceptions of reliability, competence, and predictability are not trust itself but belief-based evaluations that contribute to the formation of this trust attitude (Lee & See, 2004).

Accordingly, trust is grounded in users' experienced trustworthiness of a system, that is, the extent to which system behavior is perceived as understandable, dependable, and supportive of task goals. This distinction aligns with research emphasizing perceived trustworthiness as a key experiential design criterion in automated support systems, particularly in range-related decision contexts (Franke et al., 2015).

An EVT perceived as cooperative may foster perceived trustworthiness by enabling directability (responsiveness to driver input) and observability (transparency in decision-making; Klein et al., 2005). When trust is well-calibrated, drivers are more likely to integrate system recommendations into their decision-making while maintaining appropriate skepticism, avoiding both uncritical dependence on automation and premature rejection of system support (Pop et al., 2015). Moreover; well-calibrated trust should also be reflected in higher system acceptance (Hoff & Bashir, 2015).

In line with established usage-oriented perspectives, system acceptance is understood as an overall evaluation of a system, reflecting users' willingness to adopt and continued use, rather than momentary interaction behavior in a specific situation (Van Der Laan et al., 1997). Such evaluations capture both practical appraisals of the system's usefulness and the extent to which interacting with it is experienced as satisfying. In the context of the present study, higher system acceptance therefore reflects more favorable evaluations of using the EVT as decision support and a stronger willingness to incorporate its recommendations into trip planning and decision-making, instead of mere compliance with individual suggestions.

When perceived cooperativity is high, drivers may experience the system as more effective and engaging, leading to greater acceptance (Attig et al., 2024). In sum, EVTs that transparently communicate their decision-making processes and align with driver expectations are more likely to be trusted, accepted, and effectively integrated into long-distance EV travel.

2.3. Individual differences in human-automation interaction

Individuals differ in how they engage with automated systems, with some users actively exploring system functionalities, while others follow habitual decision-making strategies (Picco et al., 2023). A related construct in this domain is ATI, which captures individual differences in the tendency to engage with and explore technological systems (Attig et al., 2019; Franke et al., 2019). ATI reflects a context-specific personality trait that influences how individuals interact with both everyday and complex technological systems. Higher ATI is associated with greater willingness to experiment with new features, trust in automation, and proactive system use (Attig et al., 2019), while lower ATI corresponds to a preference for conventional, manual control and reduced engagement with automated assistance (Franke et al., 2019). ATI reflects a general predisposition towards interacting with technology, yet its relevance in specific automation contexts requires further investigation.

Beyond general technology affinity, context-specific interaction patterns have been identified in EV-related decision-making (Jensen et al., 2013). For instance, user-battery interaction style (UBIS; Franke & Krems, 2013; Rahmati & Zhong, 2009) describes patterns in how EV drivers manage battery range, distinguishing between those who optimize battery use and those who rely on conservative range buffers. This suggests that relatively temporally constant tendencies influence not only general technology use but also specific decisions in EV operation, such as range management and charging behavior.

Building on this concept, we introduce Driver Electric Vehicle Trip Planner Interaction Style (DEVTIS), which describes habitual differences in how EV drivers engage with system-generated trip and charging recommendations during long-distance EV travel. Importantly, DEVTIS is conceptualized as an interaction-style construct capturing how drivers typically work with system-generated recommendations, not as a normative construct. Conceptually, DEVTIS is distinct from evaluative constructs such as trust, system acceptance, and perceived cooperativity, as it reflects interaction behavior rather than drivers' evaluations of the system.

Specifically, high DEVTIS indicates more frequent modification of system-generated recommendations, whereas low DEVTIS reflects that recommendations are typically followed with little or no adjustment. Such modifications may range from selectively adjusting specific route or charging suggestions to fully overriding the system's proposed trip plan and independently planning the route and charging stops.

Similar to ATI, which can also be understood as a user diversity variable referring to individual technology interaction style differences (Franke et al., 2019), we assume that DEVTIS is partially rooted in personality traits. Specifically, we suggest ATI to be a relevant predictor for DEVTIS, as individuals with greater technology affinity tend to engage more actively with automation, critically evaluating system-generated recommendations rather than following them passively. Furthermore, we assume that DEVTIS is also partly shaped by EV experience, more specifically SRC. For instance, drivers who have acquired substantial competence in utilizing the EV range, that is, who know how to deal with very limited remaining range resources (Franke, Neumann, et al., 2012), might be more likely to modify system-generated charging stop recommendations. In sum, we hypothesize that ATI and SRC serve as antecedents for DEVTIS.

Regarding potential outcomes of DEVTIS, prior research suggests that interaction styles influence automation reliance and system acceptance (Bühler et al., 2014; Franke & Krems, 2013). The technology acceptance model (TAM; Davis, 1989; Venkatesh et al., 2003) suggests that systems requiring frequent manual intervention may be perceived as less useful, negatively impacting system acceptance. According to trust calibration models, users who frequently modify automation outputs may experience misalignment between system behavior and expectations, leading to reduced trust over time (Hoff & Bashir, 2015). Therefore, we hypothesize that system acceptance and trust are key outcome variables of DEVTIS.

Finally, DEVTIS is assumed to be associated with perceived cooperativity of the EVT. Perceived cooperativity refers to drivers' evaluation of the system's capability to incorporate user input and support joint goal attainment within the interaction (Attig et al., 2024). Accordingly, higher perceived cooperativity should be associated with less frequent modification of system recommendations (lower DEVTIS), whereas lower perceived cooperativity should co-occur with more frequent modification (higher DEVTIS). As DEVTIS and perceived cooperativity manifest in actual EVT interaction, we hypothesize perceived cooperativity to be both associated with DEVTIS and also to predict the interaction outcomes trust and system acceptance.

3. Present research

This section introduces the research framework and specifies the research questions and hypotheses examined in the present study.

3.1. Research framework

The present study examined how EV drivers interact with EVT recommendations, specifically whether they tend to follow or override system-generated suggestions (i.e., their individual DEVTIS). Furthermore, it investigates how personal characteristics variables and system-related factors shape these interactions (Ferreira et al., 2011; Shibl et al., 2013). Fig. 1 provides an overview of the research framework underlying the present study. It illustrates the hypothesized relationships between key psychological and system-related factors, offering a structured approach to understanding EVT interaction and its broader implications. Given the correlational and cross-sectional design, the arrows indicate hypothesized directions for the purpose of hypothesis formulation, not causal effects. These hypotheses are presented in detail in the following section.

3.2. Research questions and hypotheses

The objective of the present study was to enhance the understanding of psychological mechanisms underlying range regulation in long-distance EV driving. Specifically, we investigated the relationships among driver characteristics, system interaction factors and DEVTIS (see 2.3). The present study focused on the identification of key antecedents and outcomes of DEVTIS as well as their interrelations, with a particular emphasis on personal characteristics variables and perceived system cooperativity.

(Q1) How can DEVTIS be predicted by personal characteristics variables and interaction variables?

(Q1H1) According to findings on the relationship between ATI and active engagement with automation (Franke et al., 2019), see

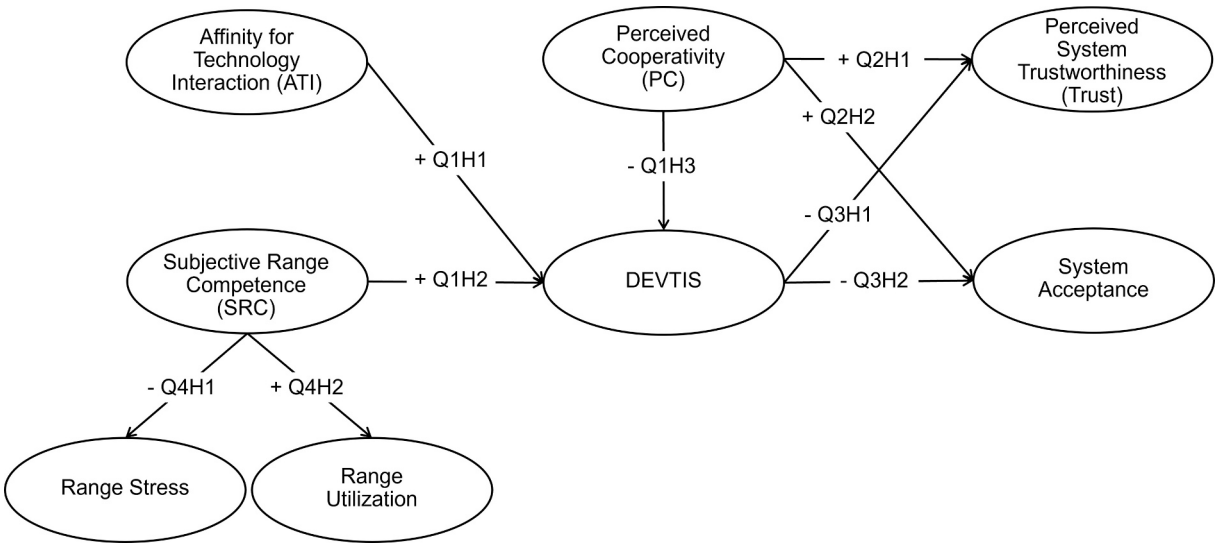

Fig. 1. Research framework with hypothesized effects. The hypothesis numbers (e.g., Q1H1) refer to the hypotheses specified in Section 3.2. Plus signs depict positive relationships, while minus signs depict negative relationships. DEVTIS = Driver electric vehicle trip planner interaction style; Range Stress = Typical experience of range stress on long-distance trips; Range Utilization = Range utilization as indicated by the lowest state of charge (SOC) ever.

2.3, we hypothesize that higher ATI predicts higher DEVTIS. Specifically, drivers with higher ATI tend to interact more proactively with technical systems by exploring and adjusting system outputs rather than accepting recommendations as given. This tendency should manifest in more frequent modification of EVT recommendations.

(Q1H2) According to findings on self-perceived competence and automation use (Franke et al., 2016), see 2.3, we hypothesize that higher SRC predicts higher DEVTIS. Consequently, drivers with higher SRC may draw more confidently on their range-related competence and situational assessment, and thus feel more comfortable deviating from system guidance when it appears suboptimal.

(Q1H3) According to findings on perceived cooperativity and automation reliance (Attig et al., 2024), see 2.2, we hypothesize that higher perceived cooperativity predicts lower DEVTIS. Accordingly, when EVT recommendations are perceived as cooperative and supportive of joint goal attainment, drivers are more inclined to keep recommendations unchanged, resulting in fewer adjustments.

(Q2) How is perceived cooperativity related to user experience represented by trust and system acceptance?

(Q2H1) According to findings on trust in automation (Klein et al., 2005) see 2.2, we hypothesize that higher perceived cooperativity predicts higher trust (perceived system trustworthiness). In line with this reasoning, perceived cooperativity reflects whether the system is experienced as responsive to driver input and supportive of joint goal attainment, which can foster trust in the system's guidance under uncertainty.

(Q2H2) According to findings on technology acceptance (Attig et al., 2024; Davis, 1989), see 2.2, we hypothesize that higher perceived cooperativity predicts higher system acceptance. From this perspective, higher perceived cooperativity is expected to be associated with higher perceived usefulness and lower perceived interaction effort, thereby strengthening users' willingness to adopt and use the system.

(Q3) How is DEVTIS related to user experience represented by trust and system acceptance?

(Q3H1) According to findings on human-automation interaction and trust calibration (Hoff & Bashir, 2015), see 2.3, we hypothesize that higher DEVTIS predicts lower trust (perceived system trustworthiness). This reasoning suggests that more frequent modification of system-generated recommendations may co-occur with lower confidence in the quality or suitability of the system's guidance, and thus with lower reported trust.

(Q3H2) According to previous research on automation reliance and system evaluation (Bühler et al., 2014), see 2.3, we hypothesize that higher DEVTIS predicts lower system acceptance. Accordingly, drivers who frequently override system recommendations may perceive the EVT as less useful or less well suited to their needs, which should be associated with lower system acceptance (i.e., lower willingness to use).

(Q4) How does subjective range competence act as a protective factor against range stress?

(Q4H1) According to action regulation theory (Frese & Zapf, 1994), see 2.1, we hypothesize that higher SRC predicts lower range stress (typical experience of range stress on long-distance trips). In range-critical situations (e.g., upon noticing an unexpectedly rapid decrease in SOC), higher subjective competence may reduce uncertainty and is therefore expected to be associated with lower range stress.

(Q4H2) According to findings on range competence and charging behavior, (Franke & Krems, 2013) see 2.1, we hypothesize that higher SRC predicts more effective range utilization, indicated by the lowest state of charge (SOC) before recharging. In other words, drivers with higher SRC may be more comfortable utilizing a larger share of the available range before recharging, reflected in lower reported minimum SOC and a more strategic use of battery capacity.

4. Method

Data were collected using an online survey designed to assess drivers' self-reported interaction patterns with EVT and related psychological constructs in a standardized manner, enabling comparable measurement across a broader sample of participants. The survey was administered via Limesurvey, following the declaration of consent to participate and provide data in accordance with German data protection law. Ethical approval was obtained by the ethics committee of the University of Lübeck (tracking number 2024–462).

4.1. Study setup

Conducting studies that investigate how actual EV drivers interact with their EVT is challenging due to the highly diverse technological ecosystem (i.e., there is a large variety of EV trip planning and charging software available). To enable robust findings regarding the psychological mechanisms underlying action regulation in long-distance EV driving, we decided to focus recruitment on participants who use the same particular EVT to ensure a relatively homogeneous sample in terms of system experience.

We defined the following criteria for EVT selection: (1) The EVT should be connected to a standardized charging network, (2) the EVT should offer comprehensive data, including real-time charging spot availability, predictive charging forecasts, and high-frequency data on actual charging speeds, (3) the EVT should be relatively popular to ensure a large study population. Following a thorough evaluation of available options, the Tesla trip planner and the Tesla supercharger network were identified as meeting the aforementioned criteria. Hence, the research was directed towards users of the Tesla trip planner[1]. The integrated Tesla Trip Planner (as

[1] The selection of Tesla's trip planner software in the present study was driven by the need to ensure comparability of participant experiences and to facilitate the recruitment of a sufficiently large sample. The software name has been retained to maintain the traceability of the study results. It is important to note that the present study was conducted independently, without any sponsorship, support, or affiliation with the manufacturer.

available at the time of data collection) provides system-generated route and charging recommendations based on vehicle range information and charging infrastructure. Drivers can follow these suggestions or manually override them (e.g., by adjusting the route, skipping suggested stops, or selecting alternative chargers). The system provides basic feedback (e.g., estimated arrival SOC and charging duration), while details of the underlying optimization logic are not explicitly communicated and driver preferences are primarily captured via navigation inputs.

4.2. Participants

Participants for the online study were recruited in-person at Tesla supercharger stations in the Hamburg and Lübeck area in northern Germany as well as digitally through a German-language online forum on electric mobility; all responses were to be given with reference to participants' own experiences using the integrated Tesla Trip Planner during long-distance EV trips. Complete participation was rewarded with EUR 10.00 via bank transfer.

Multiple online survey test runs established a minimum completion time of five minutes for fast readers, with an expected duration of 20–25 min, as communicated to participants. A total of 140 individuals finished the questionnaire. Analysis of completion times revealed that seven participants completed the survey in under five minutes, suggesting insufficient engagement. These participants were excluded from the final analysis, thus, the final sample comprised $N = 133$ participants, with single values missing for age and battery range.

To assess potential comprehension difficulties with the German language, a three-grade rating scale was used. Of the 133 participants, 131 (98.5%) reported no comprehension difficulties, 2 (1.5%) reported partial difficulties, and none reported severe difficulties. Hence, no participants were excluded due to limited language comprehension.

Table 1 presents descriptive statistics for the continuous variables used for sample characterization. As demographics, we assessed participants' age, gender, and educational background. As indicators for experience regarding electric vehicle driving we assessed total electrically driven kilometers and total EV driving experience in months. Moreover, we developed a short 4-item scale to assess e-mobility literacy (see Appendix A.5) to capture participants' interest in e-mobility topics, self-reported technical familiarity, and active information-seeking behavior. Reliability was good (Cronbach's $\alpha = 0.87$). Finally, we asked participants to indicate their EV's typical battery range on a full charge.

In summary, the study sample was predominantly male ($n = 127$, 94.5%), with 6 female participants (4.5%), and no participants identifying as nonbinary or gender non-conforming. The participants were highly educated, with 72.9% holding at least a master's degree or a bachelor's/master's degree. This distribution aligns with the broader German EV driver population, where highly educated men represent the majority (Ipsos, 2022).

All participants had prior EV experience and demonstrated a high level of interest in electric mobility topics, as reflected by their elevated e-mobility literacy scales scores ($M = 5.15$, $SD = 0.98$). Overall, the sample consisted largely of tech-savvy EV drivers.

4.3. Scales and measures

Unless otherwise stated, participants provided their responses on a 6-point Likert scale from 1 (*completely disagree*) to 6 (*completely agree*). As a reliability indicator, Cronbach's alpha is reported, with its interpretation following standard practice (Cripps, 2017) as poor ($0.5 \leq \alpha < 0.6$), questionable ($0.6 \leq \alpha < 0.7$), acceptable ($0.7 \leq \alpha < 0.8$), good ($0.8 \leq \alpha < 0.9$) or excellent (≥ 0.9). Table 2 summarizes the reliability analyses for the scales used in the regression analyses.

4.3.1. Driver electric vehicle trip planner interaction style (DEVTIS)

In order to assess DEVTIS, a unidimensional 14-item scale was developed, to capture individual differences in the degree of adherence to or deviation from system-generated charging and route recommendations during long-distance EV trips. In this context, deviation refers to drivers' modification of system-generated recommendations, that is, actively overriding or adjusting suggested routes or charging plans (e.g., skipping a suggested charging stop or selecting an alternative charger). The item development process was guided by the conceptualization of DEVTIS as a relatively temporally constant interaction style with EVTs, reflected in the extent to which drivers follow or modify system recommendations. DEVTIS was intentionally designed as unidimensional and does not distinguish between separate sub-dimensions. The scale construction process was inspired by the User-Battery Interaction Style (UBIS) scale (Franke & Krems, 2013), with items explicitly addressing behaviors indicative of adherence (e.g.,"If the trip planner suggests a charging stop, I always drive to it.") or deviation (e.g.,"I often optimize the route planning manually.") from EVT recommendations. The full scale is depicted in Appendix A.1. Reliability was excellent.

4.3.2. Perceived cooperativity

The Agent Version of the 15-item Perceived Cooperativity Scale (PCS-A; Attig et al., 2024) was used to evaluate perceived cooperativity of the EVT. The scale quantifies the extent to which participants perceive a system as fulfilling core requirements for cooperative teamwork according to joint activity theory (Bradshaw et al., 2017; Klein et al., 2005), such as directability and observability. For the present study, the instruction was adapted to align with the present study's context, the term "agent" was replaced with "trip planner" throughout the scale, and items were adapted to the past tense. Reliability was excellent.

4.3.3. Facets of system trustworthiness (FOST)

Perceived trustworthiness of the EVT was assessed using an adapted version of the 5-item Facets of Systems Trustworthiness (FOST)

Table 1
Participant Characteristics and Experience.

Variable	Min	Max	*M*	*SD*	*P*25	*P*50	*P*75
Age (years)	21	71	46.20	10.79	39.00	45.00	55.00
EV experience (months)	1	140	42.63	30.42	19.00	36.00	57.00
EV experience (km)	10	450,000	78,910	77,212	30,000	50,000	110,000
EV Literacy	1.25	6.00	5.15	0.98	4.75	5.50	6.00
Battery range (km)	100	580	461.83	66.38	414.75	465.00	510.25

Note. P25 = 25th percentile; P50 = 50th percentile; P75 = 75th percentile; $N = 133$.

Table 2
Descriptive Statistics of Key Variables.

Variable	Items	Scale Range	*M*	*SD*	Min	Max	*P25*	*P50*	*P75*	α
DEVTIS	14	1–6	3.44	0.99	1.14	5.43	2.71	3.50	4.14	0.93
PC	15	1–6	3.99	0.84	2.00	5.93	3.40	3.93	4.60	0.91
Trust	5	1–6	5.03	0.75	2.00	6.00	4.80	5.20	5.60	0.89
System Acc.	9	−2 – +2	1.28	0.61	−0.89	2.00	0.89	1.44	1.78	0.88
SRC	7	1–6	4.87	0.60	3.14	6.00	4.57	4.86	5.29	0.79
Range Stress	7	1–6	2.93	0.84	1.00	5.14	2.29	2.86	3.57	0.76
Range Util.	1	0–100	2.91	3.13	0.00	15.00	1.00	2.00	4.00	–
ATI	9	1–6	4.92	0.92	2.22	6.00	4.33	5.11	5.67	0.93

Note. DEVTIS = Driver electric vehicle trip planner interaction style; PC = Perceived cooperativity; Trust = Perceived system trustworthiness; System Acc. = System acceptance; SRC = Subjective range competence; Range Stress = Typical experience of range stress on long-distance trips; Range Util. = Range utilization; ATI = Affinity for technology interaction. P25 = 25th percentile; P50 = 50th percentile; P75 = 75th percentile; α = Cronbach's alpha; $N = 133$.

scale (Franke et al., 2015). The instruction and items were adjusted to better fit the present study's scenario (i.e., “system” was replaced with “trip planner's range and charging planning”) and are listed in Appendix A.2. Reliability was good.

4.3.4. System acceptance

EVT acceptance was evaluated using the 9-item System Acceptance Scale (Van Der Laan et al., 1997). Participants responded to semantic differentials (e.g., “useless – useful”, “annoying – pleasant”) on a bipolar 5-point response scale. The instruction was adjusted to fit the present study's scenario (“system” was replaced with “trip planner”). Reliability was good.

4.3.5. Subjective range competence (SRC)

To assess participants' perceived ability to manage the limited range of EVs, we used a 7-item scale. The first six items correspond to those of the original Subjective Range Competence (SRC) scale by Franke et al. (2016), with adaptations to item wording and instructions to better fit the context of the present study. Additionally, a seventh item was developed to extend the scale by explicitly capturing the ability to develop coping strategies in range-limited scenarios, see Appendix A.3. Reliability was acceptable.

4.3.6. Typical experience of range stress on long-distance trips (range stress)

In order to assess participants' typical experience of range stress during long-distance EV trips, a 7-item scale was developed. This scale is based on the concept of range anxiety, as described by Franke et al. (2016) and Rauh et al. (2015) and measures the subjective experience of range limitations on long-distance EV trips, emphasizing psychological stress and uncertainty. Two items were adapted from the range stress scale by Franke et al. (2016), with modifications to better align with the context of the present study. Five new items were developed to further enhance the scale's ability to capture emotional distress, including anxiety and frequent range monitoring while driving an EV on long-distance trips, see Appendix A.4. Reliability was acceptable.

4.3.7. Range utilization

The utilization of range was determined by the participants' self-reported single-item lowest state of charge (SOC) ever that had been displayed upon their arrival at a charging stop. Thus, the measure reflects the lowest SOC drivers reported having experienced before charging, rather than their typical or average charging threshold. A low SOC prior to charging is indicative of a more efficient use of available battery range, with drivers maximizing their distance traveled per charge. Accordingly, this metric captures individual differences in how far drivers have utilized the available range before recharging, with higher range utilization suggesting greater confidence in their EV's range estimation (Franke & Krems, 2013) and a more risk-tolerant approach to charging.

4.3.8. Affinity for technology interaction (ATI)

For assessing participants' general tendency to actively engage with and explore technological systems, the 9-item Affinity for Technology Interaction (ATI) Scale (Franke et al., 2019) was used. ATI captures individual differences in how users approach new technologies. The scale is designed to measure a general technology-related trait that is stable across different domains, reflecting a dispositional tendency rather than context-specific behavior. Reliability was excellent.

5. Results

5.1. Descriptive and correlational results

Table 2 provides the mean scores and distribution details for all variables included in the hypotheses.

Table 3 presents the Pearson correlations between the key variables. In accordance with Cohen (1988), correlation coefficients of $r \geq 0.10$ are interpreted as small, $r \geq 0.30$ as medium, and $r \geq 0.50$ as large effect sizes. DEVTIS correlated significantly negatively with perceived cooperativity (medium), trust (large), system acceptance (medium), and positively with range stress (small). Perceived cooperativity correlated significantly positively with trust (large), system acceptance (large), SRC (small), and ATI (small). Trust had significant positive associations with system acceptance (large) and SRC (small). System acceptance correlated significantly with ATI (small). SRC correlated significantly positively with range stress (small). All other correlations did not reach statistical significance.

5.2. (Q1) how can DEVTIS be predicted by personal characteristics variables and interaction variables?

The three hypotheses related to Q1 were tested with a multiple linear regression analysis (forced entry method). This approach ensures an unbiased estimation of each predictor's contribution without prior assumptions about their relative importance.

The assumption of normality was assessed using the Shapiro-Wilk test, which did not indicate a significant deviation from normality ($p = .084$). To further examine model assumptions, the Breusch-Pagan test for homoscedasticity was conducted, yielding non-significant results ($p = .282$), suggesting that the assumption of homoscedasticity was met. To examine potential multicollinearity among predictors, Variance Inflation Factors (VIF) were calculated. The results showed that ATI (1.08), SRC (1.06) and PC (1.10) had VIF values well below 5, suggesting no problematic multicollinearity (Daoud, 2017).

The overall model was statistically significant (see Table 4), indicating that 17.0% of the variance in DEVTIS was explained by the predictor variables. The corresponding effect size f^2 is reported in Table 4, indicating a moderate effect size according to Cohen (1988).

The first hypothesis suggested that higher ATI predicts higher DEVTIS. However, ATI was not a significant predictor of DEVTIS. Consequently, Q1H1 was not supported. The second hypothesis proposed that higher SRC predicts higher DEVTIS. However, SRC was not a significant predictor, thus, Q1H2 was not supported. The third hypothesis suggested that higher perceived cooperativity predicts lower DEVTIS. The analysis revealed a significant negative effect, confirming that this relationship was statistically reliable. Therefore, Q1H3 was supported.

Beyond the standardized regression coefficients, partial and semipartial correlations were analyzed to assess each predictor's unique contribution (see Table 4). ATI and SRC showed no meaningful unique contributions, with correlations near zero. In contrast, PC remained significantly negatively associated with DEVTIS, even when controlling for ATI and SRC, indicating that perceived cooperativity uniquely explained variance in DEVTIS.

Table 3
Pearson Correlations Between Key Variables ($r(p)$).

	DEVTIS	PC	Trust	System Acc.	SRC	Range Stress	Range Util.
PC	−0.41*** (< 0.001)	1.00					
Trust	−0.50*** (< 0.001)	0.56*** (< 0.001)	1.00				
System Acc.	−0.44*** (< 0.001)	0.65*** (< 0.001)	0.72*** (< 0.001)	1.00			
SRC	−0.05 (0.604)	0.21* (0.019)	0.23** (0.008)	0.15 (0.076)	1.00		
Range Stress	0.18* (0.043)	−0.11 (0.198)	−0.13 (0.153)	−0.12 (0.174)	−0.17* (0.048)	1.00	
Range Util.	0.02 (0.815)	0.12 (0.187)	0.11 (0.230)	0.12 (0.167)	−0.03 (0.750)	−0.14 (0.101)	1.00
ATI	−0.05 (0.543)	0.24** (0.005)	0.13 (0.140)	0.18* (0.038)	0.16 (0.068)	−0.13 (0.143)	0.07 (0.449)

Note. $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$. DEVTIS = Driver electric vehicle trip planner interaction style; Trust = Perceived system trustworthiness; System Acc. = System acceptance; SRC = Subjective range competence; Range Stress = Typical experience of range stress on long-distance trips; Range Util. = Range utilization; ATI = Affinity for technology interaction; $N = 133$.

Table 4
Regression Analyses for Q1: Predictors for DEVTIS.

Model	*F*	*p*	*R*2	*f*2	Adjusted R^2
Overall Model	8.85	< *0*.001	0.17	0.20	0.15
Predictor	*β*	95% CI	*p*	Part. *r*	Semi-part. *r*
ATI	0.04	[−0.12, 0.21]	0.601	0.05	0.05
SRC	0.04	[−0.13, 0.20]	0.655	0.04	0.04
PC	−0.43	[−0.59, −0.26]	< *0*.001	−0.41	−0.40

Note. DEVTIS = Driver electric vehicle trip planner interaction style; ATI = Affinity for technology interaction; SRC = Subjective range competence; PC = Perceived cooperativity; Part. *r* = Partial correlation; Semi-part. *r* = Semi-partial correlation; CI = Confidence Interval; f^2 = Cohen's effect size, with 0.02 = small, 0.15 = moderate, 0.35 = large (Cohen, 1988); *N* = 133.

5.3. (Q2) how is perceived cooperativity related to user experience represented by trust and system acceptance?

The two hypotheses related to Q2 were tested using simple linear regression analyses (see Table 5). For Q2H1, assumption tests revealed a slight deviation from normality in the residuals (Shapiro-Wilk test: $p = .017$). Additionally, the Breusch-Pagan test indicated a violation of homoscedasticity ($p = .001$), suggesting non-constant error variance. To account for the non-normality of residuals and ensure the robustness of the regression coefficients, bootstrapping (2000 repetitions) was conducted. Specifically, bias-corrected and accelerated (BCa) bootstrap 95% confidence intervals were computed for the regression coefficient from the simple linear regression model with perceived cooperativity as the sole predictor. The resulting confidence interval confirmed the stability of the observed effects. The regression results showed that perceived cooperativity was a significant predictor of trust, accounting for 31.5% of its variance. Hence, Q2H1 was supported.

For Q2H2, assumption tests revealed a slight deviation from normality in the residuals (Shapiro-Wilk test: $p = .040$). Additionally, the Breusch-Pagan test indicated a violation of homoscedasticity ($p = .006$), suggesting non-constant error variance. To account for the non-normality of residuals and ensure the robustness of the regression coefficients, bootstrapping (2000 repetitions) was conducted. Again, BCa bootstrap 95% confidence intervals were computed for the regression coefficient from the simple linear regression model with perceived cooperativity as the sole predictor. The resulting confidence interval confirmed the stability of the observed effects. The regression results showed that perceived cooperativity was a significant predictor of system acceptance, accounting for 42.0% of its variance. Hence, Q2H2 was supported.

5.4. (Q3) how is DEVTIS related to user experience represented by trust and system acceptance?

The two hypotheses related to Q3 were tested using simple linear regression analyses (see Table 6). For Q3H1, assumption tests revealed a slight deviation from normality in the residuals (Shapiro-Wilk test: $p = .011$), additionally the Breusch-Pagan test indicated a violation of homoscedasticity ($p < .001$), suggesting non-constant error variance. To account for the non-normality of residuals and ensure the robustness of the regression coefficients, bootstrapping (2000 repetitions) was conducted. BCa bootstrap 95% confidence intervals were computed for the regression coefficient from the simple linear regression model with DEVTIS as the sole predictor. The resulting confidence interval confirmed the stability of the observed effects. The regression results showed that DEVTIS was a significant predictor of trust, accounting for 24.8% of its variance. Hence, Q3H1 was supported.

For Q3H2, assumption tests revealed a deviation from normality in the residuals (Shapiro-Wilk test: $p < .001$). The Breusch-Pagan test indicated no violation of homoscedasticity ($p = .080$). To account for the non-normality of residuals and ensure the robustness of the regression coefficients, bootstrapping (2000 repetitions) was conducted. BCa bootstrap 95% confidence intervals were computed for the regression coefficient from the simple linear regression model with DEVTIS as the sole predictor. The resulting confidence interval confirmed the stability of the observed effects. The regression results showed that DEVTIS was a significant predictor of system acceptance, accounting for 19.6% of its variance. Hence, Q3H2 was supported.

5.5. (Q4) how does subjective range competence act as a protective factor against range stress?

The two hypotheses related to Q4 were tested with two simple linear regression analyses (see Table 7). For Q4H1, assumption tests revealed no significant deviation from normality in the residuals (Shapiro-Wilk test: $p = .193$). The Breusch-Pagan test indicated no violation of homoscedasticity ($p = .636$). Hence, no bootstrapping was conducted. Regression results showed that SRC had a small but

Table 5
Simple Regression Analyses for Q2: Effect of Perceived Cooperativity.

Hyp	Crit	*F*	*p*	*R*2	*f*2	*β*	95% CI	Bootst. 95% CI	*SE*
Q2H1	Trust	60.24	< *0*.001	0.32	0.47	0.56	[0.42, 0.70]	[0.43, 0.68]	0.06
Q2H2	System Acc.	94.90	< *0*.001	0.42	0.72	0.65	[0.52, 0.78]	[0.36, 0.67]	0.08

Note. Hyp = Hypotheses; Crit = Criterion; Trust = Perceived system trustworthiness; System Acc. = System acceptance, CI = Confidence interval; Bootst. 95% CI = Bootstrapped 95% CI = Bias-corrected and accelerated confidence interval based on 2000 resamples. *SE* = Standard error of bootstrapped estimate. f^2 = Cohen's effect size, with 0.02 = small, 0.15 = moderate, 0.35 = large (Cohen, 1988). *N* = 133.

Table 6
Simple Regression Analyses for Q3: Effect of DEVTIS.

Hyp	Crit	*F*	*p*	*R2*	*f2*	*β*	95% CI	Bootst. 95% CI	*SE*
Q3H1	Trust	43.23	< *0.*001	0.25	0.33	−0.50	[−0.65, −0.35]	[−0.61, −0.36]	0.06
Q3H2	System Acc.	31.98	< *0.*001	0.20	0.24	−0.44	[−0.60, −0.29]	[−0.37, −0.18]	0.05

Note. Hyp = Hypotheses; Crit = Criterion; DEVTIS = Driver electric vehicle trip planner interaction style; Trust = Perceived system trustworthiness; System Acc. = System acceptance, CI = Confidence interval; Bootst. 95% CI = Bootstrapped 95% CI = Bias-corrected and accelerated confidence interval based on 2000 resamples. *SE* = Standard error of bootstrapped estimate. f^2 = Cohen's effect size, with 0.02 = small, 0.15 = moderate, 0.35 = large (Cohen, 1988). *N* = 133.

significant negative effect on experienced range stress, accounting for 3% of its variance. Hence, Q4H1 was supported.

For Q4H2, assumption tests revealed a significant deviation from normality in the residuals (Shapiro-Wilk test: $p < .001$). The Breusch-Pagan test indicated no violation of homoscedasticity ($p = .939$). To account for the non-normality of residuals and ensure the robustness of the regression coefficients, bootstrapping (2000 repetitions) was conducted. BCa bootstrap 95% confidence intervals were computed for the regression coefficient from the simple linear regression model with SRC as the sole predictor. The resulting confidence interval confirmed the stability of the observed effects. The regression results showed that SRC was not a significant predictor of effective range utilization and did not explain a meaningful portion of its variance. Hence, Q4H2 was not supported.

5.6. Summary of hypothesis testing

The results of the regression analyses provided mixed support for the hypotheses. While perceived cooperativity significantly predicted DEVTIS (Q1H3), trust (Q2H1), and system acceptance (Q2H2), no significant effects were observed for ATI (Q1H1) or SRC (Q1H2) on DEVTIS. Moreover, DEVTIS exhibited a significant negative association with both trust (Q3H1) and system acceptance (Q3H2). SRC emerged as a weak but significant predictor of range stress (Q4H1), while no significant effect was found on range utilization (Q4H2).

Fig. 2 provides a consolidated summary of the supported and unsupported hypotheses. The figure summarizes observed associations and does not imply causal directionality.

6. Discussion

6.1. Summary of results

Automated electric vehicle (EV) trip planners (EVTs) can support range management and alleviate range-related concerns, which are known psychological barriers to EV adoption for nonexperienced EV drivers (Thorhauge et al., 2024). With the present correlational study, we gained first insights into the psychological mechanism underlying effective range regulation in long-distance EV travel when supported by EVTs.

Our findings indicate that perceived cooperativity was the strongest predictor of driver electric vehicle trip planner interaction style (DEVTIS). Perceived cooperativity was negatively associated with DEVTIS, suggesting that drivers who perceived the EVT as more cooperative tended to follow its recommendations rather than modifying them. In contrast, affinity for technology interaction (ATI) and subjective range competence (SRC) did not significantly predict DEVTIS, meaning that within our sample, no measurable association with two of the variables that we suggested serve as antecedents for DEVTIS was found. Importantly, the sample consisted predominantly of experienced and technology-savvy EV drivers. This may have restricted variance in ATI and SRC, potentially limiting their predictive power.

Furthermore, perceived cooperativity positively predicted both trust and system acceptance, highlighting its central role in fostering confidence in EVT guidance. These results underscore the importance of designing trip planners that are perceived as cooperative to support higher system acceptance. At the same time, DEVTIS was associated with lower levels of trust and system acceptance, that is, drivers reporting more frequent modification of EVT recommendations also reported lower trust and system acceptance. Importantly, these associations are non-directional and do not imply causality, but reflect co-occurring differences in interaction behavior and evaluative appraisals. DEVTIS should not be interpreted as an evaluative assessment of the system, but as a

Table 7
Simple Regression Analyses for Q4: Effect of Subjective Range Competence.

Hyp	Crit	*F*	*p*	*R2*	*f2*	*β*	95% CI	Bootst. 95% CI	*SE*
Q4H1	Range Stress	4.00	0.048	0.03	0.03	−0.17	[−0.34, −0.00]	–	–
Q4H2	Range Util.	0.10	0.750	0.00	0.00	−0.03	[−0.20, 0.15]	[−1.08, 0.68]	0.44

Note. Hyp = Hypotheses; Crit = Criterion; Range stress = Typical experience of range stress on long-distance trips; Range Util. = Range utilization; CI = Confidence interval; Bootst. 95% CI = Bootstrapped 95% CI = Bias-corrected and accelerated confidence interval based on 2000 resamples (only for Q4H2). *SE* = Standard error of bootstrapped estimate. f^2 = Cohen's effect size, where 0.02 = small, 0.15 = moderate, 0.35 = large (Cohen, 1988). *N* = 133.

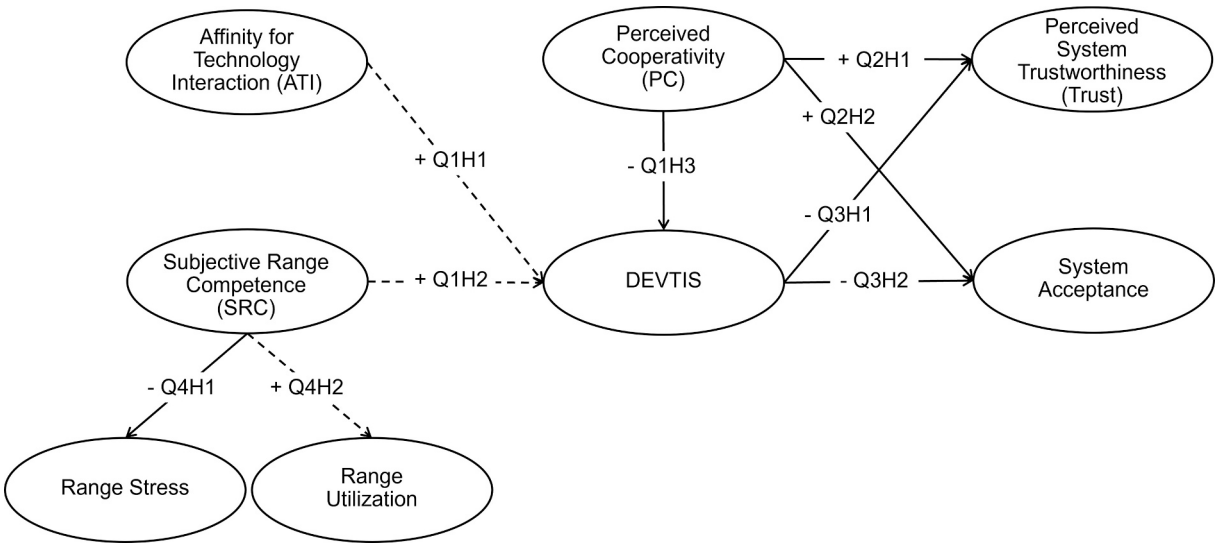

Fig. 2. Summary of hypothesis testing results. The hypothesis numbers (e.g., Q1H1) refer to the hypotheses specified in Section 3.2. Plus signs depict positive relationships, while minus signs depict negative relationships. Solid arrows indicate supported hypotheses; dashed arrows indicate hypothesized relationships that were not supported. DEVTIS = Driver electric vehicle trip planner interaction style; Range Stress = Typical experience of range stress on long-distance trips; Range Utilization = Range utilization as indicated by the lowest state of charge (SOC) ever.

descriptive indicator of how drivers work with system-generated recommendations, ranging from largely following to actively modifying them.

Because perceived cooperativity and DEVTIS were correlated and both related to trust and system acceptance, we did not estimate joint multivariate models; given the cross-sectional design and sample size, doing so would have increased the risk of unstable estimates.

This finding raises the possibility that frequent manual intervention could be linked to a perceived misalignment between user expectations and system performance. This aligns with previous research on trust calibration in human-automation interaction (Hoff & Bashir, 2015), suggesting that frequent manual intervention may disrupt the expected balance between system reliability and driver autonomy. Similarly, the negative relationship between DEVTIS and system acceptance supports findings on automation reliance and system evaluation (Bühler et al., 2014), indicating that drivers who deviate from system recommendations may develop a lower overall evaluation of its usefulness.

Regarding range-related experiences, SRC was weakly but significantly associated with lower range stress, indicating a limited role in mitigating stress during long-distance EV travel. However, SRC did not significantly predict range utilization, suggesting that confidence in range estimation alone is not sufficient to determine efficient battery use, underscoring the complexity of user-range interaction. Overall, interaction variables, particularly perceived cooperativity, appeared to be more closely associated with DEVTIS than personal characteristics variables (i.e., ATI, SRC), at least within the context of our sample.

Taken together, the findings suggest a coherent pattern in which interaction-related evaluations, particularly perceived cooperativity, were more strongly associated with drivers' interaction behavior and system evaluations than personal characteristics variables within the present sample. Perceived cooperativity was consistently linked to lower modification behavior (DEVTIS) as well as higher trust and system acceptance, whereas ATI and SRC showed weaker or more selective associations. Notably, SRC was related to lower range stress but not to range utilization, suggesting that perceived competence may primarily shape affective experience rather than actual energy management behavior during long-distance EV travel.

6.2. Theoretical and methodological contributions

The present study introduced DEVTIS as a novel construct to capture individual differences in how EV drivers engage with system-generated recommendations of EV trip planners, thereby extending the understanding of interaction patterns in human-automation cooperation. By conceptualizing DEVTIS as an interaction-style construct rather than an evaluative or reliance-based measure, the present approach complements established trust- and reliance-focused frameworks, shifting attention to how drivers work with automated recommendations in practice.

Moreover, we developed a questionnaire instrument to assess DEVTIS quantitatively. The results indicate that perceived cooperativity plays a crucial role in shaping interaction behavior with EVTs, reinforcing the need for automation systems to align with driver goals and expectations and decision-making processes.

Importantly, given the cross-sectional and correlational design of the present study, associations between DEVTIS, trust, and system acceptance should not be interpreted as evidence of directional or causal effects. While lower trust may plausibly precede more

frequent modification of system-generated recommendations, it is equally possible that repeated modification experiences shape subsequent trust evaluations, or that both constructs are jointly influenced by unobserved factors. Accordingly, trust and system acceptance are conceptualized here as evaluative correlates of interaction style rather than as determinants of DEVTIS. Disentangling these potential directional and unique effects remains an important task for future longitudinal or experimental research.

The findings further contribute to research on trust calibration in automation. Previous research suggests that user trust in automation should ideally align with system capabilities to ensure optimal reliance (Hoff & Bashir, 2015; Kraus & Baumann, 2024). The observed negative association between DEVTIS and trust indicates that frequent manual intervention in EVT recommendations may co-occur with lower trust, potentially due to inconsistencies between system recommendations and driver expectations, goals, or preferences. However, this association should be interpreted cautiously, as the present design does not allow separating unique variance contributions of correlated predictors.

Against this backdrop, the present findings underscore that perceived cooperativity is also relevant in decision-support automation such as EV trip planning. Specifically, perceived cooperativity aligns with cooperative automation principles such as directability and interpretability of system suggestions (Klein et al., 2005), suggesting that EVT interaction can be meaningfully framed as cooperative human–automation coordination even in non-autonomous decision-support systems.

Moreover, the negative relationship between DEVTIS and system acceptance is consistent with findings on automation reliance and system evaluation (Bühler et al., 2014). Drivers who frequently adjust system-generated recommendations may perceive the EVT as less reliable or less suited to their needs, leading to lower acceptance.

Notably, DEVTIS is not conceptualized as a normative construct. In contrast to trust calibration approaches that often imply optimal levels of reliance, DEVTIS describes stable differences in interaction behavior without assuming that either high or low levels are inherently desirable. Instead, the adaptiveness of different interaction styles is likely to be context-dependent, varying with system characteristics and perceived cooperativity.

This suggests that design features fostering perceived cooperativity and, where appropriate, transparency may support system acceptance by facilitating the interpretation and integration of recommendations into drivers' decision-making.

Finally, the present study also contributes to research on range-related stress and competence by showing that SRC is weakly associated with lower range stress, yet unrelated to range utilization. This highlights the need for further research on how perceived competence translates into actual energy management behavior in real-world driving contexts (Franke & Krems, 2013; Nazari et al., 2023).

6.3. Practical implications

To better accommodate diverse driver needs, EVTs could offer more advanced customizable settings, such as preferred routing strategies or charging preferences. Providing drivers with greater control over these settings may increase perceived cooperativity, making system recommendations feel more aligned with individual preferences. Beyond direct customization, EVTs could also utilize real-time as well as historical driving and charging behavior data to refine their recommendations over time, ensuring these better reflect individual habits and vehicle constraints. Additionally, integrating feedback loops that allow the system to learn from driver preferences may further improve both perceived cooperativity and the suitability of recommendations. By combining these adaptive mechanisms, such a learning-based approach could enable EVTs to evolve dynamically, offering increasingly tailored recommendations (Shafipour & Stein, 2022).

The following implications reflect theory-informed design considerations based on the observed interaction patterns and were not directly assessed or experimentally manipulated in the present study.

Beyond adaptation (Picco et al., 2023; Pichelmann et al., 2013), greater transparency in EVTs has been proposed as a design strategy to foster trust and system acceptance (Thill et al., 2018). Findings on smart charging agents suggest that greater information disclosure enhances trust, even if it does not improve user performance (Attig et al., 2023; Schrills et al., 2024). Clearly communicating the rationale behind recommendations, for instance, regarding energy consumption estimates, real-time charging station availability (Shafipour & Stein, 2022); or estimated SOC, could reduce uncertainty and improve confidence in automation (Wang, Huang, Tu, & He, 2023). However, transparency alone may not ensure better understanding, highlighting the need for explainability beyond mere traceability.

Advancing EVT design towards more interactive and comprehensible systems (Stiegemeier et al., 2024) could strengthen trust where appropriate, supporting a smoother transition to EV-based long-distance mobility.

6.4. Limitations and future research

The sample of the present study primarily consisted of experienced EV drivers recruited from online forums and public charging stations, likely overrepresenting individuals who are very familiar or even enthusiastic regarding EV technology and EVTs. This may limit the applicability of findings to less experienced drivers or those still hesitant to adopt EVs. For instance, the low association of SRC and range stress might not be directly transferable to inexperienced EV drivers. Moreover, the present sample had a particularly high ATI score ($M = 4.92$) exceeding the averages reported in a previous study for a quota-representative sample ($M = 3.61$) and the male subsample contained therein ($M = 4.13$; Franke et al., 2019). Thus, results regarding ATI and EV experience might be affected by the sample composition. In future studies, more diverse participants with varying EVT experience and ATI should be recruited to assess the generalizability of findings.

The present study focused on the Tesla Trip Planner to minimize variability in system experience within the diverse landscape of

EVTs. However, this particular EVT, while widely used, may not be representative of all EVTs, rather, as trip-planning solutions differ across EVT ecosystems in design and interaction features (e.g., functionality, adaptability, or integration with third-party charging networks). Accordingly, the observed interaction patterns may partly reflect characteristics of a single, tightly integrated EVT ecosystem rather than general driver characteristics, and the prevalence and interpretation of interaction styles may therefore differ across ecosystems that vary, for example, in transparency, flexibility, or degree of automation integration. Future research should examine whether the findings generalize to alternative EVTs, including third-party apps and manufacturer-integrated systems.

For assessing the study variables, we utilized retrospective self-reports, which may be affected by recall bias or social desirability effects, particularly in assessing EVT adherence and trust-related appraisals. As data were collected via an online survey, the study design provides limited insight into drivers' situational reasoning and real-time decision processes during long-distance EV trips. Future research should therefore complement survey-based measures with real-time behavioral tracking or naturalistic driving data and, where appropriate, interview-based approaches to obtain more precise and context-sensitive insights into EVT interaction and range-related decision-making.

In addition, range utilization was operationalized as participants' retrospectively reported lowest SOC prior to charging. While this indicator reflects an experienced minimum SOC, it may be situation-dependent (e.g., by trip characteristics or charging availability) and does not necessarily represent drivers' typical charging thresholds. Future research could therefore complement this operationalization with measures of average or situationally anchored charging behavior.

The cross-sectional correlational design of this study limits causal inferences about the relationships between variables, as unmeasured confounding variables may have influenced the results. Moreover, as all variables were assessed at the same point in time, directional assumptions were theoretically motivated rather than empirically tested. For instance, we assumed that perceived cooperativity predicted DEVTIS; however, the causal direction may be reversed or cyclical. Longitudinal designs or experimental manipulations (e.g., with varying system feedback characteristics or interaction affordances) would be needed to better evaluate causal links and examine long-term driver adaptation to EVT. Larger samples and multivariate modeling could further clarify unique and potentially interactive contributions of perceived cooperativity and DEVTIS to trust and system acceptance, enabling more robust estimation of unique variance contributions.

To further strengthen the conceptual foundation and measurement reliability of DEVTIS, future research should focus on refining and validating the DEVTIS scale. Despite high internal consistency, the current scale length and potential item redundancy suggest developing a shorter version and conducting factor-analytic validation in larger samples.

Beyond scale refinement, it would be valuable to investigate whether the tendency to accept or reject recommendations from decision-support systems or recommendation algorithms represents a relatively temporally constant interaction pattern in other human-automation contexts.

6.5. Conclusion

The present study introduced driver electric vehicle trip planner interaction style (DEVTIS) as a construct to capture individual differences in EVT interaction, contributing to research on human-automation interaction patterns. The results emphasize the importance of perceived cooperativity in shaping trust and system acceptance, reinforcing the role of cooperative system design in EVT development. While perceived cooperativity was significantly associated with adherence to EVT trip and charging stop recommendations, ATI and SRC were not, suggesting that interaction variables had a stronger impact than personal characteristics variables. Furthermore, the findings indicate that frequent modification of EVT recommendations, as captured by DEVTIS, was associated with lower trust and system acceptance. This suggests that manual intervention may contribute to a perceived misalignment between driver expectations and system performance, potentially undermining confidence in EVT guidance. Additionally, SRC demonstrated a weak association with range stress but showed no relationship with range utilization, emphasizing the complexity of driver-range interaction in range-related decision-making. Given our sample of experienced, tech-savvy EV drivers, these findings may not be fully transferable to the wider population of EV drivers. By integrating cooperative system design, transparency, and adaptive driver-centered features, EVTs may enhance trust and thereby improve driver support. Future research should explore how these elements can optimally balance automation with driver involvement to further advance electric mobility solutions.

CRediT authorship contribution statement

Beate Stattkus-Fortange: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Christiane Attig:** Writing – review & editing, Methodology, Conceptualization. **Christiane Wiebel-Herboth:** Writing – review & editing, Supervision, Project administration. **Thomas Franke:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the authors used ChatGPT 4.o in order to improve language quality. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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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. Self-constructed or adapted questionnaire scales

Appendix A1. Driver Electric Vehicle Trip Planner Interaction Style (DEVTIS)

1. If the trip planner suggests a charging stop, I always drive to it.
2. I change the suggested charging stops manually.
3. I often optimize the route planning manually.
4. I am trying to improve the trip planner's charging stop planning by making adjustments.
5. I try to plan better routes myself.
6. I prefer to select the charging stops myself.
7. I prefer to leave the planning of the charging stops completely to the trip planner.
8. I question the trip planner's recommendations.
9. I tend to simply follow the trip planner's recommendations on the long-distance trip.
10. I rely completely on the trip planner's charging stop planning.
11. I would never think of interfering with the trip planner's charging stop planning.
12. During the journey, I actively look for ways to realize better charging stop planning than the trip planner.
13. I examine the trip planner's recommendations critically.
14. I take the trip planning as a suggestion, not as a directive.

Appendix A2. Facets of System Trustworthiness (FOST)

1. The trip planner is reliable.
2. The trip planner's range and charging planning is precise.
3. The trip planner's range and charging planning is traceable.
4. I can trust the trip planner's range and charging planning.
5. I cannot depend on the trip planner's range and charging planning.

Appendix A3. Subjective Range Competence (SRC)

1. I can precisely estimate the range of my electric car under various conditions.
2. I know how far I can go on one battery charge.
3. I can precisely estimate the influence of different factors on the range of my electric car.
4. The range of my electric car is largely determined by factors over which I have no influence.
5. How far I can get with my electric car (what range I achieve) essentially depends on me.
6. The range I can achieve with my electric car depends largely on factors that I can control.
7. I know strategies that I can use in situations with low remaining range.

Appendix A4. Typical Experience of Range Stress on Long-Distance Trip (Range Stress)

1. During long-distance trips with my electric car, I am often concerned about the range.
2. I rarely worry about the remaining range.
3. I often think about the range.
4. I hardly ever have concerns about the range.
5. I check the range/charge level display frequently.
6. I hardly pay attention to the range/charge level display.
7. I'm still completely relaxed even though the battery is almost empty.

Appendix A5. E-Mobility Literacy

1. I deal intensively with the technology of my electric car.
2. I actually have hardly any technical background knowledge about my electric car.
3. I regularly use media to find out about e-mobility (e.g., blogs, podcasts, videos).
4. It's important for me to keep up to date with electromobility topics.

Data availability

The authors do not have permission to share data.

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